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Research on Intelligent Fabric Texture Classification Based on Mathematical Modeling and Image Processing

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ABSTRACT

Fabric texture recognition is a critical component in the automation of the textile industry, placing high demands on the perception and classification of complex texture features. To address the limitations of traditional methods—namely, low recognition accuracy and poor robustness in multi-category scenarios—this study develops an intelligent fabric texture classification system that integrates image processing with mathematical modeling. Experimental results demonstrate that the improved Principal Component Analysis-Fusion Convolutional Neural Network-Support Vector Machine (PFCS) algorithm achieves an average recognition accuracy of 94.2%. Notably, the classification accuracies for denim and coral fleece reach 96.4% and 95.9%, respectively. Five-fold cross-validation reveals a minimum model accuracy of no less than 91.7% across different data partitions, indicating strong generalization capability. This research offers a viable approach for high-precision, intelligent classification of multi-category fabric textures and exhibits significant potential for engineering applications.

KEYWORDS

fabric classification, automated fabric inspection, convolutional neural networks

INTRODUCTION

With the deep integration of the textile industry and intelligent manufacturing, automatic fabric texture recognition technology has become a vital enabler for intelligent quality inspection, fabric classification, and automation of production processes. High-quality texture classification enhances product consistency and finds extensive application in areas such as fabric traceability, automated sorting, and defect detection. Currently, the textile industry generally requires a fabric classification accuracy exceeding 90%, with error tolerances for certain high value-added products controlled within 5% [1]. These requirements necessitate greater accuracy and stability from existing algorithms [2,3].

However, most traditional fabric texture recognition methods depend on manual expertise or simple grayscale thresholding, which are inadequate for processing large-scale, multi-category, and highly variable image data in modern production environments. The rapid advancement of image processing technologies and machine learning methods has introduced innovative solutions for fabric texture classification [4,5]. Classic image feature techniques, such as the gray-level co-occurrence matrix (GLCM) and wavelet analysis, offer certain advantages for extracting local statistical information and frequency structures. Nevertheless, these methods lack sufficient expressive power when addressing complex scenarios involving blurred inter-class boundaries, strong texture repeatability, or indistinct local details [6].

Deep learning models have demonstrated strong performance in image recognition tasks, benefiting from end-to-end modeling capabilities and effective spatial information extraction. However, purely deep models are highly sensitive to the scale of training data and exhibit limited feature interpretability [7]. In application settings characterized by highly similar texture categories and limited sample sizes, issues such as overfitting and reduced generalization performance often arise.

To overcome these challenges, this paper proposes an intelligent fabric texture classification method that combines traditional feature engineering with deep neural network architectures. The goal is to enhance classification accuracy while maintaining stability, interpretability, and industrial deployment feasibility [8,9]. The primary innovations of this work include: (1) an adaptive grayscale transformation method that incorporates weight parameters related to texture complexity, thereby enhancing high-frequency texture structure information and feature sensitivity; (2) construction of a multi-dimensional feature space integrating GLCM and wavelet transform, with an improved principal component analysis (PCA) for efficient feature dimension reduction, addressing redundancy and collinearity among multi-source features; and (3) a hybrid classification framework that fuses Support Vector Machine (SVM) and Convolutional Neural Network (CNN) outputs using a confidence fusion mechanism, fully leveraging the boundary learning capabilities of shallow models and the spatial expressiveness of deep models to improve recognition accuracy and robustness in complex texture scenarios.

Recognizing the stringent real-time requirements of industrial production—particularly in high-speed assembly line detection—this study systematically analyzes the computational complexity and inference latency of the algorithm across varying feature dimensions, ensuring millisecond-level response times while maintaining high accuracy to meet practical industry needs. Moreover, the promotion of intelligent fabric classification is expected to substantially reduce labor costs associated with manual quality inspection, increase production efficiency, and minimize inspection variability due to human factors. These advancements are anticipated to yield significant social and economic benefits by elevating the overall intelligence of the industry [10-12].

In summary, this paper aims to develop an intelligent fabric texture classification system that satisfies precision requirements, offers industrial applicability, and delivers social benefits, thereby providing a practical pathway for high-precision recognition of multi-category and multi-scale fabrics.

MATHEMATICAL MODELING AND ALGORITHM CONSTRUCTION FOR INTELLIGENT FABRIC TEXTURE CLASSIFICATION

Fabric Texture Image Preprocessing Method

To ensure stable recognition accuracy across different sources, lighting conditions, and acquisition environments, systematic preprocessing is applied to the original fabric images to suppress noise and standardize image scale and grayscale characteristics. For original color images, conversion to grayscale is performed using a brightness weighting method to enhance sensitivity to high-frequency texture structures. Unlike the traditional Y-channel weighting, the improved grayscale function introduces an adaptive weighting coefficient based on texture complexity, as shown below:

$$
\begin{gathered}
I_g(x,y) = \alpha R(x,y) + \beta G(x,y) + \gamma B(x,y) \\
\alpha = \frac{s_R}{\sum_c s_c}, \quad \beta = \frac{s_G}{\sum_c s_c}, \quad \gamma = \frac{s_B}{\sum_c s_c}, \quad s_c = \lambda \frac{H_c}{\sum_k H_k} + (1-\lambda)\frac{V_c}{\sum_k V_k}
\end{gathered} \tag{1}
$$

Here, the weight parameters α, β, γ are computed from the global entropy and variance of each color channel and normalized to ensure stable grayscale conversion, enabling adaptive enhancement of texture gradient information, particularly in the green (G) channel for complex textures. *R*, *G*, and *B* represent the red, green, and blue channel values of the original image, respectively, and *I* denotes the pixel intensity in the converted grayscale image. To suppress salt-and-pepper and Gaussian noise introduced during acquisition, a composite median–wavelet joint filtering strategy is employed. A 5×5 median filter removes isolated noise points, followed by multi-scale wavelet denoising to decompose and reconstruct image details. An improved soft threshold function, incorporating the directionality of image texture, is introduced during wavelet threshold processing as follows:

$$\widehat{w}_{i,j} = \begin{cases} sign(w_{i,j}) \cdot (|w_{i,j}| - T_{i,j}) \cdot (\frac{|w_{i,j}|}{|w_{i,j}|+T_{i,j}})^{\delta}, |w_{i,j}| > T_{i,j} \\ 0, \qquad otherwise \end{cases}, \delta \in [0,1] \quad (2)$$

In this equation, $w_{i,j}$ represents the wavelet coefficient at position (i,j) after wavelet transformation. $T_{i,j}$ denotes the local adaptive threshold, and $\delta \in [0, 1]$ is a control parameter for detail preservation. Specifically, the proposed thresholding scheme introduces a scale-preserving attenuation factor, which adjusts the shrinkage strength of the wavelet coefficients. Coefficients with magnitudes below $T_{i,j}$ are fully suppressed, while coefficients exceeding the threshold are adaptively attenuated to balance noise suppression and texture detail preservation.

Feature Extraction and Modeling

The effectiveness of feature extraction in intelligent fabric texture classification directly influences subsequent model performance. Due to varying material structures, fabric images exhibit multi-scale and multi-directional texture patterns, making traditional single-description methods insufficient for comprehensive spatial and frequency characterization. To address this, a multi-dimensional feature space integrating grayscale statistics and multi-scale frequency domain information is constructed, with PCA used for optimization [13,14].

The study utilizes an improved GLCM approach to extract statistical texture features, in line with Ghosh's findings [15]. To overcome the directional sensitivity limitations of traditional GLCM, a weighted directional fusion strategy is introduced, processing four principal directions (0°, 45°, 90°, 135°) and generating a weighted, directionally invariant feature matrix as follows:

$$GLCM_f(i,j) = \sum_{k=1}^{4} w_k \cdot GLCM^{\theta_k}(i,j), \sum_{k=1}^{4} w_k = 1, w_k \geq 0 \quad (3)$$

Among them, w_k is the dynamic weight for each direction, automatically adjusted based on the energy distribution of image gradients, thereby enhancing adaptability to anisotropic textures. From the fusion matrix, statistics such as energy, contrast, and homogeneity are extracted to form a preliminary feature vector. To supplement spatial frequency information, the image undergoes two-dimensional discrete wavelet transform (DWT), yielding four sub-bands: LL (low-frequency approximation), LH, HL, and HH (high-frequency details). In the high-frequency sub-bands, a local response enhancement-based detail quantization strategy is proposed, increasing sensitivity to edge and texture directionality. For example, the HH sub-band energy feature is defined as follows:

$$E_{HH}^{enh} = \sum_{(x,y)} |HH(x,y)|^{\alpha} \cdot exp\left(-\frac{\|\nabla I(x,y)\|^2}{\beta}\right) \quad (4)$$

Among them, α the control parameter for high-response amplification, with a value greater than 1, β is a gradient suppression parameter, $\|\nabla I(x,y)\|$ which indicates the gradient amplitude at a given pixel. During feature fusion, PCA is employed to reduce dimensionality and mitigate the effects of high-dimensional redundancy and multicollinearity. The improved PCA scheme utilizes a weighted covariance matrix to enhance the discriminability of principal components. The reduced and fused features are then supplied as inputs to the SVM and CNN classification models, ensuring efficient and discriminative representation.

Classification Algorithm Design

The classification module is pivotal to the overall recognition accuracy and robustness of the intelligent fabric texture classification system. The diversity of fabric textures, nonlinear boundaries, and overlapping patterns present significant challenges for traditional shallow models [16,17]. Recent research shows that CNN-based classifiers, in conjunction with high-frequency signal processing techniques such as the short-time Fourier transform, excel at capturing detailed textural patterns, especially subtle surface differences [18].

Accordingly, this study constructs a hybrid classification framework combining SVM and CNN using a confidence fusion mechanism, thereby enhancing nonlinear recognition ability while preserving interpretability and generalization. SVM, grounded in structural risk minimization, is well-suited for high-dimensional, small-sample pattern recognition tasks [19,20]. To accommodate the multi-source, heterogeneous feature space and uneven sample distributions of fabric textures, an adaptive scale adjustment term is incorporated into the kernel function, ensuring robust boundary discrimination even in the presence of sample sparsity. The improved radial basis kernel function is as follows:

$$K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad \sigma = \kappa \cdot median_{p,q} \| x_p - x_q \| \quad (5)$$

Among them, σ is adaptively determined based on the median pairwise distance of the training samples, which provides a robust estimate of the global kernel width under uneven sample distributions. This adaptive scaling strategy enhances class discrimination while reducing the sensitivity of the SVM to outliers. Consequently, a convolutional neural network is introduced as the primary classifier to extract spatial local structural information from the original images. The network architecture consists of three convolutional layers, each followed by max pooling and Dropout, to bolster nonlinear modeling and prevent overfitting. Convolution kernel size is set to 3×3, stride to 1, and the ReLU activation function is employed to optimize gradient propagation. The Dropout ratio is fixed at 0.5 to regulate model complexity.

During training, a cross-entropy loss function with label smoothing is used to mitigate overfitting and enhance generalization. Unlike traditional hard label loss functions, label smoothing introduces confidence perturbations, reducing the network's tendency to overfit noise labels. The loss function is defined as:

$$L_s = -\sum_{i=1}^{C}\left[(1-\varepsilon)\cdot y_i + \frac{\varepsilon}{C}\right] log(\hat{y}_i) \tag{6}$$

Among them, y_i is the unique hot encoding of the true label, $\hat{y}_i$ is the model output probability, ε and is the smoothing coefficient The value is 0.1, C and is the number of categories. This strategy guides the model to learn structural relationships among classes while emphasizing the target class. The update strategy is as follows:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{7}$$

Among them, θ_t represents the neural network parameter vector at the t-TH iteration. $\hat{m}_t$ and $\hat{v}_t$ represent the bias correction terms for the first and second moment estimates, η is the learning rate, and ε is a numerical stability term. AMSGrad enforces a non-decreasing variance estimate, preventing training instability due to excessive learning rates.

The integrated classification strategy leverages the strengths of shallow and deep models via a confidence threshold fusion system: CNN serves as the main classifier, outputting class probability distribution of each category P. If the highest confidence $max(p_i)$ exceeds a predefined threshold T, the CNN prediction is accepted; otherwise, the SVM performs secondary classification. The overall algorithm flow is depicted in Figure 1.

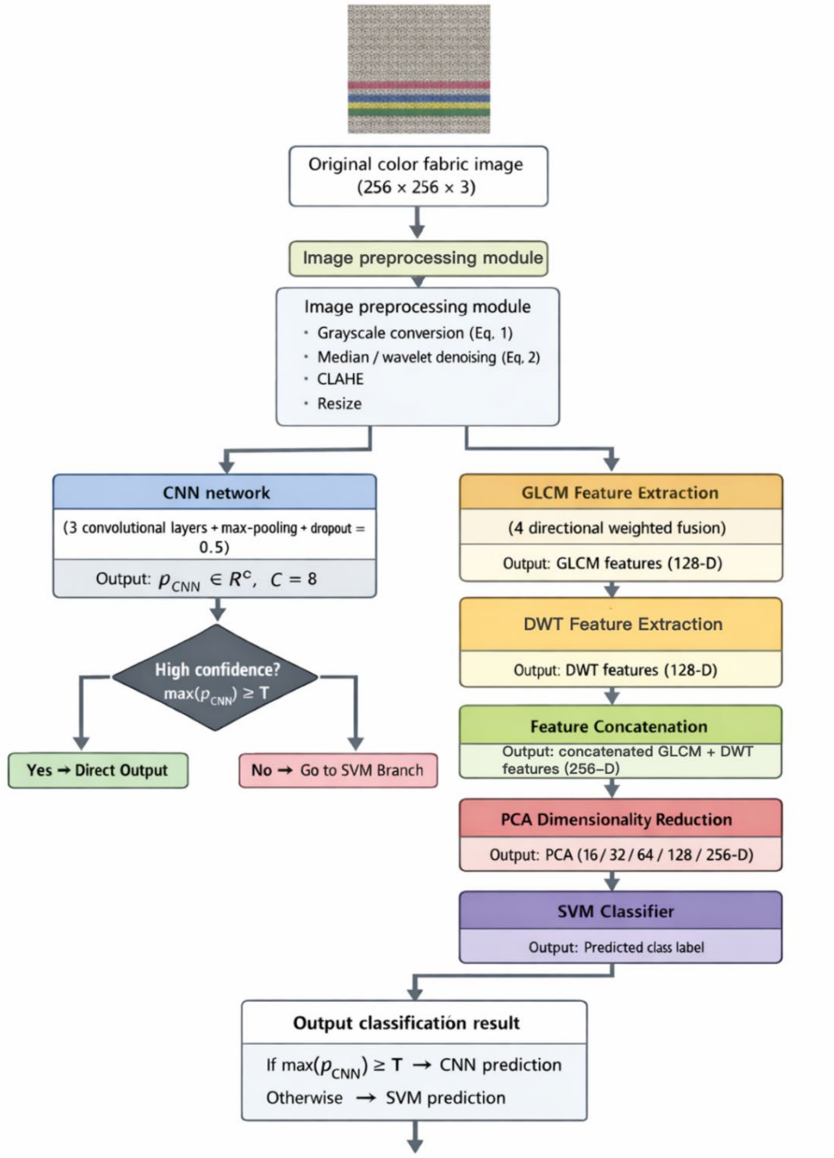

Figure 1. Comprehensive Algorithm Flow

In summary, the classification module combines the boundary constraints of SVM and the deep feature extraction of CNN, supported by a confidence scheduling mechanism and label smoothing, to enhance overall system performance, robustness, and generalization in challenging texture scenarios.

SYSTEM IMPLEMENTATION AND EXPERIMENTAL ANALYSIS

Experimental Dataset Construction

The experiments were conducted at the Image Intelligence Laboratory of a university in Suzhou, Jiangsu Province, from October 2024 to January 2025. A total of 720 fabric images were collected, representing eight common fabric types used in apparel and home textiles: cotton twill, nylon taffeta, polyester Oxford, woolen fabric, chiffon, denim, Tencel, and coral fleece. Each fabric type included samples from three different manufacturers. Image acquisition spanned various lighting conditions—morning, noon, and evening—to maximize data diversity and environmental robustness. The dataset was labeled and partitioned into training (70%), validation (15%), and test (15%) sets. The sample distribution is detailed in Table 1.

Table 1. Dataset Sample Distribution

Fabric Type	Total Samples	Training Set	Validation Set	Test Set
Cotton Twill	90	63	13	14
Nylon Taffeta	90	62	14	14
Polyester Oxford	90	65	12	13
Woolen Fabric	90	64	13	13
Chiffon	90	61	14	15
Denim	90	63	13	14
Tencel	90	66	11	13
Coral Fleece	90	64	13	13
Total	720	508	103	109

Labeling was performed by two professional engineers with over three years of textile industry experience, covering texture category, surface structure grade, and preliminary weaving method annotation to ensure high industry relevance. Benchmark methods for comparison included GLCM+SVM [13], DWT+SVM [15], and CNN-based classifiers [6], all retrained on the same dataset under unified settings for fair evaluation.

Experimental Results Analysis

Performance Analysis of Different Algorithms Across Texture Categories

To assess algorithmic performance in multi-category fabric texture recognition, three alternative model architectures were compared. The proposed PFCS algorithm, which fuses principal component features with a CNN-SVM hybrid model, demonstrated superior recognition performance across all eight fabric types, with accuracy rates exceeding 91%. Particularly, denim and coral fleece achieved accuracies of 96.4% and 95.9%, respectively. In contrast, the CNN model performed below 90% on low-contrast fabrics like woolen and chiffon, and traditional GLCM+SVM and DWT+SVM methods performed notably worse, especially on challenging textures. Table 2 presents a detailed comparison.

Table 2. Performance Analysis of Different Algorithms by Fabric Type

Fabric Type	GLCM+SVM Accuracy (%)	DWT+SVM Accuracy (%)	CNN Accuracy (%)	PFCS Accuracy (%)
Cotton Twill	84.6	87.5	91.1	95.3
Nylon Taffeta	82.1	86.3	88.7	93.6
Polyester Oxford	85.4	89.2	90.3	94.1
Woolen Fabric	78.9	83.1	89.6	92.7
Chiffon	81.0	84.6	87.2	91.5
Denim	88.2	90.5	93.1	96.4
Tencel	80.5	85.9	89.7	93.8
Coral Fleece	86.7	88.0	92.3	95.9
Average Accuracy	83.4	86.9	90.3	94.2

These results confirm that the PFCS algorithm outperforms single-model approaches, especially in complex and low-contrast scenarios, ensuring high classification stability and broad applicability.

Analysis of Feature Dimension and Classification Performance

The relationship between feature dimensionality and classification performance was systematically examined, evaluating training time, inference latency, and model stability (as measured by the standard deviation of accuracy across random seeds) for various models and feature dimensions (16, 32, 64, 128, 256). Results, detailed in Table 3, show that PFCS maintains superior stability (standard deviation 0.6–0.7) and low latency (<10 ms at 256 dimensions) compared to other methods, supporting industrial real-time deployment. In contrast, traditional methods exhibited greater instability and inefficiency, especially at higher dimensions. Overall, PFCS not only delivers high accuracy but also excels in stability and computational efficiency, underscoring its practicality for engineering deployment.

Table 3. Feature Dimension vs. Classification Performance

Feature Dimension	GLCM+SVM Stability/Time (ms)/Latency (ms)	DWT+DT Stability/Time (ms)/Latency (ms)	PCA+SVM Stability/Time (ms)/Latency (ms)	PFCS Stability/Time (ms)/Latency (ms)
16	4.7 / 130 / 12	4.2 / 110 / 10	3.5 / 95 / 9	1.2 / 88 / 7
32	3.9 / 180 / 15	3.6 / 135 / 12	2.8 / 112 / 10	0.9 / 98 / 7
64	3.2 / 240 / 18	3.1 / 165 / 14	2.4 / 130 / 11	0.7 / 112 / 8
128	2.9 / 340 / 21	2.7 / 190 / 16	2.2 / 160 / 13	0.6 / 127 / 9
256	2.8 / 490 / 27	2.6 / 250 / 20	2.1 / 205 / 17	0.6 / 140 / 10

Model Generalization Ability Evaluation

To assess generalization across diverse data partitions, five-fold cross-validation was performed. As shown in Table 4, PFCS achieved a minimum accuracy of 91.7% and the lowest fold variance (2.3%), far surpassing alternative models. In contrast, GLCM+SVM and DWT+DT recorded minimum accuracies below 82% and higher variances, indicating weaker generalization. These findings confirm the strong transferability and generalization of the PFCS model in real-world industrial environments.

Table 4. Model Generalization Ability Evaluation

Model Name	Minimum Accuracy (%)	Fold Variance (%)	Robust Coverage (%)
GLCM+SVM	78.6	9.2	40
DWT+DT	81.4	7.5	60
PCA+SVM	85.2	5.1	80
PFCS	91.7	2.3	100

Confusion Analysis Between Fabric Types

To visualize misclassification trends, a normalized error heatmap based on the confusion matrix was constructed for the test set (see Figure 2).

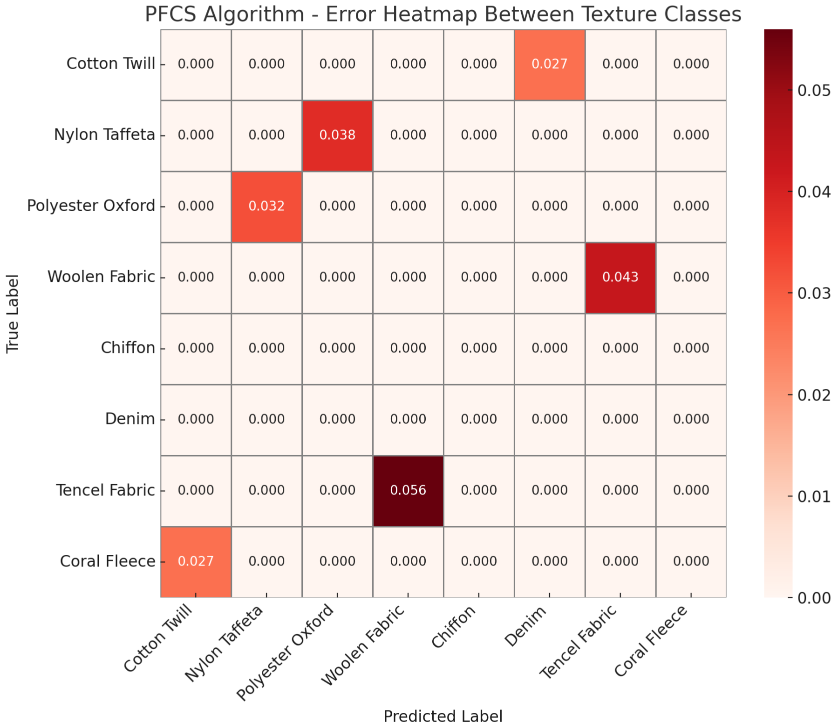

Figure 2. Confusion Matrix: Error Distribution Across Fabric Types

Errors predominantly occurred between similar fabric pairs: woolen fabric was misclassified as Tencel in 4.3% of cases, and vice versa in 5.6%, reflecting the challenge of distinguishing these textures. Misclassifications between nylon taffeta and polyester Oxford were 3.8% and 3.2%, likely due to similar smoothness and reflectivity. Coral fleece was misclassified as cotton twill in 2.7% of cases, possibly due to blurred edge transitions during preprocessing. For most other categories, misclassification rates were below 3%, indicating concentrated, rather than random, error patterns and affirming the PFCS model's high category-level accuracy.

Ablation Study and Robustness Testing

Additional experiments examined the impact of model structure parameters, convolution kernel size, and robustness to challenging conditions:

- **Dropout Ratio:** Models were trained with Dropout values of 0.3, 0.5, and 0.7 to assess overfitting control.
- **Convolution Kernel Size:** Performance was compared for 3×3 and 5×5 kernel configurations.
- **Robustness Test (Extreme Lighting and Occlusion):** The test set included 160 images under extreme lighting (overexposure, high reflection, low light) and 140 partially occluded images (fabric patches, folding, etc.).

- **Model Complexity:** Parameter counts, floating-point operations (FLOPs), and inference latency per image were measured.

Results are summarized in Table 5.

Table 5. Model Performance and Resource Consumption Under Different Experimental Settings

Setting	Average Accuracy (%)	Stability (Std)	Accuracy (Extreme Lighting) (%)	Accuracy (Occlusion) (%)	Parameters (M)	FLOPs (G)	Inference Latency (ms)
Dropout 0.3, Kernel 3×3	92.8	0.9	90.2	88.7	2.31	5.8	8.7
Dropout 0.5, Kernel 3×3	94.2	0.6	92.3	91.5	2.31	5.8	9.0
Dropout 0.7, Kernel 3×3	93.5	0.8	91.0	89.2	2.31	5.8	9.5
Dropout 0.5, Kernel 5×5	93.9	0.7	91.8	90.8	4.12	9.7	14.6

When Dropout is set to 0.5, the model achieves the highest average accuracy (94.2%) and exhibits superior performance under extreme lighting and occlusion, demonstrating strong generalization and robustness. Although the 5×5 kernel offers marginally greater robustness, it increases parameter count and computational load by 78.4%, with a corresponding rise in inference latency to 14.6 ms. For industrial deployment efficiency, the 3×3 kernel is preferred. Under default settings (Dropout 0.5, 3×3 kernel), the PFCS model contains approximately 2.31 million parameters, requires 5.8 GFLOPs per inference, and achieves a latency of 9.0 ms, meeting real-time assembly line requirements.

CONCLUSIONS

As the textile industry accelerates its transition to intelligent manufacturing, automatic recognition and classification of fabric textures have become central to smart manufacturing and quality inspection. Addressing the challenges of unstable classification accuracy and poor adaptability to multi-category fabrics in complex environments, this study introduces an intelligent fabric texture classification system integrating image processing and mathematical modeling.

The proposed PFCS algorithm achieved an average recognition accuracy of 94.2% across eight common fabric types, with denim and coral fleece accuracies reaching 96.4% and 95.9%, respectively. Feature dimension control experiments revealed that, within the 64–128 dimension range, the PFCS model sustains high accuracy, maintains training time within 127 ms, inference latency below 10 ms, and a stability standard deviation of only 0.6–0.7. This demonstrates its suitability for industrial-grade, real-time deployment. Nevertheless, the PFCS model has certain limitations in distinguishing low-contrast fabrics, such as lightweight materials.

Future research directions include: (1) introducing multimodal texture descriptors and integrating infrared, near-infrared, or hyperspectral imaging to improve detail capture in low-contrast fabrics; (2) incorporating self-supervised or few-shot learning mechanisms to enhance generalization in limited-data scenarios; and (3) developing local attention mechanisms for specific fabric categories to increase sensitivity to subtle texture differences.

In terms of hardware integration, future work will explore: (1) combining high-resolution industrial cameras with area array scanners for detailed texture acquisition; (2) deploying multi-spectral or hyperspectral sensors for comprehensive microstructure and material property analysis; (3) integrating 3D laser scanning to extract microscopic surface undulations; and (4) employing flexible tactile sensors to capture fabric softness and elasticity, supporting multi-dimensional intelligent classification. From an engineering perspective, the PFCS system can be seamlessly incorporated into existing textile quality inspection lines, with modular deployment allowing flexible configuration based on production speed and spatial constraints. Its low inference latency and modest hardware requirements ensure strong industrial viability, promising significant reductions in manual inspection costs and improvements in detection efficiency.

In conclusion, the intelligent fabric texture classification system presented herein not only delivers notable improvements in accuracy and efficiency but also provides a practical pathway for intelligent quality inspection and flexible manufacturing within the textile industry, offering broad industrial application prospects.

Author Contributions

Yunfan Yang and Ruizhi Zheng designed the study; all authors conducted the study; Yunfan Yang and Ruizhi Zheng collected and analyzed the data. Ruizhi Zheng and Yunfan Yang participated in drafting the manuscript, and all authors contributed to critical revision of the manuscript for important intellectual content. All authors gave final approval of the version to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work were appropriately investigated and resolved.

Conflicts of Interest

The authors declare no conflict of interest.

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