"MODEL BASED APPROACH ON TEXTILE QUALITY CONTROL USING IMAGE PROCESSING WITH ANN"

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Abstract: The textile industry is undergoing a significant revolution propelled by computer technology and continuous development. This paper explores the integration of image processing techniques, particularly through MATLAB software, in quality control within textile manufacturing. Leveraging computer technology and artificial neural networks, this approach enables the rapid and precise detection of fabric defects, ultimately enhancing production quality. The utilization of image processing offers a promising path for future development, ensuring high-quality products through efficient fault detection and correction.

Keywords: Computer technology, Quality control, Image processing, MATLAB, Artificial Neural Network, Textile Industry.

1. Introduction:

In the textile industry, various fabric processes are utilized to produce apparel and other outputs for specific markets, including household items and automotive sectors. However, these processes often lead to the occurrence of flaws or defects in the final products, particularly during knitting activities. These flaws result in additional costs and potential financial losses due to customer complaints, returns, and undervalued items. To maintain high standards, it's crucial to address textile flaws through inspection operations, which serve to identify issues and prevent the distribution of subpar materials. Imaging and image processing methods are being researched for offline and online visual examination of fabric to detect flaws efficiently.

2. Research Objectives of the Study:

The study aims to develop an automated online fault detection system using image processing, replacing human-based offline systems. Objectives include improving textile quality, reducing errors, gathering real-time performance data, enhancing manufacturer credibility, and creating tools for analyzing textile images to improve well-being.



3. Research Methodology

The study utilized secondary and current data along with advanced tools and computer techniques to achieve its goals. MATLAB software was employed for image processing algorithms. Fabric inspection aims to address texture segmentation and defect identification. The algorithm used includes filtering, histogram analysis, thresholding, segmentation, morphological operations, and an Artificial Neural Network classifier for fabric flaw identification.

4. Literature Review:

Here's a concise summary of the key insights from the reviewed studies:

1. **Shahrabadi et al. (2022)**: They emphasize the significance of computer vision and machine learning methods, particularly deep learning, in automating fabric fault detection processes. The transition towards automation aims to minimize human error and improve efficiency in quality control operations.

2. **Rebhi et al. (2016)**: This study proposes a unique technique that combines local homogeneity and mathematical morphology for fabric defect identification. Morphological operations play a crucial role in analyzing fabric structures and detecting imperfections.

3. **Agilandeswari et al. (2014)**: Their research focuses on fabric quality testing using image processing filters to identify defective clothing materials. Mathematical morphology techniques are employed to analyze fabric textures and detect faults accurately.

4. **Khowaja and Nadir (2019)**: They provide insights into automated fabric fault detection approaches, emphasizing the importance of pattern recognition algorithms and image processing techniques. Their study aims to enhance the accuracy and efficiency of defect detection systems.

5. **Almeida et al. (2021)**: This research explores fabric defect detection using deep learning techniques, particularly convolutional neural networks (CNNs). Strategies such as false negative reduction and rejection zone techniques are proposed to improve defect detection accuracy.

6. **Patel et al. (2013)**: The study proposes a digital image processing technique for fabric fault detection, aiming to reduce manufacturing expenses and time associated with manual inspection. MATLAB tools are utilized for image analysis and defect identification.

7. **Sabeenian et al. (2012)**: They highlight the importance of computer vision-based defect detection systems in handloom silk fabrics. An automated defect identification system could enhance product quality and efficiency in textile manufacturing.



8. **Priya et al. (2011)**: The paper presents a novel approach for fabric defect detection using digital image processing, focusing on segmenting fabric images and identifying defects through mathematical morphology techniques.

9. **Jmali et al. (2014)**: Their research focuses on fabric defect detection using image processing and neural networks. They propose a systematic approach involving image acquisition, preprocessing, database training, and testing for defect identification.

10. **Jacintha and Karthikeyan (2019)**: The study conducts a survey on various fabric defect detection methods, including local uniformity, mathematical morphology, Gabor filters, and Histogram of Oriented Gradients (HOG). These methods aim to enhance fabric quality control through automated defect detection processes.

11. ******Bangare et al. (2017)******: Address the necessity for automated fabric inspection to maintain quality and reduce costs associated with manual inspection. Their proposed fabric fault detection system employs segmentation and RGB to HSV techniques for image processing, aiming to improve detection accuracy and streamline the inspection process. The study emphasizes the importance of efficient algorithms and consistent lighting conditions to ensure accurate fault detection.

12. ** Shih (2022)** : Explores the application of digital image processing in the textile and garment industry to enhance garment quality inspection. The study emphasizes the integration of computer vision technologies, such as neural networks and support vector machines, to improve the accuracy and efficiency of garment detection. It also discusses the challenges and future directions in virtual fabric simulation and intelligent clothing recommendation systems, highlighting the importance of advancing research in this field for the apparel industry's progress.

5. Flow of system:

The research gap is in exploring how various preprocessing and feature extraction methods affect classification accuracy. Specifically, comparing normal vs. median filters for preprocessing and expanding feature extraction beyond color movement to include histogram, shape, and texture features. Despite achieving 95.20% accuracy, there's room for improvement. The proposed system, with 98.3% accuracy, suggests further investigation into these techniques and their combinations for better performance in image classification. Figure 1 shows system flow chart of proposed system.



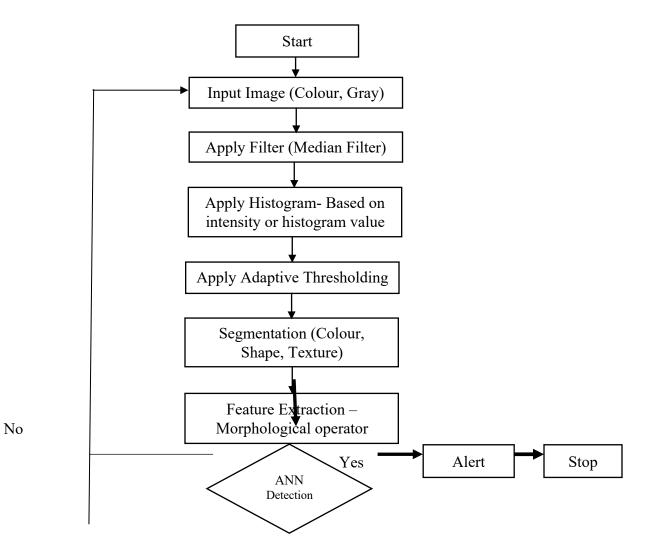


Figure 1 Flow of System



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Here's a summary of the steps:

- 1. Retrieve an image from the database, which can be color or grayscale.
- 2. Apply a Median filter to remove noise from the image.
- 3. Analyze the image properties using a histogram.
- 4. Determine appropriate intensity values.
- 5. Implement Adaptive thresholding on the image.
- 6. Perform segmentation based on criteria such as Color, Shape, and Texture.
- 7. Extract features to identify significant components.

8. Use Morphological operators to highlight significant regions, emphasizing boundaries with specific colors.

9. Employ an Artificial Neural Network for precise detection and categorization of fabric faults, moving to the next image if no faults are detected.

6. Results

The results obtained from different inputted images are summarized as follows: Figure 2: Original image used as input in MATLAB.

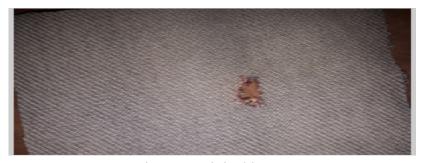


Figure 2 Original image Figure 3: Image after applying a median filter to eliminate noise.



Figure 3 Filter image

Figure 4: Segmented image extracted using Sobel and Canny-based segmentation approaches.



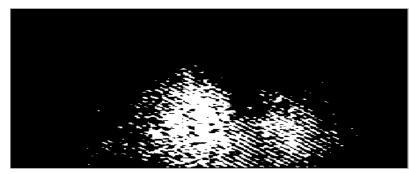


Figure 4 Segmentation image

Figure 5: Detection of defects in the segmented image after applying a specific morphological operator.

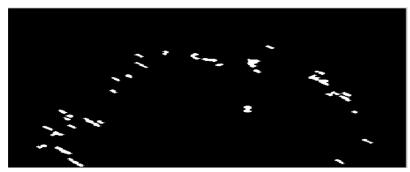


Figure 5 Detection after morphological operator

Figure 6: Extracted features from various image portions, including grayscale, filtered image, and highlighted defect portion, followed by removal of irrelevant content using standard deviation.



Figure 6 Extracted feature



Figure 7: ANN (Artificial Neural Network) training model utilized for detecting and classifying images based on extracted features.

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Figure 7 ANN (Artificial Neural Network)

Figure 8: Image after applying the ANN training model, with detected defects highlighted in red dotted color.



Figure 8 Detection image



7. Comparison of Proposed and Existing System:

In this section comparison of Proposed and Existing system are discussed.

Existing System:

- Utilizes a Kaggle dataset.
- Images are resized to 256x256.
- Preprocessing is performed using a normal filter.
- Feature extraction method includes Color Movement.
- Segmentation and Morphological operations are applied.
- Artificial Neural Network (ANN) with 100-500 epochs.
- Achieves an accuracy of 95.20%.

Proposed System:

- Also utilizes a Kaggle dataset.
- Images are resized to 256x256.
- Preprocessing is done using a Median filter.
- Feature extraction methods include Color Movement, Histogram, Shape, and Texture.
- Segmentation and Morphological operations are employed.
- Artificial Neural Network (ANN) with 100-500 epochs.
- Achieves an improved accuracy of 98.3%.

8. Findings:

The findings of the study indicate that the proposed system achieves higher accuracy (98.3%) in defect detection compared to the existing method (95.20%). The proposed system employs a Median filter and Histogram in addition to Color Movement, allowing for more precise fault detection. Moreover, it utilizes Canny and Sobel features to identify shape faults, which were not addressed in the existing method, potentially reducing fabric wastage. By incorporating SIFT for texture analysis and utilizing ANN to classify color, shape, and texture separately, the proposed system offers a comprehensive approach. This hybrid approach aims to reduce costs and improve fabric quality by addressing shape, color movement, and texture issues more effectively. Additionally, automation reduces human errors and ensures timely and accurate results.



9. Conclusion:

The proposed system enhances fault detection in textiles by incorporating color movement, shape, and texture analysis, alongside median filtering. Compared to the existing method utilizing color movement and normal filtering with ANN, it achieves a higher accuracy of 98.3% versus 95.2%. This slight difference in accuracy translates to significant savings in production costs and improved textile quality. Despite the need for technical expertise during implementation, the benefits outweigh the costs, with potential for further research to streamline implementation processes. Overall, the proposed system promises substantial benefits, including cost reduction, improved product standards, and enhanced international competitiveness for textile manufacturers.

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