# Fabric Defect Detection Using Histogram Equalization and Convolutional Neural Network

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***Abstract*—Defect detection is a vital yet traditionally manual process in textile quality control, resulting in inefficiencies and inaccuracies. This study proposes an automated fabric defect detection method employing histogram equalization (HE) for image preprocessing and a ResNet-50-based convolutional neural network for classification. Experiments were performed on a dataset of 25,600 fabric images, with 15% allocated for validation and testing. Without HE, the model achieved 90.2% accuracy but predominantly classified images as "good," leading to low precision and recall for minority defect classes. With HE, overall accuracy dropped to 87.1% due to reduced recall for the "good" class; however, detection performance for low-contrast defects improved significantly, with higher recall and F1-scores. These results demonstrate that HE enhances the model's ability to differentiate subtle defect features despite a trade-off in accuracy caused by dataset imbalance. The proposed approach promises to reduce inspection time and cost in industrial settings. Future plans include extending the model's applicability to diverse fabric types, including solid dyed, yarn-dyed and printed fabrics, to ensure robustness and adaptability across various scenarios.**

***Keywords: fabric defect detection, histogram equalization, convolutional neural networks (CNN), resnet-50, textile quality control.***

## I. Introduction

The global textile industry is a trillion-dollar sector that not only provides livelihoods to millions of workers worldwide but also serves as a cornerstone of global trade. However, the labor-intensive nature of garment production poses significant challenges to scaling operations efficiently. One critical aspect is fabric defect detection, which directly impacts the quality, appearance, and durability of textile products. Traditionally, defect detection has relied on manual visual inspection—where fabric is unrolled on an inspection table—a method that is inherently inefficient, prone to human error, and achieves an accuracy of only 60–65% with detection rates limited to 15 meters of fabric per minute [1], [2]. Fatigue, subjectivity, and inconsistent evaluations further exacerbate these issues, leading to increased labor costs and wastage.

As market demands push for higher efficiency and precision, the textile industry is rapidly transitioning towards automated inspection systems [3]. Recent efforts have focused on integrating defect detection directly into the manufacturing process by attaching detection systems to knitting machines, thereby eliminating the need for separate inspection stations. Such innovations promise to reduce costs, improve throughput, and enhance quality control, ensuring manufacturers remain competitive in a fast-paced global market.

Over the years, numerous approaches have been explored for fabric defect detection, ranging from statistical and spectrum-based methods to traditional machine learning and advanced deep learning techniques [4]. In particular, Convolutional Neural Networks (CNNs) have emerged as the most effective, achieving accuracy levels exceeding 90% in controlled environments. However, several studies have highlighted limitations in existing CNN-based models. For instance, researchers have noted that these models often struggle to detect defects on fabrics with solid-dyed, yarn-dyed, and printed patterns due to complex, variable backgrounds and low contrast between defects and non-defective regions [5], [6]. Additionally, many approaches require extensive computational resources and large, diverse datasets to generalize well—a significant barrier for real-time, on-line quality control.

Recent advances in deep learning have further pushed the boundaries of fabric defect detection. For example, researchers have investigated transfer learning and attention mechanisms to enhance defect recognition in complex textile patterns [7]. In another study, multi-scale feature fusion was employed to better handle variations in fabric texture and color, resulting in improved detection of subtle defects [8]. Moreover, emerging techniques such as unsupervised and semi-supervised learning have been explored to mitigate the challenges posed by limited annotated datasets [9]. These advancements highlight the continuous evolution of automated inspection systems and underscore the need for robust preprocessing methods—like histogram equalization—to further improve CNN performance in diverse textile applications.

In response to these challenges, this research proposes integrating histogram equalization (HE) at the preprocessing stage with a deep learning framework based on ResNet-50 to improve defect detection specifically in grey fabrics. HE, as a contrast enhancement technique, is hypothesized to enhance feature visibility by redistributing pixel intensity values, thereby enabling the CNN to better distinguish subtle defect features. Unlike prior studies that focused solely on traditional CNN architectures, our approach evaluates the performance of ResNet-50 with and without HE to understand its impact on defect classification. This study also addresses the common gap of limited generalization in models trained on imbalanced datasets, as grey fabric defects often exhibit lower contrast and higher variability.

## II. Literature Review

The field of computer vision (CV) has revolutionized numerous industries by automating complex visual tasks, including defect detection. In the textile industry, CV-based systems have gained significant attention for their ability to identify fabric defects, replacing inefficient and error-prone manual inspection methods. Over the years, several approaches have been proposed, ranging from traditional statistical techniques to advanced deep learning-based models. While each has contributed to the development of automated defect detection, challenges such as handling complex patterns, noisy data, and varied defect types persist [10],[11].

Traditional methods for defect detection often relied on statistical and spectrum-based techniques, such as edge detection, histogram analysis, and wavelet transforms. These methods primarily focus on extracting low-level features like texture, color, and intensity variations. Although computationally efficient, these approaches struggle with diverse and intricate defect patterns commonly found in modern fabrics. Spectrum-based methods, while effective for periodic defects, are less capable of addressing irregularities, limiting their applicability in real-world scenarios. The advent of deep learning has largely addressed these limitations, providing powerful tools for learning complex patterns and achieving higher accuracy in defect detection tasks. Convolutional Neural Networks (CNNs) have emerged as the most promising deep learning architecture for defect detection [4],[12]-[14].

Anum Khowaja and Dinar Nadir (2021) proposed a MATLAB-based approach using histogram equalization to detect fabric defects by enhancing contrast between defective region and undefective region. Tested on smooth fabrics, the system achieved 90% fault categorization accuracy. However, its reliance on manual parameter tuning limited its applicability to diverse defect patterns and real-world scenarios [12].

Wai Hin Cheung and Qingping Yang (2024) developed CNN models based on GoogLeNet and ResNet50 for six defect classes. ResNet50 achieved superior accuracy (95.45%) compared to GoogLeNet (89.84%), highlighting the potential of transfer learning. Challenges included dataset imbalance and inconsistencies caused by uneven lighting, necessitating optimized hardware setups for deployment [10].

Suryarasmi et al. (2023) introduced FN-Net, a lightweight CNN designed for industrial use. FN-Net achieved an F1 score of 0.86, outperforming MobileNetV2 and DenseNet in efficiency and resource utilization. Despite its lightweight design, FN-Net's evaluation was primarily on synthetic datasets, leaving its robustness under real-world conditions untested [16].

Hatami Varjovi et al. (2022) proposed a customized CNN architecture for circular knitting fabrics, achieving 97% accuracy on a dataset of 13,820 images. This model outperformed pre-trained architectures like InceptionV3 and ResNet50. However, generalization to other fabric types remains a challenge, highlighting the need for further exploration [17].

Yuan et al. (2021) integrated a Convolutional Block Attention Module (CBAM) into Faster R-CNN, enhancing defect detection by refining feature extraction. Tested on a dataset with scratches, holes, and stains, the model achieved 95.31% accuracy but faced generalization challenges for printed and dyed fabrics due to dataset limitations [18].

Sharma et al. (2023) compared YOLOv5, YOLOv8, and MobileNetV2 on a seven-class defect dataset. YOLOv8 achieved the highest mAP (84.8%), excelling in accuracy and inference speed in comparison to 84.5% and 77.09% achieved by YOLOv5 and MobilenetSSD FPNLite respectively. However, it struggled with noisy and misaligned images, emphasizing the importance of robust preprocessing techniques [19].

Liu et al. (2019) introduced FabricNet, which incorporated Feature Pyramid Networks (FPN) and Deformable Convolutions (DC) into Faster R-CNN to address multi-scale defects. While achieving moderate success with a 62.07% mAP 97.37% AP50 on the DAGM 2007 dataset, the model struggled with subtle and complex patterns, necessitating more sophisticated training strategies [20].

Doe et al. (2020) explored the integration of attention mechanisms in CNNs for fabric defect detection, improving the model's focus on defective regions. Their approach achieved superior accuracy on patterned textiles but remained dependent on large labeled datasets, limiting its adaptability [7].

Zhang et al. (2019) proposed a multi-scale feature fusion technique to enhance defect detection across varied textures and colors. By combining low-level and high-level features, their model demonstrated improved robustness but required higher computational resources, posing deployment challenges [8].

Kumar and Gupta (2020) investigated semi-supervised learning for textile inspection, leveraging unlabeled data to enhance model generalization. While reducing reliance on manual annotations, their approach struggled with model drift when exposed to novel fabric designs, highlighting the need for more adaptive learning strategies [9].

## III. METHODOLOGY

This study proposes a systematic methodology to enhance fabric defect detection using histogram equalization as a preprocessing step combined with advanced CNN architectures. The methodology includes dataset preparation, image preprocessing, model selection, and performance evaluation. The detailed explanation of each step is as follows:

### *A. Dataset Preparation*

The dataset used for this research consists of 25,600 fabric images, each with a resolution of 64×64 pixels. It includes five classes: defect-free samples (good fabric) and four defect types: holes, scratches, stains, and thread errors. The number of images for each class is as follows: 23,170 images for the defect-free class, 337 images for holes, 837 for objects, 636 for oil spots, and 620 for thread errors. The dataset was collected from Kaggle, where it is widely used for fabric defect detection tasks. To ensure robust training and evaluation, the dataset is split into 70% for training, 15% for validation, and 15% for testing. However, the dataset is highly imbalanced, with the defect-free class (good fabric) comprising 90.5% of the images. This imbalance presents a challenge in model training, as it may bias the model towards the dominant class, potentially affecting the detection accuracy of the defect classes.

## B. Image Preprocessing

Preprocessing is a critical step to prepare the images for effective training and defect detection. It involves the following:

1) *Grayscale Conversion:* The input images, originally in RGB format, are converted into grayscale to reduce computational complexity while preserving critical defect information. A grayscale image represents intensity values where each pixel contains a single intensity level ranging from 0 (black) to 255 (white), unlike RGB images that store three intensity values for red, green, and blue channels. This conversion eliminates unnecessary color information while focusing on defect-relevant features [9].

2) *Noise Removal and Filtering:* During image acquisition, noise such as random pixel intensity variations can obscure defect patterns. A gaussian filter is applied to remove such noise while retaining the edges of the defects, ensuring that the processed images are clean and ready for analysis [9].

3) *Histogram Equalization:* Histogram equalization is employed to enhance the contrast of grayscale images by redistributing pixel intensity values. This method improves the visibility of subtle defects, particularly in low-contrast areas, enabling CNNs to extract features more effectively. The process adjusts the intensity range across the image, making defects more distinguishable from their surroundings [9].

4) *Normalization:* To ensure uniformity across the dataset, pixel intensity values are scaled to the range [0, 1] using min-max normalization. This step stabilizes the training process by standardizing the input data.

## C. Model Selection

For this study, ResNet-50 is chosen as the deep learning model for fabric defect detection. ResNet-50, a 50-layer deep residual network, is well-suited for feature extraction in complex image classification tasks. Its skip connections mitigate the vanishing gradient problem, allowing efficient training of deep networks while preserving important defect features.

ResNet-50's architecture enables it to detect both subtle and high-contrast defects in fabric images with improved precision. By leveraging residual learning, the model can differentiate between defect-free and defective regions more effectively, making it a suitable choice for defect detection in industrial applications.

## D. Evaluation Metrics

The performance of the selected CNN architectures is evaluated using standard metrics that provide a comprehensive assessment of classification and localization accuracy:

- Precision measures the proportion of correctly identified defects among all predicted defects, indicating the model's ability to avoid false positives [13].

$$\mathrm{P} = \frac{TP}{TP+FP} \tag{1}$$

- Recall assesses the proportion of actual defects correctly identified, reflecting the model's sensitivity to defect detection [13].

$$\mathrm{R} = \frac{TP}{TP+FN} \tag{2}$$

- F1 Score provides a harmonic mean of precision and recall, offering a balanced metric for overall performance evaluation [13].

$$\mathrm{F1} = 2 \times \frac{P \times R}{P+R} \tag{3}$$

## E. Comparative Analysis

In this study, a comparative analysis is conducted to evaluate the impact of histogram equalization (HE) on the performance of the ResNet-50-based CNN model for fabric defect detection. Two experimental setups are used: one with histogram equalization applied during preprocessing and the other without it. The models are evaluated using three standard metrics: precision, recall, and F1-score. Precision measures the proportion of correctly identified defects among all predicted defects, indicating the model’s ability to avoid false positives. Recall evaluates the proportion of actual defects correctly identified, reflecting the model's sensitivity to defect detection. The F1-score provides a harmonic mean of precision and recall, offering a balanced metric for overall performance evaluation. These metrics are computed for each defect class, allowing for a detailed assessment of the model’s ability to detect different defect types under both conditions. Additionally, the overall average precision, recall, and F1-score are analyzed to determine the effectiveness of HE in improving defect detection. The confusion matrices for both models will be analyzed to identify the number of false positives and false negatives, helping assess whether HE reduces misclassifications, particularly for low-contrast defects. This approach enables a comprehensive understanding of how histogram equalization influences the balance between detection accuracy and recall, highlighting any trade-offs that may exist between overall model performance and the detection of subtle defects in imbalanced datasets.

# IV. Results & Discussion

In this study, we evaluated the performance of a ResNet-50-based deep learning model for fabric defect classification across five defect categories: holes, objects, oil spots, thread errors, and good fabric. The model was trained and tested on a dataset containing 25,600 images, with 15% of the data (3,840 images) used for testing and another 15% for validation. To assess the impact of histogram equalization (HE) on model performance, we conducted experiments both with and without HE as a preprocessing step.

The model demonstrated a strong ability to classify defects, achieving high accuracy for the good fabric class due to its large number of samples. However, defect classes with fewer images (e.g., thread errors, oil spots, and holes) exhibited relatively lower performance, indicating challenges in learning discriminative features for rare defects. The application of histogram equalization (HE) improved feature contrast, leading to a noticeable increase in classification performance, particularly for defect categories with subtle visual variations.

To evaluate the model's performance on the test dataset, we present the confusion matrix, which provides a detailed breakdown of the model's predictions across the five fabric defect categories. The confusion matrix highlights the number of correctly classified samples (diagonal values) and misclassifications (off-diagonal values), offering insights into the model's strengths and weaknesses. The confusion matrices are presented in Fig. 1 & Fig. 2, illustrating the distribution of correct and misclassified predictions across the defect categories for models trained with and without histogram equalization.

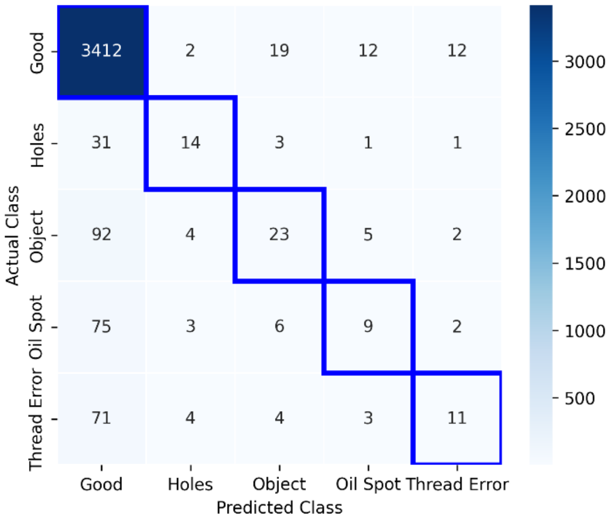


*Fig. 1. Confusion matrix without histogram equalization*

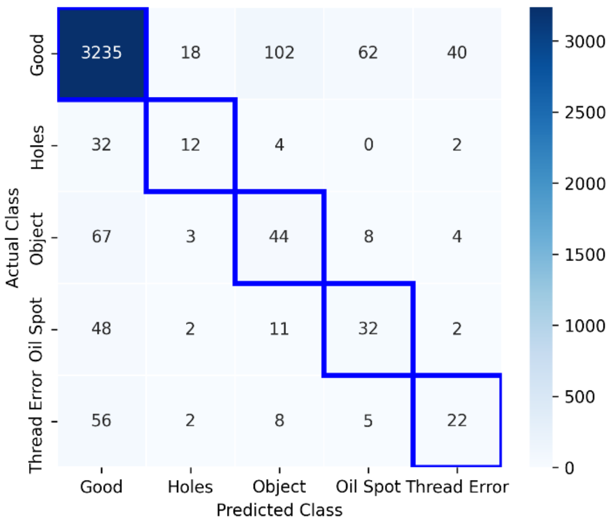


*Fig. 2. Confusion matrix with histogram equalization*

The confusion matrix provides a comprehensive view of the classification performance of the model, both with and without histogram equalization (HE). In both matrices, the rows represent the true classes, and the columns represent the predicted classes. The diagonal entries indicate the number of instances correctly classified, while off-diagonal entries show the misclassifications.

In the case of the model without HE, we observe that the "Good" fabric class dominates the matrix, with the highest number of correct predictions (3412), which is expected due to its dominance in the dataset. However, defects such as holes, objects, oil spots, and thread errors have relatively high misclassification rates, as evidenced by the off-diagonal entries. For example, objects are often misclassified as good fabric (19 times) or oil spots (12 times), while thread errors are misclassified as oil spots (75 times) or good fabric (71 times).

With the application of histogram equalization (HE), there is a noticeable shift in the confusion matrix. The "Good" fabric class still has the highest accuracy but with more misclassifications, particularly with objects (102) and oil spots (62). Defect classes like holes, objects, and thread errors show an improvement in their correct classifications, especially for objects (44) and thread errors (22). However, some defects, such as holes, are still misclassified as good fabric (32), and oil spots remain prone to misclassification (48).

By comparing the confusion matrices for models trained with and without histogram equalization (HE)**,** we analyze the impact of preprocessing on classification performance. The HE-enhanced model demonstrates improved recognition of minority classes, indicating that contrast enhancement helps the network learn more distinguishable features.

To further assess the model's performance, we present key classification metrics—precision, recall, and F1-score—for each defect class. The following tables show these metrices for each class, comparing the results with and without histogram equalization (HE).

*TABLE 1. CLASSIFICATION TABLE BEFORE HE*

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Good | 0.927 | 0.986 | 0.956 | 3457 |
| Holes | 0.519 | 0.280 | 0.364 | 50 |
| Object | 0.418 | 0.183 | 0.254 | 126 |
| Oil Spot | 0.300 | 0.095 | 0.145 | 95 |
| Thread Error | 0.393 | 0.118 | 0.181 | 93 |
| accuracy | | | 0.902 | 3821 |
| macro avg | 0.511 | 0.332 | 0.380 | 3821 |
| weighted avg | 0.879 | 0.902 | 0.885 | 3821 |

*TABLE 2. CLASSIFICATION TABLE AFTER HE*

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Good | 0.946 | 0.936 | 0.941 | 3457 |
| Holes | 0.324 | 0.240 | 0.276 | 50 |
| Object | 0.357 | 0.349 | 0.353 | 126 |
| Oil Spot | 0.296 | 0.337 | 0.315 | 95 |
| Thread Error | 0.314 | 0.237 | 0.270 | 93 |
| accuracy | | | 0.871 | 3821 |
| macro avg | 0.447 | 0.420 | 0.431 | 3821 |
| weighted avg | 0.861 | 0.861 | 0.860 | 3821 |

While the classification tables provide the precise numerical values for precision, recall, and F1-score for each defect class, the following bar charts offer a visual comparison that makes it easier to discern trends and trade-offs.

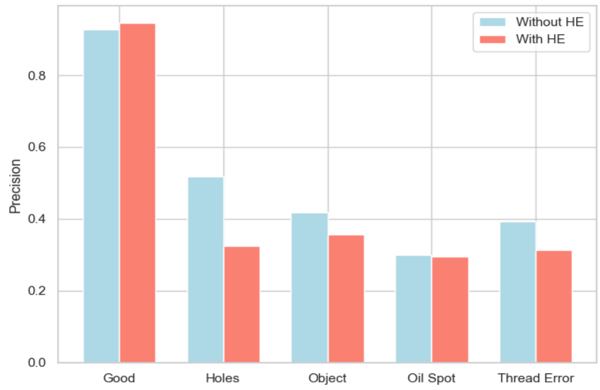


*Fig. 3. Precision comparison before and after HE*

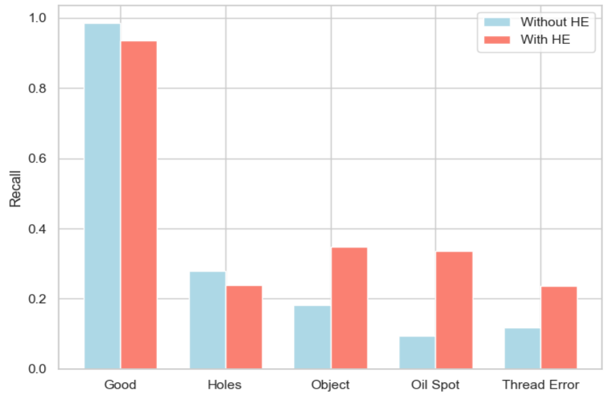


*Fig. 4. Recall comparison before and after HE*

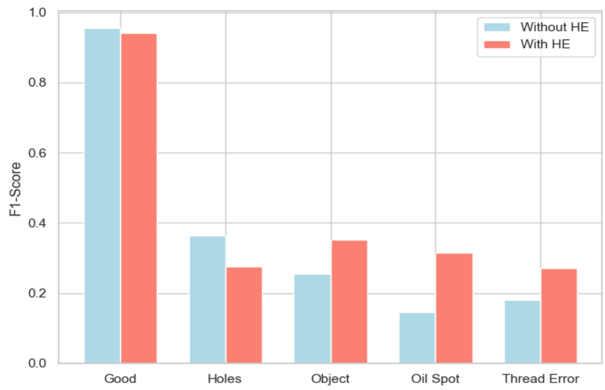


*Fig. 5. F1-score comparison before and after HE*

By comparing the classification metrics for models trained with and without histogram equalization (HE), we analyze the effect of preprocessing on defect detection accuracy. Histogram equalization improves contrast, potentially leading to better feature extraction and classification, particularly for minority defect classes.

The results, presented in a classification chart, illustrate that HE generally enhances recall and F1-score for defect categories with lower contrast, such as object, oil spot and thread errors. However, for the dominant class (good fabric), the impact is minimal, as the model already performs well on this class. Interestingly, the detection of the "good fabric" class has slightly reduced after applying HE. This could be due to the increased contrast causing the model to misclassify some of the good fabric images as defects.

The results reveal several important trends. Without histogram equalization (HE), the ResNet-50 model is heavily biased toward classifying images as “good,” as evidenced by a high precision of 92.7%, a near-perfect recall of 98.6%, and an F1-score of 95.6% for the Good class (support = 3457), resulting in an overall accuracy of 90.2%. However, the minority defect classes exhibit much lower performance—for example, the Object class achieves only 41.8% precision, 18.3% recall, and an F1-score of 25.4%, while Oil Spot and Thread Error classes show similarly low scores.

After applying HE, the model’s behavior shifts. The precision for the Good class increases slightly to 94.6%; however, its recall decreases to 93.6%, and the F1-score drops to 94.1%. This indicates that while the model is more cautious (leading to fewer false positives), it now misses some instances of the Good class that were previously correctly classified. In contrast, for defect classes that suffer from low contrast—such as Object, Oil Spot, and Thread Error—the application of HE improves the detection performance. For instance, the recall for the Object class increases dramatically from 18.3% to 34.9%, with the F1-score rising from 25.4% to 35.3%. Similarly, Oil Spot recall improves from 9.5% to 33.7% (F1-score from 14.5% to 31.5%), and Thread Error recall improves from 11.8% to 23.7% (F1-score from 18.1% to 27.0%). However, for the Holes class—already a high-contrast category—both precision and recall decrease (from 51.9% and 28.0% to 32.4% and 24.0%, respectively).

These observations suggest a clear trade-off: HE reduces the model’s tendency to over-generalize by classifying nearly all images as “good,” thereby improving the detection rates of minority, low-contrast defect classes, even though it leads to a slight degradation in the performance of the dominant class. Overall accuracy declines to 86.1% with HE, largely due to the reduction in recall for the Good class, which constitutes about 90% of the dataset. Nonetheless, the improvement in precision, recall, and F1-score for defects that are visually similar to Good images (except for holes) indicates that HE enhances the model’s capacity to differentiate subtle defect features.

## V. Conclusion

This study explores the impact of histogram equalization (HE) on fabric defect detection using a ResNet-50-based convolutional neural network. Without HE, the model achieved high overall accuracy (90.2%) but exhibited bias toward the dominant “good” class, leading to poor classification of low-contrast defects. Applying HE improved the model’s ability to distinguish subtle defect features, increasing recall and F1-scores for object, oil spot, and thread error classes. However, it slightly reduced overall accuracy (87.1%) due to a decline in recall for the majority class. These findings highlight the trade-off between general accuracy and defect detection capability in imbalanced datasets.

The proposed approach demonstrates the potential of automated defect detection in textile manufacturing, reducing reliance on manual inspection. Future work will focus on further optimizing preprocessing techniques and extending the model to diverse fabric types, ensuring broader applicability in real-world industrial settings.

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