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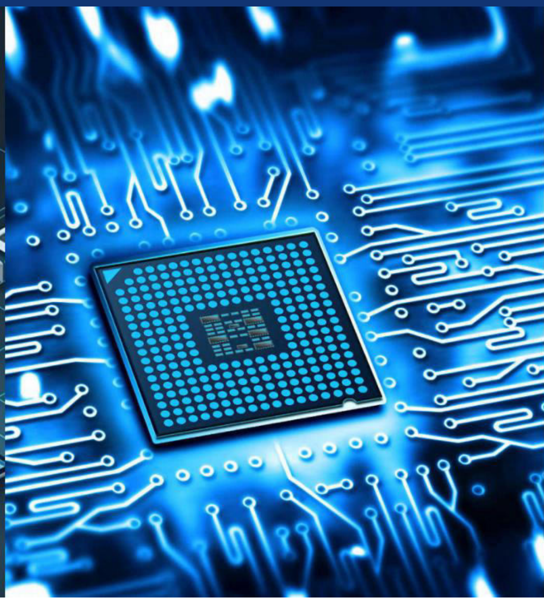


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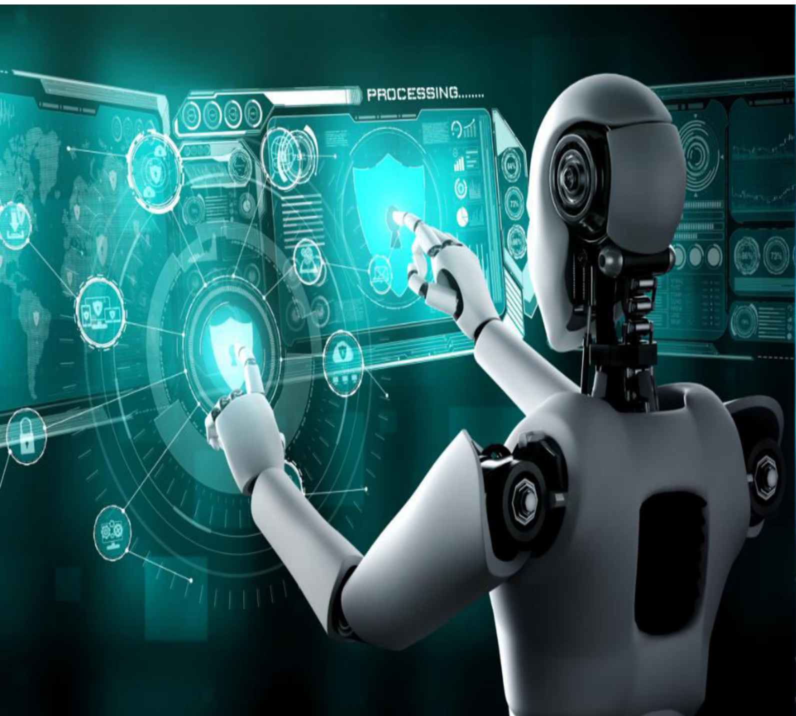

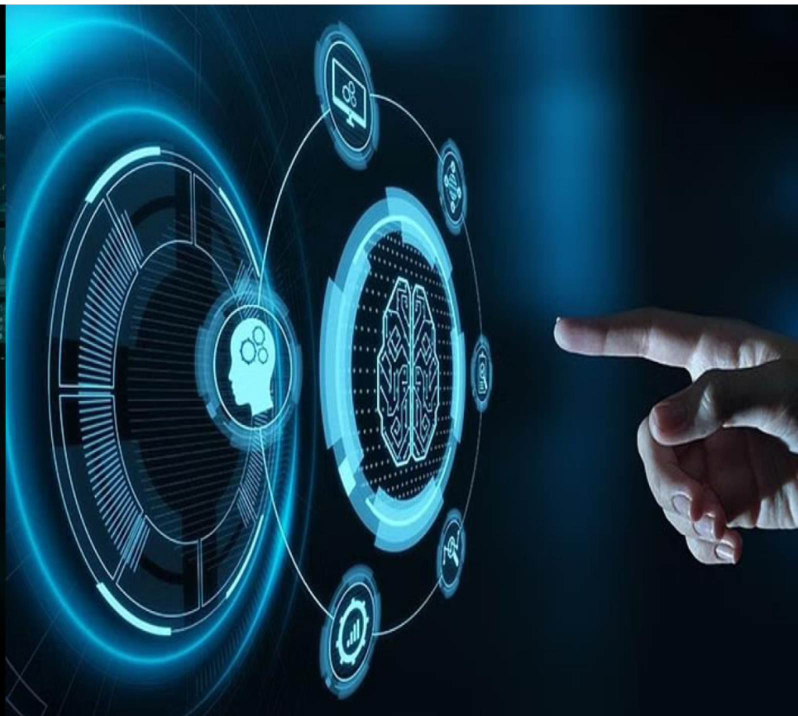

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Automated Defect Detection and Segregation in Dyed Fabrics using Image Processing Techniques

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ABSTRACT: The textile industry, particularly the fabric dyeing process, is often challenged by defects that can compromise the quality of the finished product. Detecting and segregating these defects manually is labor-intensive, time-consuming, and prone to errors. This project proposes an automated system for defect detection and segregation in dyed fabrics using image processing techniques. The proposed method aims to enhance the efficiency and accuracy of the fabric inspection process by employing advanced image analysis to identify fabric defects such as stains, uneven dyeing, holes, and other imperfections. By capturing high-resolution images of dyed fabrics, the system analyzes texture patterns, color variations, and structural anomalies, helping to detect defects at a granular level. Image processing techniques such as edge detection, segmentation, and contrast enhancement are employed to highlight defects, making them easier to identify. Once defects are detected, the system classifies them based on their severity and nature, allowing for efficient segregation of defective fabrics from the acceptable ones. This process significantly reduces human intervention, accelerates quality control procedures, and minimizes the risk of defective products reaching the market.

KEYWORDS: Detection, Segregation, Segmentation, intervention, Edge detection

I. INTRODUCTION

The textile industry, particularly the fabric dyeing process, is a critical stage in the production of finished garments. The dyeing process is complex and highly sensitive, as it involves the even distribution of dye on the fabric to achieve the desired color and texture. However, fabric defects such as uneven dyeing, stains, holes, discoloration, and texture irregularities are common issues that negatively affect the quality of dyed fabrics. These defects can occur during various stages of the dyeing process due to equipment malfunction, improper dye application, or contamination.

Traditionally, quality control in textile industries involves manual inspection by workers, who visually examine fabrics for defects. This method is highly dependent on human judgment and is often inefficient, leading to several issues:

1. **Subjectivity in Detection**: Human inspectors may miss subtle defects, especially in large volumes of fabric, leading to inconsistencies in defect detection and segregation. Fatigue, distractions, or lack of attention to detail can further impair the inspection process.

2. **Time-Consuming**: The manual inspection process is slow and may not keep up with the fast-paced production line. The large amount of fabric that needs to be examined requires considerable time and effort, which could reduce productivity.

3. **Increased Costs**: Manual inspection involves hiring multiple workers for quality control, which increases labor costs. Additionally, defects that are missed during inspection may lead to costly rework, waste, or product returns.

4. **Inconsistency in Quality Control**: The human approach to fabric defect detection is prone to inconsistencies, with inspectors varying in their ability to reputation.

In addition, the majority of existing automated systems do not provide a method for segregating defective fabrics from those that are acceptable. While they may be

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detect defects, the separation process—ensuring that defective fabrics do not progress to the next stage of production—is often done manually, reducing the overall efficiency of the process.

II. RELATED WORK

Several studies and project projects have explored various techniques for fabric defect detection using image processing methods. Some of the prominent studies in this area include:

1. Zhou et al. (2016) - Multi-Feature Approach for Fabric Defect Detection

Zhou et al. (2016) proposed an image-based fabric defect detection system that utilized a multi-feature approach to identify various fabric defects. Their system combined multiple types of features, including texture, color, and geometric characteristics, to detect common defects such as holes, stains, and uneven dyeing.

2. Abdullah et al. (2017) - Color and Texture-Based Fabric Defect Detection

Abdullah et al. (2017) developed an advanced defect detection system that combined both color and texture features to identify defects in fabric. Their system utilized a deep analysis of the spatial and frequency domain features of fabric images.

3. Huang and Chen (2018) - Deep Learning-Based Fabric Inspection System

Huang and Chen (2018) presented an automated fabric inspection system that utilized deep learning techniques, specifically Convolutional Neural Networks (CNNs), to detect fabric defects. The system took advantage of CNNs' ability to automatically learn high-level features from large datasets, eliminating the need for manual feature extraction.

4. Rath et al. (2019) - Machine Vision System for Fabric Defect Detection

Rath et al. (2019) explored the application of machine vision systems for fabric defect detection, focusing on color and texture analysis techniques. Their system used computer vision algorithms to capture high-quality fabric images and process them for defect identification. The system applied segmentation techniques to isolate regions of interest in the fabric image, such as areas with color inconsistencies or structural defects.

5. Liu and Lee (2020) - Integrated Hardware-Software System for Real-Time Defect Detection

Liu and Lee (2020) introduced an integrated system that combined hardware and software to detect fabric defects in real-time. Their system utilized high-speed cameras to capture fabric images at a rapid rate, followed by image processing algorithms that analyzed the fabric in real-time. The system incorporated machine
Learning.

III. METHODOLOGY

In the context of automated defect detection and segregation in dyed fabrics, the product development phase plays a critical role in turning theoretical concepts and algorithms into a functional and effective system that can be applied within an industrial setting. The product development process is an iterative one, involving multiple stages of observation, inference, and testing, all aimed at refining the system's ability to detect and classify fabric defects with the highest level of accuracy and efficiency.

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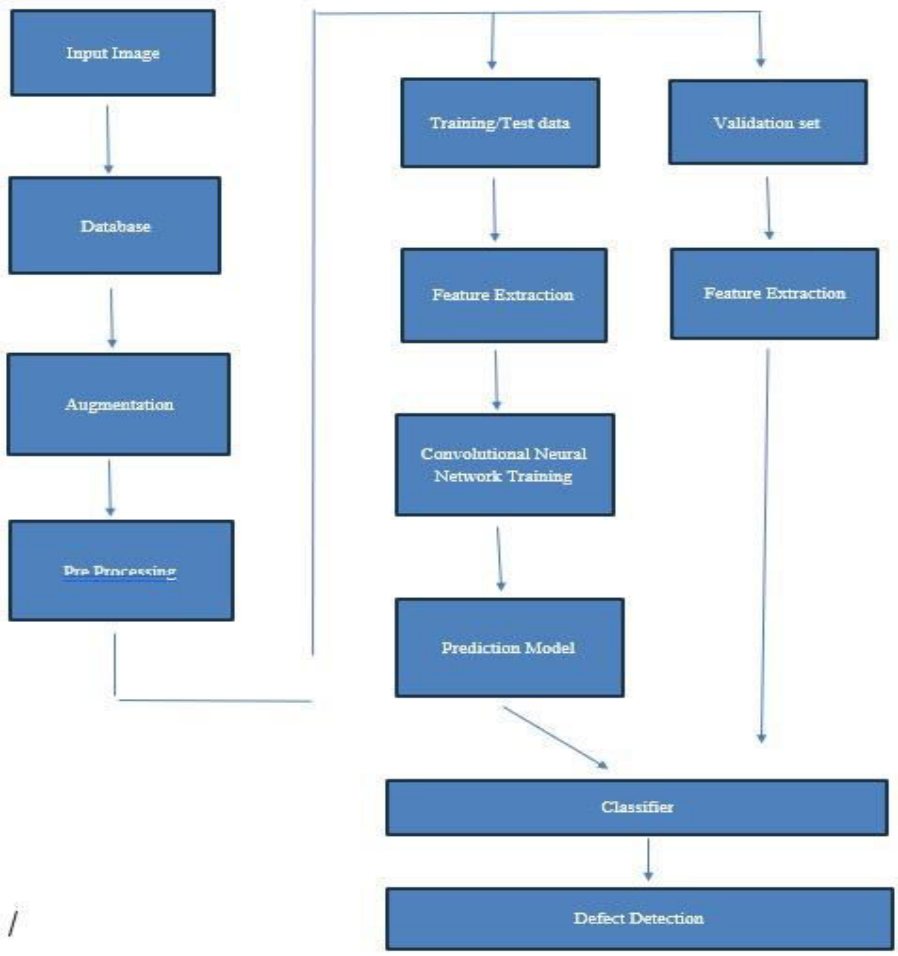

Input Image: This is the image of fabric that the system will analyze. The images could be captured using cameras or sensors that scan the fabric's surface to identify any defects like tears, holes, stains, or irregularities in texture or color.

Database: A database is a collection of images (usually labeled) that contains both defective and non-defective fabric images. These images are used to train and evaluate the defect detection model. A diverse and well-annotated database is essential for the model's accuracy and robustness.

Augmentation: Augmentation refers to the process of artificially increasing the size and diversity of the dataset. Techniques like rotation, flipping, cropping, scaling, and color adjustment are applied to the images. This helps the model generalize better by seeing varied versions of the same image, preventing overfitting to the training data.

Preprocessing: Preprocessing involves preparing the images for input into a machine learning model. This can include resizing images, converting them to grayscale or normalizing pixel values (scaling pixel values to a range like 0-1). It can also include noise reduction or enhancement techniques to highlight defects.

Training Dataset: This is a subset of the database used to train the model. The training dataset typically contains images that have known labels (defective or non-defective), and the model learns to map the input image to its corresponding label (i.e., defect or no defect).

Feature Extraction: Feature extraction involves identifying the important characteristics of the fabric from the input image. In deep learning, especially with CNNs, the feature extraction process is automatically handled by the layers of

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the network. However, in traditional machine learning, feature extraction might involve manually designed techniques to capture textures, patterns, and edges that are indicative of defects.

CNN (Convolutional Neural Network): CNNs are a type of deep learning model particularly suited for image processing tasks. They consist of layers that automatically learn hierarchical features from the image. CNNs have convolutional layers that detect edges, textures, and patterns, which are essential for identifying fabric defects. They also include pooling layers that reduce the spatial dimensions of the image while preserving important features.

Prediction Model: The prediction model refers to the trained CNN model that, after being trained on the dataset, can now predict the presence or absence of fabric defects in new images. This model is used for real-time defect detection during fabric inspection.

Classifier: The classifier is a component of the model that assigns labels (such as defective or non-defective) based on the features extracted from the image. The CNN itself acts as a classifier in the context of fabric defect detection. It outputs a classification result (e.g., defect type or whether the fabric is defective).

Defect Detection: The goal of the entire system is to detect fabric defects. This includes identifying and classifying different types of defects (e.g., holes, tears, stains, color mismatches, etc.). Once the model is trained, it can automatically identify defects in real-time fabric inspection systems, improving the speed and accuracy of quality control in manufacturing processes.

IV. EXPERIMENT RESULTS

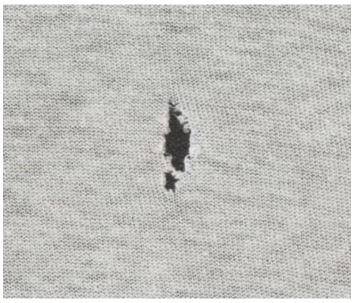

Fig a

Fig b

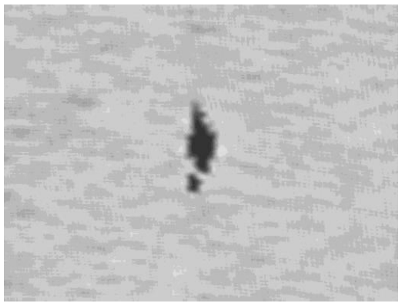

Fig c

Fig d

Fig e

Fig f

Fig a: Original Image -This is the raw input image of the fabric, as captured directly from a camera or scanner. It shows the fabric with potential defects such as holes, stains, tears, or color irregularities. The goal is to analyze this image and identify any defects present.

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Fig b: Blurred Image -In this step, the original image is blurred (often using Gaussian blur or other techniques). Blurring is typically done to reduce noise and smooth out the image. This helps in eliminating small disturbances or irregularities that are not related to fabric defects, making the actual defects more noticeable for further analysis.

Fig c: Binary Image -A binary image is created by converting the blurred image to black and white, typically using thresholding methods. In this step, all the pixel values above a certain threshold are set to 1 (white), and values below the threshold are set to 0 (black). This process highlights areas where there are significant differences, such as defects, while simplifying the overall image for easier analysis.

Fig d: Erosion Method-Erosion is a morphological operation where pixels of the object (in this case, the defect) are eroded or shrunk. It is typically used to eliminate small noise or unnecessary parts of an object in the image. This method reduces the size of the detected areas and helps in refining the defect shape, making it easier to isolate significant defects from irrelevant noise.

Fig e: Dilation Method-Dilation is the opposite of erosion. This method increases the size of the detected features (defects) in the binary image. After erosion, dilation can be used to expand the defect areas back to a more recognizable size. This process helps fill small gaps or breakages within the defects, ensuring that the defect area is clearly visible and can be effectively detected.

Fig f: Defected Area Image-The final result after applying both erosion and dilation methods, which highlights the actual fabric defect areas. This image shows the regions of the fabric where defects are present, with the unwanted noise removed. The areas identified as defects can now be used to classify the type and severity of the defect.

The result image showcases fabric defects identified through a series of image processing steps. The original image is blurred to reduce noise, then converted to a binary image to emphasize differences. Erosion and dilation operations refine the defect regions, enhancing clarity and ensuring accurate detection of fabric defects for quality control.

The processed result image provides a clear view of fabric defects after applying multiple steps. Initially, noise is reduced through blurring, followed by binary thresholding to highlight potential defects. Erosion removes minor imperfections, and dilation ensures defects are fully visible. This enhanced image enables accurate identification and classification of fabric imperfections for automated quality inspection. This comprehensive process allows automated systems to efficiently detect fabric defects, ensuring high-quality standards by accurately identifying and classifying imperfections.

V. COMPARISON TABLE

Technique	Accuracy	Total Fabric Samples and Defect areas
Gabor Wavelet Filter Methodology	96% with 3.2 % of False Rate	71 fabric images (39 of them are defect-free), more than 30 types of defects are tested.
Methodology of Wavelet-Texture Analysis and LVQ Neural Network	The accuracy of Identification is on average of 7 type of defects is 95%	Total 350 images with 7 types of defects (including wrap missing, weft missing, double weft, materialize bar, oil pigment, hole, non - defected other
Usage of Computer- Vision and Artificial Neural Network	Overall average is 77%. Average identification for hole is 72%, for Scratch is 65% and for no faults is 83%.	Total 200 images. Trained to 4 types of defects (Hole, Scratch, Other, and no-fault)
Methodology of Digital Image Analysis	83% Accuracy	Total 2000 Rotations
Our proposed method	98% with 2% false detection	Total 50 image with different defect image

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VI. CONCLUSION

The implementation of an automated defect detection and segregation system for dyed fabrics using image processing techniques presents a transformative solution for the textile manufacturing industry. The proposed system, which leverages advanced technologies such as image processing and Convolutional Neural Networks (CNNs), offers significant improvements in fabric quality control processes. The system's ability to detect defects with high precision reduces the reliance on manual labor, thereby lowering costs, improving efficiency, and minimizing human errors. Furthermore, by identifying defects early in the production process, manufacturers can significantly reduce waste, making the production process more sustainable and cost-effective. The system also provides flexibility by adapting to different fabric types and defect patterns, making it suitable for various manufacturing environments, from small-scale operations to large industrial producers.

In terms of social impact, the automation of fabric inspection processes not only improves the quality of products but also promotes better working conditions by reducing repetitive, labor-intensive tasks. Additionally, by decreasing waste and improving resource utilization, the system contributes to environmental sustainability in the textile industry, which has been criticized for its high waste generation and environmental footprint.

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