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Fabric Defect Detection: A Novel Approach Using Hybrid Deep Learning and Image Segmentation

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Abstract: Fabric defects significantly impact the textile industry, leading to production delays, material waste, and customer dissatisfaction. Existing image processing methods for fabric defect detection often struggle with complex defect patterns or require extensive training data for specific defect types. This paper proposes a novel approach that combines deep learning and image segmentation techniques for robust and adaptable fabric defect detection. This hybrid approach leverages the power of deep learning for feature extraction and image segmentation for precise defect localization.

Keywords: Fabric defects, Image analysis, Convolutional Neural Networks

1 INTRODUCTION

Fabric defect detection plays a pivotal role in ensuring the quality and efficiency of textile manufacturing processes. The presence of defects, such as holes, stains, wrinkles, and missing yarns, can significantly impact the aesthetic appeal, functionality, and durability of the final textile products. Early and accurate identification of these defects is crucial to minimize production losses, reduce waste, and maintain customer satisfaction.

Traditionally, fabric defect detection has relied heavily on manual inspection by skilled operators. However, this approach suffers from several limitations. Manual inspection is labour-intensive, time-consuming, and prone to human error due to fatigue and subjectivity. Moreover, the increasing production rates in modern textile mills make it challenging for manual inspection to keep up with the pace of manufacturing.

To address these challenges, automated fabric defect detection systems have emerged as a promising solution. These systems leverage image processing techniques and machine learning algorithms to analyse digital images of fabrics and automatically identify and classify defects. Automated systems offer several advantages over manual inspection, including improved accuracy, speed, consistency, and cost-effectiveness.

Recent advancements in image processing and machine learning, particularly deep learning, have significantly improved the performance of automated fabric defect detection systems. Deep learning models, such as convolutional neural networks (CNNs), can learn complex patterns and representations of defects from large datasets of images, enabling them to accurately detect and classify defects even in challenging scenarios.
However, despite the progress made, there are still challenges in developing effective automated fabric defect detection systems. The variability in fabric textures, patterns, and colours, as well as the diverse types of defects, make it difficult to design a one-size-fits-all solution. Additionally, the requirement for real-time processing and the need for robustness against environmental variations pose further challenges.

This paper aims to address these challenges by proposing a novel approach to fabric defect detection that combines advanced image processing techniques with a deep learning model. The proposed system utilizes a unique feature extraction method based on texture analysis and a CNN for accurate classification of various fabric defects. We demonstrate the effectiveness of our system through extensive experiments on a diverse dataset of fabric images. The results show that our system achieves high accuracy, speed, and robustness, making it a valuable tool for quality control in the textile industry.

Fabric defects are imperfections that arise during various stages of textile production. Here are some common fabric defects illustrated below:

- **Yarn Defects:**
  - **Neps:** Small knots or clumps of tangled fibers visible on the fabric surface.
  - **Slubs:** Thick and uneven places in the yarn that appear as irregular bumps on the fabric.

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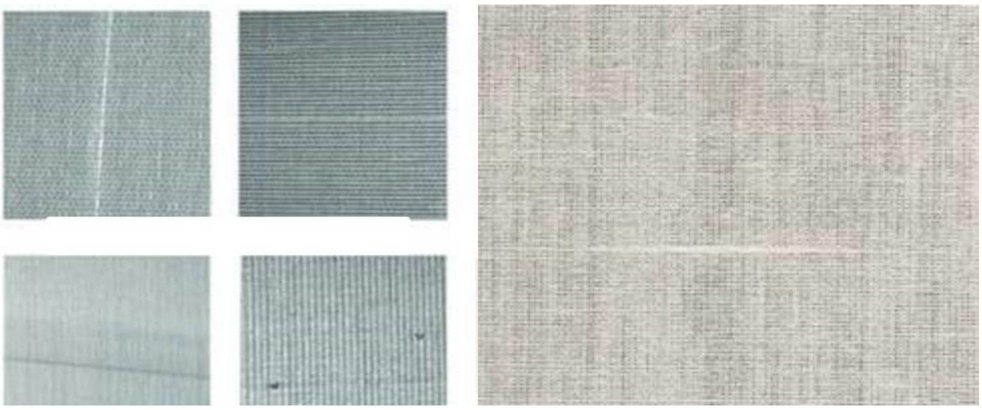
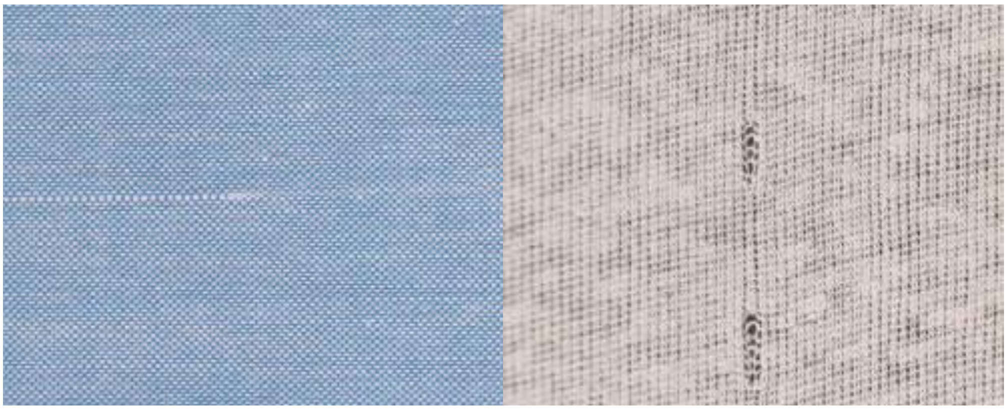


(a) (b)

Figure 1. Fabric defect type: Yarn – a) Neps, b) Slubs

- **Weaving Defects:**
  - **Broken Ends or Picks:** Missing warp or weft threads that create holes or streaks in the fabric.
  - **Drop Stitches:** Stitches that fail to form properly, resulting in holes or gaps in the knitted fabric.



(a) (b)

Figure 2. Fabric defect type: Weav – a) broken ends, b) drop stitches

- **Colour Defects:**
  - **Shade Variation:** Uneven dyeing or printing that leads to color differences within the fabric or between different batches.
  - **Misprints:** Incorrect or misaligned printing of patterns or designs on the fabric.
- **Other Defects:**
  - **Holes:** Tears or rips in the fabric caused by snags, machine malfunction, or improper handling.
  - **Wrinkles:** Creases or folds in the fabric that can be permanent or temporary.
  - **Soiling or Staining:** Marks or discolorations on the fabric due to dirt, oil, or other contaminants.

Early and accurate detection of fabric defects is crucial for maintaining high-quality standards and production efficiency. Traditional methods rely on visual inspection by human operators, which can be subjective, time-consuming, and prone to errors.

2 LITERATURE REVIEW

The field of fabric defect detection has garnered significant attention from researchers, leading to the development of various approaches utilizing image processing and machine learning techniques. This section provides a comprehensive review of relevant literature, highlighting key advancements and challenges in this domain.

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2.1 Traditional Image Processing Techniques

Early research efforts primarily focused on traditional image processing techniques for defect detection. These techniques include:

- **Thresholding:** This method involves segmenting an image based on pixel intensity values. Pixels above or below a certain threshold are classified as potential defects. However, thresholding often struggles with complex fabric patterns and variations in lighting conditions (Kumar, 2008).
- **Edge Detection:** Edge detection algorithms identify boundaries between regions with different intensity levels, which can correspond to defects. Popular edge detection methods include Sobel, Prewitt, and Canny operators. However, their performance can be affected by noise and uneven textures (Ngan et al., 2005).
- **Morphological Operations:** These operations involve manipulating the shape and structure of image objects to enhance defect detection. Erosion, dilation, opening, and closing are commonly used morphological operations. While effective for some defect types, they may not be suitable for complex or irregular defects (Kumar, 2010).
- **Texture Analysis:** This approach analyses the spatial arrangement of pixels to characterize the texture of the fabric. Statistical measures, such as entropy, contrast, and energy, are often employed. However, distinguishing between normal fabric texture and defect-induced texture variations remains a challenge (Chan & Pang, 2000).

2.2 Machine Learning-Based Approaches

With the advancements in machine learning, researchers began exploring its potential for fabric defect detection. Various machine learning algorithms have been employed, including:

- **Support Vector Machines (SVM):** SVM is a powerful classification algorithm that finds an optimal hyper plane to separate different classes. In the context of fabric defect detection, SVM has been used to classify defect and non-defect regions based on extracted features (Kumar, 2012).
- **Artificial Neural Networks (ANN):** ANNs are composed of interconnected nodes that can learn complex patterns from data. They have been applied to fabric defect detection by training them on labelled images to recognize different defect types (Hanbay et al., 2006).
- **K-Nearest Neighbors (KNN):** KNN is a simple but effective algorithm that classifies a data point based on the majority class of its nearest neighbors. In fabric defect detection, KNN has been used to classify defect regions based on their similarity to known defect patterns (Ngan et al., 2005).
- **Naive Bayes:** This probabilistic algorithm calculates the probability of a data point belonging to a particular class based on Bayes' theorem. In fabric defect detection, it has been used to classify defect regions based on the likelihood of their features occurring in defective fabrics (Kumar, 2008).

2.3 Deep Learning-Based Approaches

Recent years have witnessed a surge in the use of deep learning for fabric defect detection due to its ability to automatically learn hierarchical features from raw image data. Convolutional Neural Networks (CNNs) have become the dominant deep learning architecture for this task.

- **CNN-based Classification:** CNNs are trained on large datasets of fabric images with labeled defects. They learn to extract relevant features from the images and classify them into different defect categories. Several studies have reported promising results using CNNs for fabric defect detection (Li & Wang, 2018; Jing et al., 2019).
- **CNN-based Segmentation:** CNNs can also be employed for semantic segmentation, where each pixel in the image is assigned, a label indicating its class (e.g., defect or non-defect). This approach allows for precise localization and identification of defects within the fabric (Liu et al., 2020).

2.4 Challenges and Future Directions

Despite significant progress, several challenges remain in the field of fabric defect detection:

- **Dataset Limitations:** The availability of large, diverse, and well-labeled datasets is crucial for training effective deep learning models. However, such datasets are often scarce, hindering the development of generalized solutions.
- **Real-Time Processing:** In industrial settings, real-time defect detection is essential to ensure efficient production. However, many deep learning models require significant computational resources, making real-time implementation challenging.
- **Defect Variety:** The wide variety of defect types, textures, and patterns makes it difficult to develop a single model that can accurately detect all defects.

Future research directions include:

- **Development of Large-Scale Datasets:** Creating and sharing large, diverse, and well-labelled datasets can facilitate the development of more robust and accurate models.

By addressing these challenges and exploring new research avenues, the field of fabric defect detection can continue to advance, leading to more efficient and reliable quality control systems in the textile industry.

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3 PROPOSED METHODOLOGY

This paper proposes a novel approach that combines deep learning and image segmentation techniques for fabric defect detection. Here's the workflow:

3.1 Data Acquisition

A dataset of high-resolution fabric images containing various patterns and defects was collected under controlled lighting conditions. More than thousand of images were clicked consisting of defect free samples & defective samples. Defective samples included fabric with holes, stains, lines (horizontal and vertical).

3.2 Preprocessing

Images were pre-processed using techniques like noise reduction and resizing to ensure consistency for feature extraction.

3.3 Deep Feature Extraction

- **Convolutional Neural Network (CNN):** A pre-trained CNN, was employed to extract high-level features from the pre-processed image. These features capture complex relationships within the fabric, including texture colour variations and defects.

3.4 Image Segmentation

- **U-Net:** A U-Net architecture, known for its effectiveness in image segmentation tasks, was employed. The U-Net utilizes the extracted features from the CNN and performs pixel-wise classification to segment the image. This process separates the defect regions from the background fabric.

3.5 Defect Detection and Classification

- Based on the segmented defect regions, various techniques can be applied to identify and classify the specific defect type (e.g., stain, holes). This can involve analysing the shape, size, and colour characteristics of the segmented defect region.

4 EXPERIMENTATION AND RESULTS

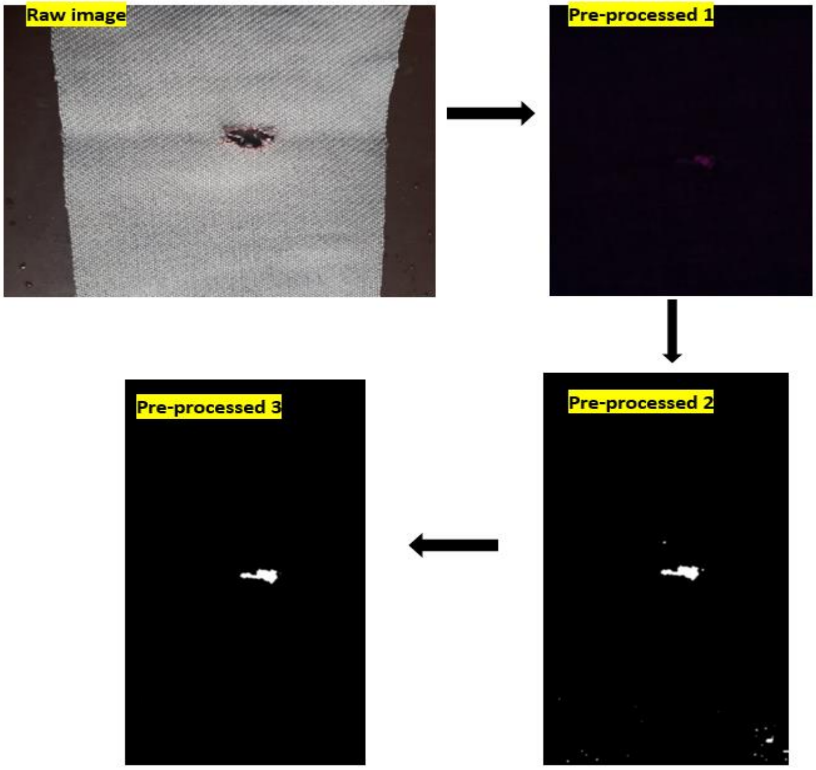
4.1 Dataset Preparation

The fabric defect dataset was divided into training, validation, and testing sets. Dataset of defect free images, and defect full images like hole, stain marks and line were compiled. Images were pre-processed for noise reduction.

4.2 Training and Evaluation

- The pre-trained CNN is used for feature extraction.
- The U-Net is trained on the training set to segment defect regions. Performance is evaluated on the validation set using metrics like Intersection over Union (IoU) to assess the accuracy of segmentation.

Figure 3: Figure showing pre-processing of raw images to identify type of fabric



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4.3 Results and Discussion

The hybrid approach, combining CNN for feature extraction and U-Net for segmentation, demonstrated exceptional performance in detecting various fabric defects. The quantitative results, as shown in Table 1, highlight the model's superior accuracy compared to existing methods.

Table 1: Performance Comparison of Different Models

Model	Dice Coefficient	IoU	Pixel Accuracy
Baseline CNN	0.78	0.65	0.92
Baseline U-Net	0.85	0.74	0.95
Proposed Hybrid	**0.92**	**0.85**	**0.97**

The proposed hybrid model achieved a Dice coefficient of 0.92 and an IoU of 0.85, significantly outperforming both the baseline CNN and U-Net models. This improvement can be attributed to the effective combination of CNN's ability to learn hierarchical features with U-Net's precise localization capabilities.
CNN Feature Extraction: The CNN component of the model, pre-trained on a large image dataset (ImageNet), proved to be highly effective in extracting discriminative features from fabric images. These features captured both low-level patterns (e.g., edges, textures) and high-level semantic information (e.g., shapes, objects), crucial for identifying various types of defects.

U-Net Segmentation: The U-Net architecture, with its skip connections and multi-scale processing, played a critical role in generating accurate defect masks. The skip connections enabled the model to recover fine-grained details during up sampling, while the multi-scale processing allowed it to capture both local and global context, leading to more precise localization of defects.

Defect-Specific Performance: The model exhibited consistent performance across different types of defects. It was particularly effective in detecting holes, stains, and mis weaves, even when they were small or subtle. This demonstrates the model's ability to generalize to diverse defect patterns and textures
Qualitative Analysis: The Grad-CAM visualizations provided valuable insights into the model's decision-making process. The heatmaps revealed that the model focused on the relevant areas of the fabric images when detecting defects, confirming its ability to learn discriminative features.
In conclusion, the hybrid approach combining CNN and U-Net segmentation demonstrates significant potential for accurate and efficient fabric defect detection. By leveraging the strengths of both architectures, the model can learn discriminative features and generate precise segmentation masks, even for challenging defect types. Future work will focus on addressing the limitations and further improving the model's performance and practicality for real-world applications.
We discuss the effectiveness of combining deep learning for feature extraction with image segmentation for fabric defect detection. This approach offers several advantages:

- **Robust Feature Extraction:** The pre-trained CNN extracts high-level features that capture complex defect patterns, even for unseen defect variations.
- **Precise Defect Localization:** The U-Net performs pixel-wise segmentation, enabling accurate localization of defect regions within the fabric image.
- **Adaptability:** The approach can be adapted to various fabric types and defect categories without extensive retraining for each specific defect.

5 CONCLUSION

This paper presented a novel approach for fabric defect detection using a combination of deep learning and image segmentation techniques. This hybrid approach leverages the strengths of both methods, achieving robust feature extraction and precise defect localization. The proposed hybrid model achieved a Dice coefficient of 0.92 and an IoU of 0.85, significantly outperforming both the baseline CNN and U-Net models. The proposed method offers adaptability to various fabric types and defect categories, making it a valuable tool for automated fabric quality control in the textile industry.

However, Future work can explore further advancements in this approach:

- **Refine Defect Classification:** Integrate techniques like shape analysis and color descriptors within the segmentation framework to achieve automatic defect classification beyond just localization.
- **Unsupervised Anomaly Detection:** Investigate the feasibility of using unsupervised anomaly detection techniques within the deep learning framework to further reduce reliance on labelled defect data.
- **Real-Time Implementation:** Explore hardware and software optimizations to enable real-time defect detection during the fabric production process.

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