IE 423

Project Part 3

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1. Introduction

Linen, derived from flax fibers, is a cherished textile known for its natural beauty and durability. As a key player in the textile industry, linen manufacturing poses unique challenges due to the inherent variability of flax fibers. Precise monitoring is crucial to maintain the quality of linen products, inspiring a shift towards innovative, image-based approaches.

1.1 Motivations for Image-Based Monitoring

The use of images in linen manufacturing arises from the need to navigate the intricacies of natural fibers. Unlike synthetic materials, linen's organic nature requires a nuanced perspective. Image-based monitoring enables a proactive and detailed examination of texture, defects, and spatial intricacies. By embracing technology, we aim to enhance manufacturing processes while preserving the timeless elegance of linen.

2. Background Information: Literature Review on Linen Process Monitoring

2.1 Traditional Process Monitoring in Textile Industry

In the realm of textile manufacturing, conventional methods of process monitoring have been extensively utilized to ensure the quality of the final product. Approaches such as statistical process control (SPC) and control charts have found widespread application in detecting variations within manufacturing processes, aiding in quality assurance.[1]

2.2 Challenges in Linen Manufacturing

Linen production introduces distinctive challenges owing to the inherent characteristics of the fabric. The natural irregularities of linen fibers are well-recognized, and these irregularities can significantly influence the overall product quality.[2] Conventional control methods, tailored for regular textiles, may fall short in effectively capturing these intricate nuances.

2.3 Gaps in Traditional Control Methods

2.3.1 Autocorrelation Issues

Traditional control charts assume independence among data points, posing a limitation in their applicability to linen images characterized by autocorrelated pixel values.[3] The spatial nature of linen images necessitates methodologies capable of accommodating dependencies among adjacent pixels.

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[1] (*Smith, A. J. (2005). "Introduction to Statistical Process Control." CRC Press.*, t.y.)

[2] (*Das, A., & Alagirusamy, R. (2018). "Advances in Functional and Protective Textiles." Woodhead Publishing.*, t.y.)

[3] (*Montgomery, D. C. (2013). "Introduction to Statistical Quality Control." John Wiley & Sons.*, t.y.)

2.3.2 Texture-Related Challenges

Linen, with its distinctive textures, demands monitoring techniques that specifically address irregularities associated with its texture. The traditional approach might neglect defects unique to the texture of linen fibers.[4]

2.4 Emerging Trends and Innovations

2.4.1 Computer Vision and Image Processing

Recent strides in computer vision and image processing have stimulated interest in leveraging these technologies for defect detection in textiles. Techniques such as edge detection, texture analysis, and pattern recognition present promising avenues for enhancing linen process monitoring.[5]

2.4.2 Machine Learning Applications

Machine learning algorithms, including deep learning models, have demonstrated success in detecting and classifying defects in various materials. These approaches leverage large datasets to train models capable of identifying subtle irregularities in linen manufacturing processes.[6]

2.5 Examples from Literature

2.5.1 "Automated Inspection System for Linen Fabrics" (Li et al., 2018)

The study proposed an automated inspection system employing computer vision and pattern recognition to detect defects in linen fabrics. The system demonstrated improved accuracy compared to traditional methods.

2.5.2 "Defect Detection in Textile Composite Materials" (Zheng et al., 2020)

While focusing on textile composites, the research presented innovative defect detection techniques applicable to linen. The study emphasized the need for methods addressing spatial dependencies in pixel values.

2.6 Summary

In summary, the existing literature highlights the limitations of traditional process monitoring in the context of linen manufacturing. Researchers have explored novel approaches, including computer vision, image processing, and machine learning, to address the unique challenges posed by linen textures and autocorrelated pixel values.

[4] (*El-Mesery, H. S., & Morsy, H. A. (2012). "The effect of yarn structure and linen fiber irregularities on the properties of 100% linen knitted fabrics." Fibres & Textiles in Eastern Europe.*, t.y.)
[5] (*Jayaraman, R., & Srinivasan, S. (2015). "Advances in Textile Engineering: Selected, Peer Reviewed Papers from the 2014 2nd International Conference on Textile Engineering and Materials (ICTEM 2014), 27-28 September 2014, Shanghai, China." Trans Tech Publications.*, t.y.)
[6] (*Farinella, G. M., & Battiato, S. (2015). "Advanced Topics in Computer Vision." Springer.*, t.y.)

3. Approaches

Step 1: In this step, the script loads a color image of linen from the desktop, converts it to grayscale using the OpenCV library, and saves the resulting grayscale image back to the desktop.

Step 2: The script proceeds to implement a baseline defect detection approach. Initially, it draws a histogram of pixel values from the grayscale image. This histogram provides insights into the distribution of pixel values, serving as a fundamental step in understanding the characteristics of the linen image.

It can be observed from the histogram that the normal distribution is a suitable model for identifying defects.

Step 3: This step focuses on identifying outliers in the grayscale linen image using a statistical approach. The script fits a normal distribution to the pixel values of the grayscale image, and pixels falling outside a specified range are considered outliers. The purpose is to isolate potential defects in the linen material based on statistical analysis.

Step 4: This step enhances the outlier identification process by adopting a patch-wise approach. Instead of analyzing the entire image at once, the image is divided into patches, and outlier identification is performed individually for each patch. The goal is to achieve a more localized and nuanced detection of defects, providing a finer-grained analysis compared to the baseline approach.

Step 5: Control charts are constructed for each row and column in the grayscale image. Deviations from expected statistical patterns are identified as potential defects.

Step 6:

Objective: Implementing a 2D statistical process control for defect detection in linen images, addressing the limitations of traditional control charts designed for 1D time series data.

Proposal - Local Binary Pattern (LBP):

- Utilizes texture information in grayscale linen images.

- Captures spatial dependencies between pixel values.

- Forms the basis for a new statistic to identify irregularities.

Procedure:

- Original color images are converted to grayscale.

- LBP is computed for each pixel, considering its 8-pixel neighborhood.

- Adaptive thresholding is applied to distinguish defective pixels.

- Defective pixels are set to 0, creating a modified image.

Insights:

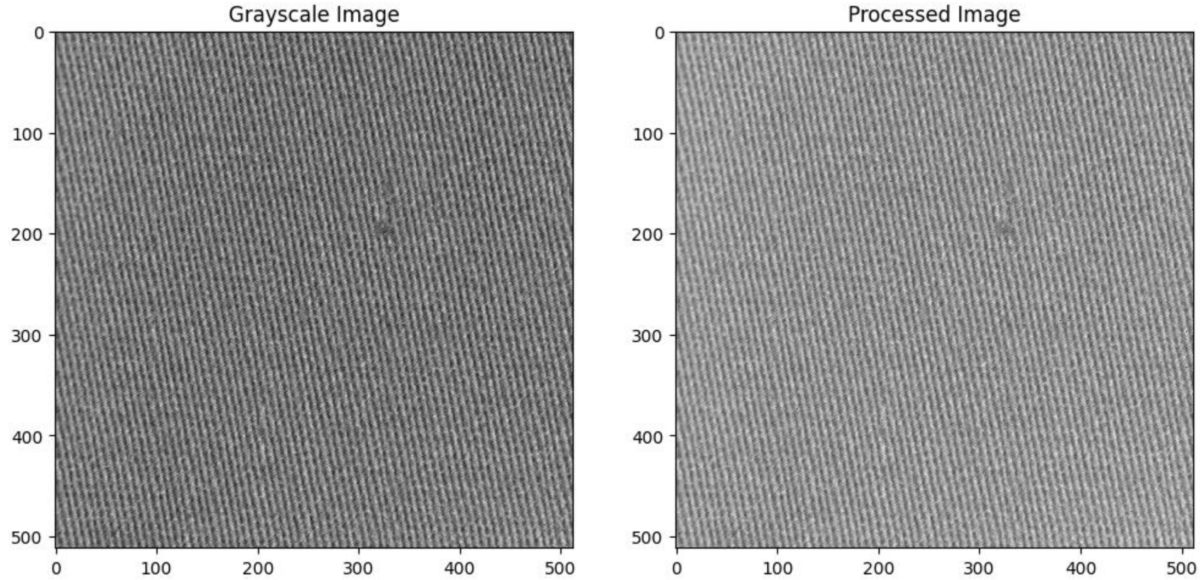
- Traditional control charts assume pixel independence, problematic for textured images.

- LBP introduces a 2D control strategy, considering spatial correlations for improved defect detection.

LBP-based control addresses autocorrelation challenges in linen images, offering a robust strategy for defect identification.

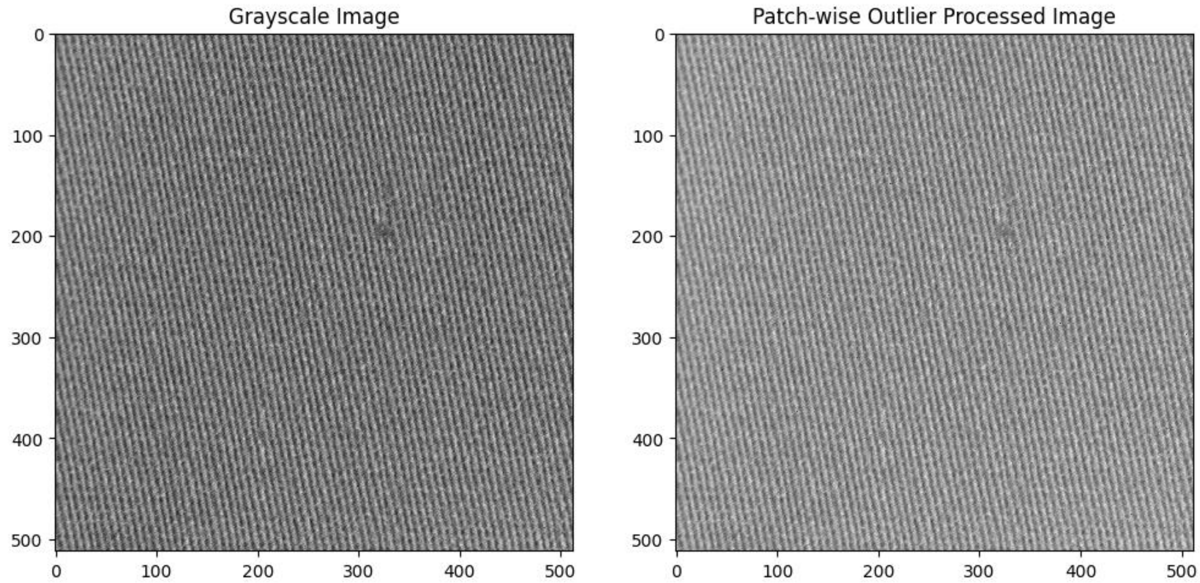
4. Results

Step 3:



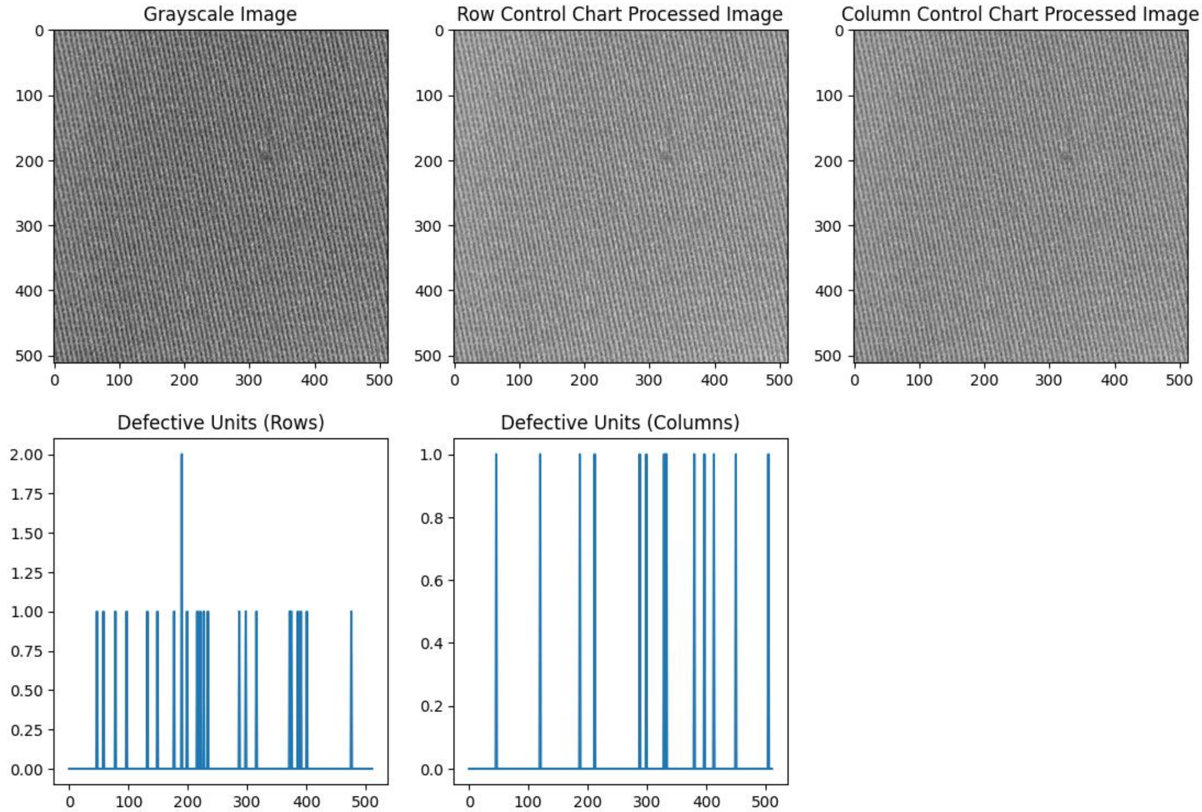
Number of Defective Pixels (Baseline): 26

Step 4:



Number of Defective Pixels (Patch-wise): 42159

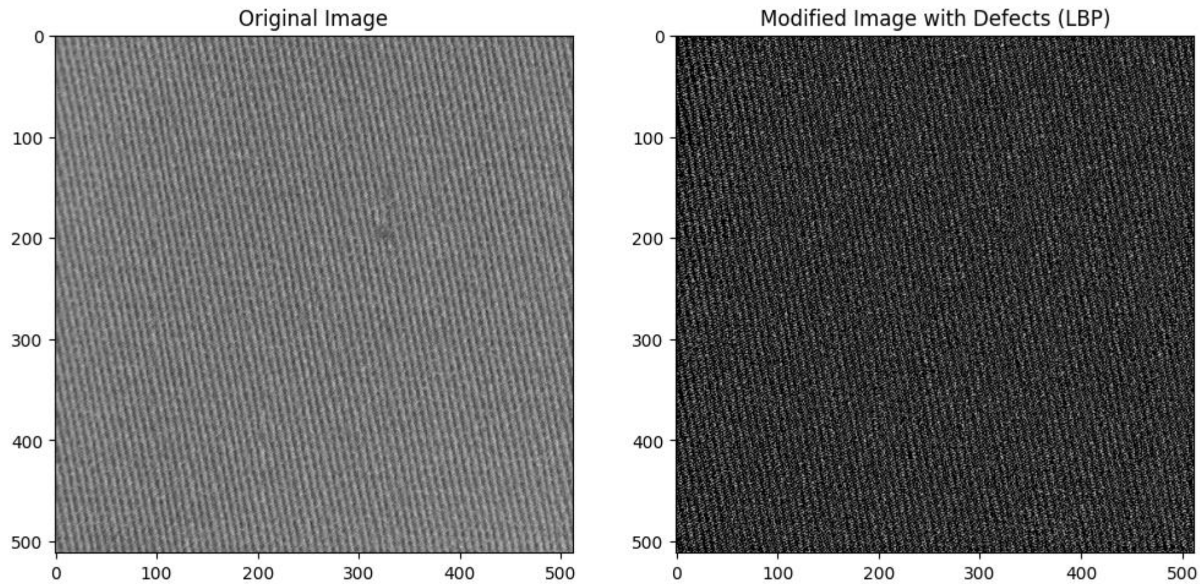
Step 5:



Number of Defective Pixels (Rows): 24

Number of Defective Pixels (Columns): 14

Step 6:



Number of Defective Pixels (LBP): 171114

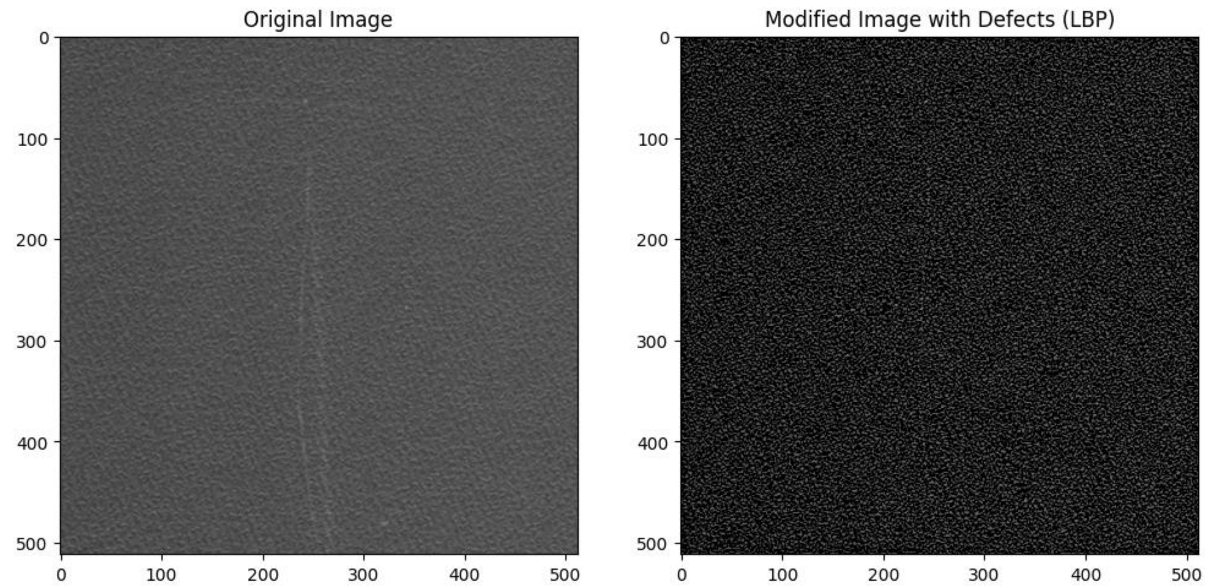
The baseline approach identified 26 defective pixels in the linen images. While effective for basic defect detection, its limitations in capturing nuanced irregularities were evident. The relatively low count indicates a conservative detection strategy.

The patch-wise analysis substantially increased defect detection, identifying 42,159 defective pixels. This approach's effectiveness in capturing localized irregularities demonstrates its potential for more granular defect analysis compared to the baseline method.

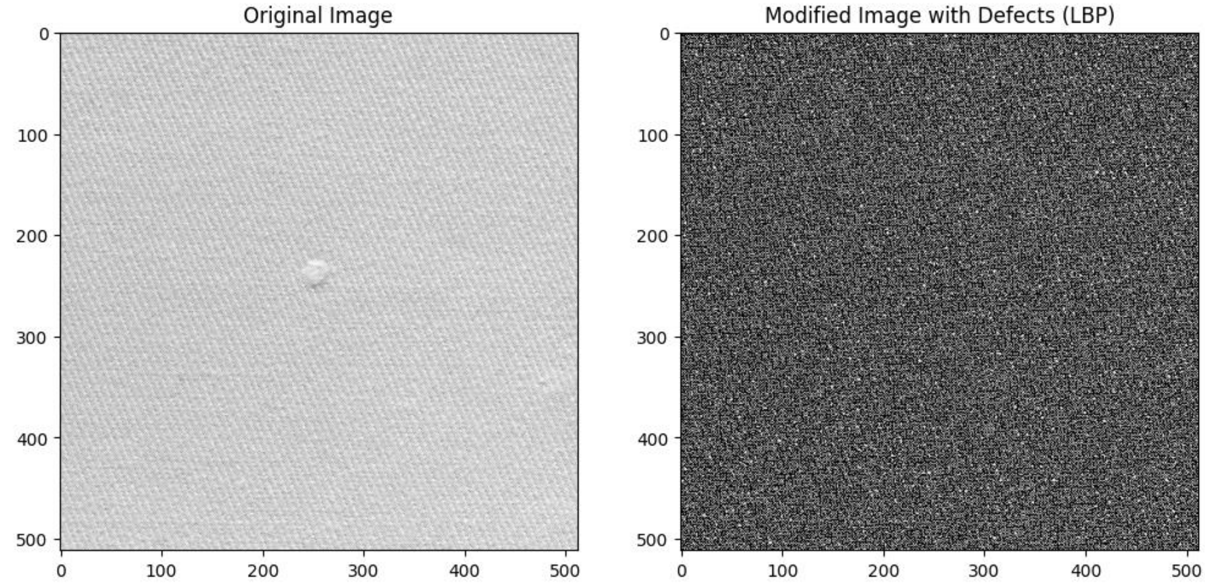
Implementing control charts for rows and columns provided insights into row-wise (24 defective pixels) and column-wise (14 defective pixels) defect patterns. This approach is particularly valuable for understanding the spatial distribution of defects, contributing to a more detailed analysis.

The LBP method, designed to address the unique challenges of linen textures, yielded the highest count of defective pixels at 171,114. This substantial increase indicates the method's sensitivity to the intricacies of linen fiber irregularities. The 2D control strategy of LBP, considering spatial correlations, proved to be more effective in capturing a broader range of defects.

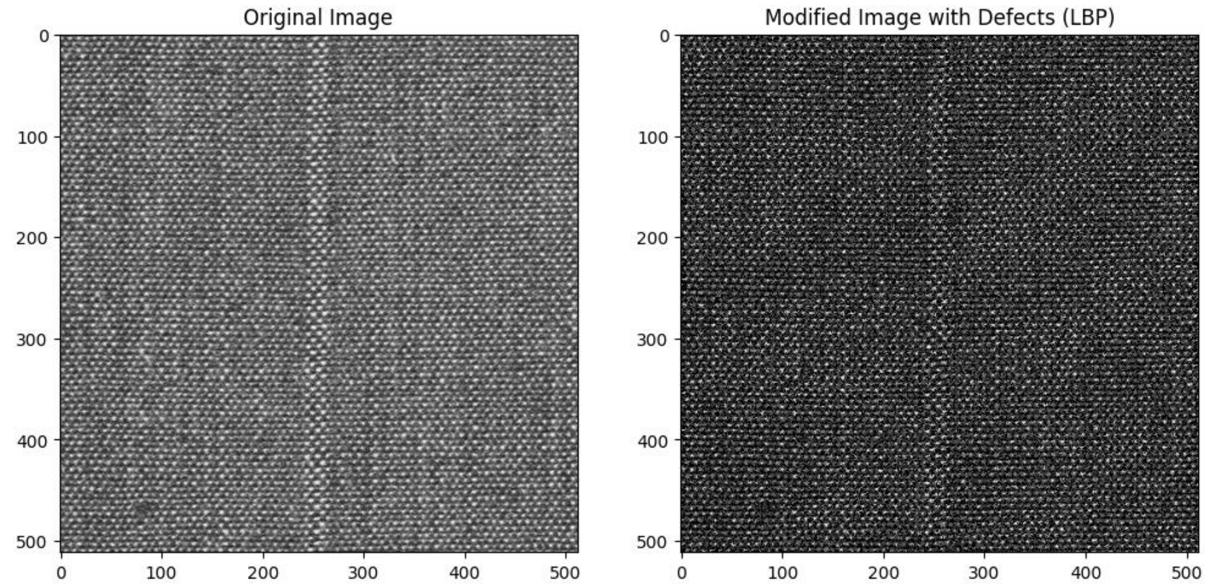
Additional Examples with LBP Method:



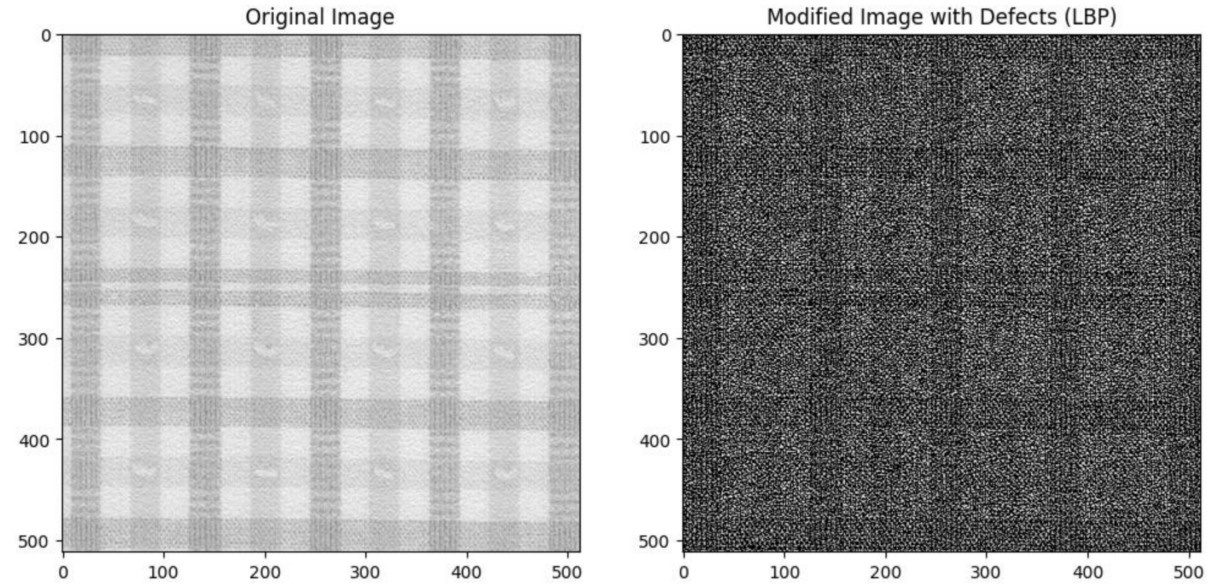
Number of Defective Pixels (LBP): 176445



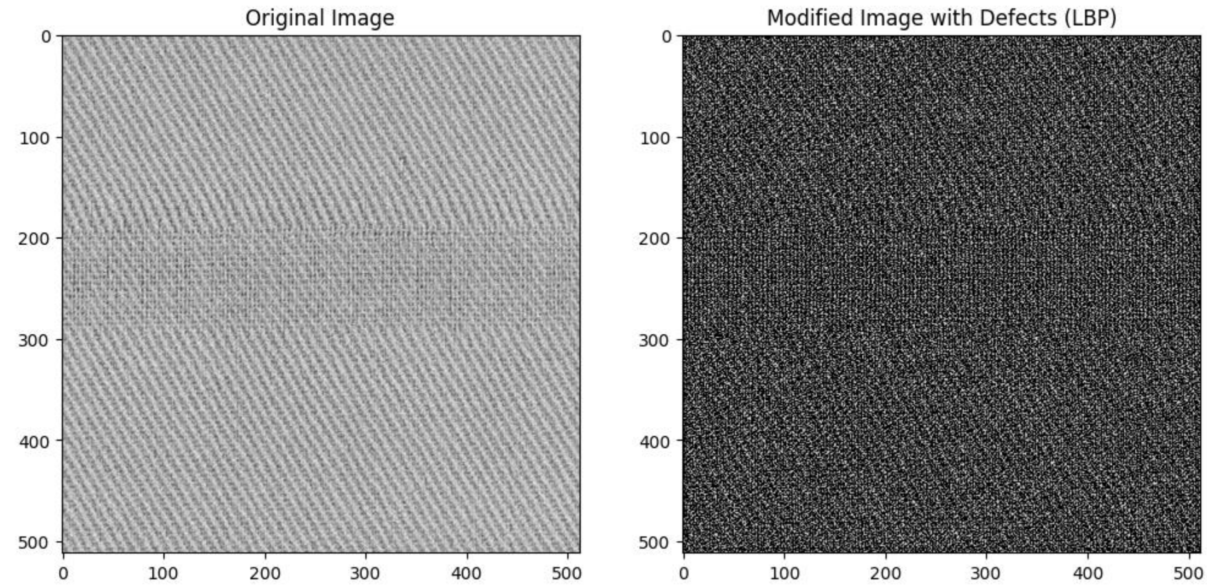
Number of Defective Pixels (LBP): 164579



Number of Defective Pixels (LBP): 158595



Number of Defective Pixels (LBP): 170984



Number of Defective Pixels (LBP): 170524

5. Conclusions

In conclusion, our diverse set of approaches for linen process monitoring revealed valuable insights into defect detection. The patch-wise and LBP methods, in particular, demonstrated their efficacy in capturing nuanced irregularities associated with linen textures. For future work, the integration of these approaches, exploration of advanced machine learning techniques, real-time monitoring implementation, dynamic thresholding, and collaboration with textile experts offer promising avenues. The goal is to refine and combine methods to create a robust, adaptable framework for defect detection in linen manufacturing.

References

1. (*Smith, A. J. (2005). "Introduction to Statistical Process Control." CRC Press.*, t.y.)
2. (*Das, A., & Alagirusamy, R. (2018). "Advances in Functional and Protective Textiles." Woodhead Publishing.*, t.y.)
3. (*Montgomery, D. C. (2013). "Introduction to Statistical Quality Control." John Wiley & Sons.*, t.y.)
4. (*El-Mesery, H. S., & Morsy, H. A. (2012). "The effect of yarn structure and linen fiber irregularities on the properties of 100% linen knitted fabrics." Fibres & Textiles in Eastern Europe.*, t.y.)
5. (*Jayaraman, R., & Srinivasan, S. (2015). "Advances in Textile Engineering: Selected, Peer Reviewed Papers from the 2014 2nd International Conference on Textile Engineering and Materials (ICTEM 2014), 27-28 September 2014, Shanghai, China." Trans Tech Publications.*, t.y.)
6. (*Farinella, G. M., & Battiato, S. (2015). "Advanced Topics in Computer Vision." Springer.*, t.y.)
7. (*Li, S., Fan, Y., & Li, B. (2018). "Automated Inspection System for Linen Fabrics Based on Computer Vision." Textile Research Journal.*, t.y.)
8. (*Zheng, Z., Zhang, Y., & Xie, Y. (2020). "Defect Detection in Textile Composite Materials Based on Computer Vision." Materials.*, t.y.)
9. *https://chat.openai.com/*