IE 423 - Quality Engineering

Project Part 3 - Report

Group 1
Elif Melisa Avcı
Doğa Yıldız
Zümra İnci

1. *Introduction*

Linen is a textile made from the fibers of the flax plant, it is valued for its exceptional coolness and freshness in hot weather and is famous for its strength, absorbency, and durability. Linen is used for a variety of purposes, from bed and bath fabrics, home and commercial furnishing items, apparel, to industrial products.

Figure 1: Linen fabric

The process of producing linen is laborious and time-consuming, which can make it more expensive than other fibers like cotton. So, monitoring the processing of linens is crucial. Firstly, the quality of linen products significantly affects their performance and lifespan. High-quality linen is more durable, less likely to pill, and maintains its aesthetic appeal over time. Secondly, the efficiency of linen manufacturing has a direct impact on both cost and environmental resources. By ensuring that processes are optimized and defects are minimized, manufacturers can reduce waste, save on raw materials, and increase the overall sustainability of their operations.

The motivations for using images and identifying defects in linen manufacturing are due to achieving quality assurance and process optimization. Imaging technology allows for non-destructive testing and evaluation of linen products. By capturing images of linens during production, manufacturers can inspect the fabrics for various types of defects, such as irregular weaves, color inconsistencies, and structural faults. This visual inspection helps to detect and correct defects early, automate quality control, maintain consistent product standards and enhance traceability so that the manufacturers can trace back and identify potential issues in the production line.

2. Background information

In the middle ages, quality standards were determined by guilds. If the producers did not obeyed to these standards, they were punished. Royals also had the right to specify their needs in detailed ways. By the time of World War I, process monitoring became more critical, since unsafe military equipments would be lethal. As time went by, society valued quality higher and companies developed their process monitoring systems. Nowadays, most of the process monitoring systems are based on technologic equipments.

In fabrics such as linens, traditional monitoring depended on human force too. But since human workforce is costly & may create incorrect verdicts, companies started to implement automated visual inspection systems. These systems involve the analysis and interpretation of images obtained from inspection processes. The goal is to identify defects & anomalies in products with a high level of accuracy. These systems are widely used in ceramic tile production and can be suitable for monitoring linen production.

3. Approach

To construct some strategies with different methods, we follow the following steps:

Histogram and Probability Distribution Analysis: First, we load the grayscale image and plot its histogram to observe the distribution of pixel values. Based on our observations, we suggest a probability distribution that best fits the histogram.

Parameter Estimation: With the chosen probability distribution, we estimate the relevant parameters. For example, for a normal distribution, we estimate the mean and variance.

Outlier Detection and Modification: Using the estimated parameters, we calculate the upper and lower bounds that leave decided probability on both tails of the distribution. We then identify the outlier pixels that fall outside these bounds. These outlier pixels are modified to black (value zero). Finally, we display the modified image alongside the original for visual comparison.

In the first method, we use 2 different approaches. To determine the outliers and detect the defects, we use the whole pixel value, which is 512x512, and it is the same with picture resolution. The other approach is patch-based analysis.

Patch-based Analysis: For this approach, we divide the image into 51x51 patches. We repeat the outlier detection and modification process for each patch, marking outlier pixels as black. The modified image with marked pixels is displayed, allowing us to compare it to the original image.

To construct **the second method**, we perform defect detection based on control charts for each row and column of the image.

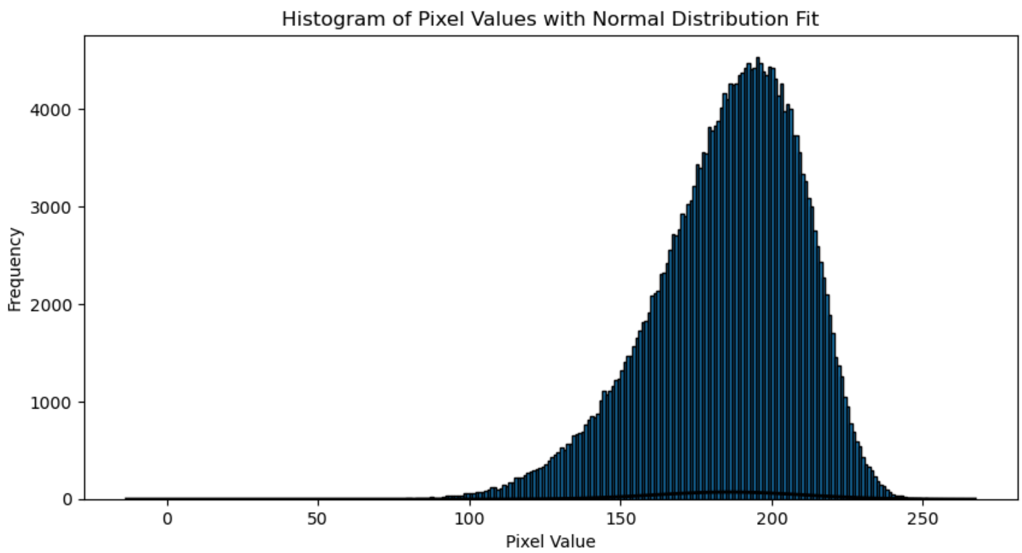
First, we calculate the mean and variance for each row and column separately. Then we construct control charts (**X-bar and R charts**) for monitoring the mean and variance of pixel values for each row and column. We identify the pixels that are out of control based on the control chart criteria (by using **3-sigma** UCL and LCL). Then the value of these pixels are changed to black (zero) in the modified image.

For the **third method, our proposal**, we chose the **Local Binary Patterns (LBP) approach** for defect detection due to its effectiveness in capturing and analyzing **texture patterns** within images like we use in this assignment. We start by examining each pixel in the image within a defined neighborhood. This neighborhood's size is determined by a radius **R**, and we consider a specific number of surrounding pixels, denoted as **P**. We compare their values to the value of the central pixel. If a neighbor's value is greater than or equal to the central pixel's value, we assign **1**; otherwise, it's assigned **0**. The binary patterns are then converted into decimal numbers, resulting in an LBP code for each pixel in the image. To identify potential defects, we calculate the mean and standard deviation. Then we define control limits, and any LBP code frequency exceeding these limits suggests abnormal patterns and possible defects.

4. Results

Method 1: Statistical Data Analysis Approach

The first method treats pixel values as individual data points in a distribution and looks for statistical outliers. We identified the histogram of pixel values to find the appropriate distribution of pixels. First, we assumed they follow a lognormal distribution, but we ended up with a very high upper bound and the algorithm could not detect the defects, so we switched to the Normal Distribution assumption.



After this assumption, we calculated the mean, standard deviation and lower and upper bounds with predetermined significance values.

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Estimated Mean (mu): 185.83
Estimated Standard Deviation (std): 24.61
Lower Bound (0.001 probability): 109.78
Upper Bound (0.999 probability): 261.89
```

First we found 0.001 probability limits and tried to detect defects using these limits, however the limits were too wide and we could not detect defects. So, we changed 0.001 probability to 0.05.

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Lower Bound (0.05 probability): 145.35
Upper Bound (0.95 probability): 226.32
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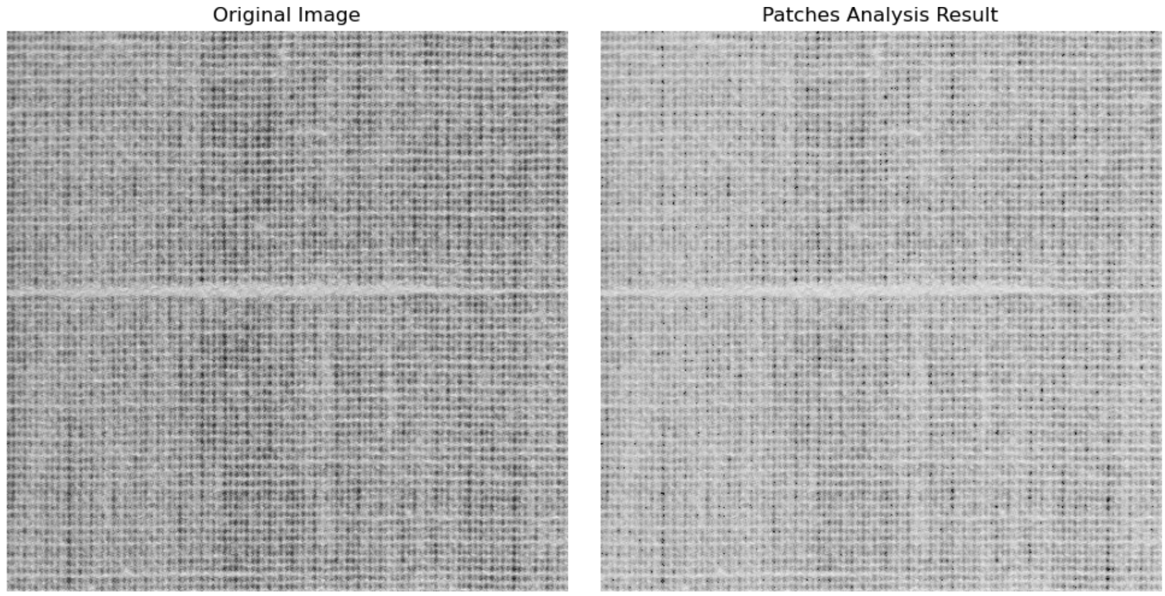
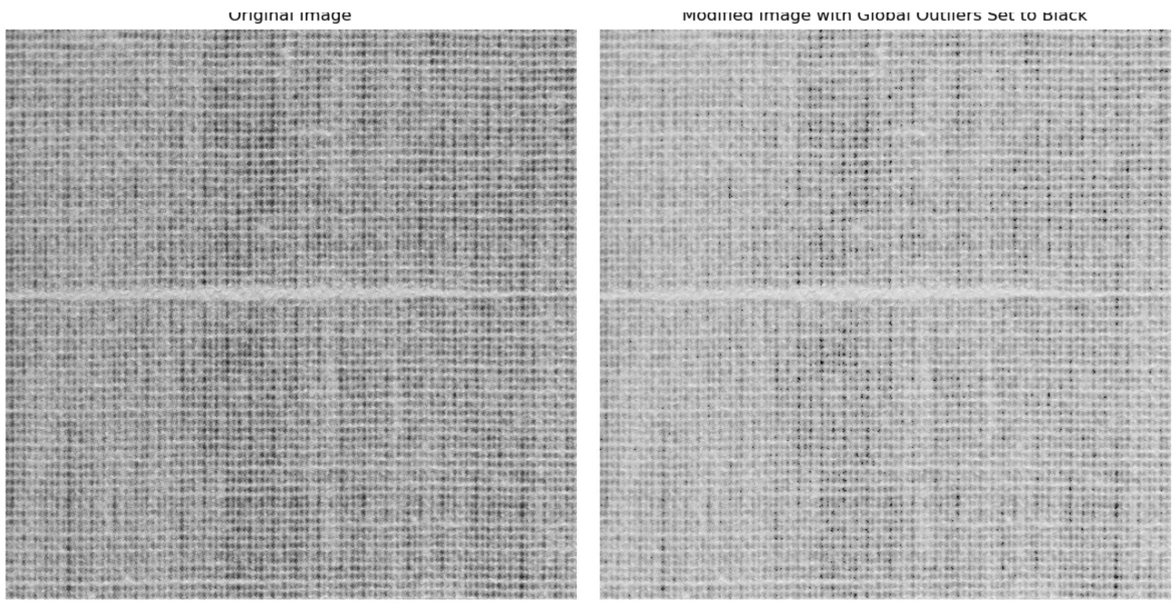
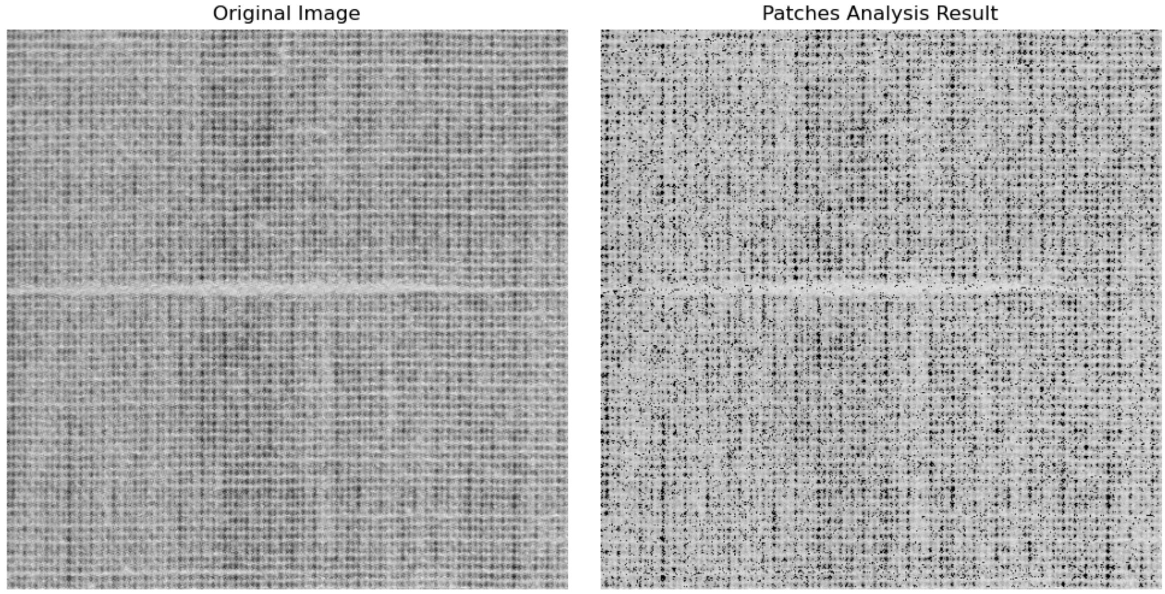
Lastly, we applied this statistical data analysis approach to patches of an image, each of size 51x51, which offers a more localized perspective compared to analyzing the entire image as a whole.

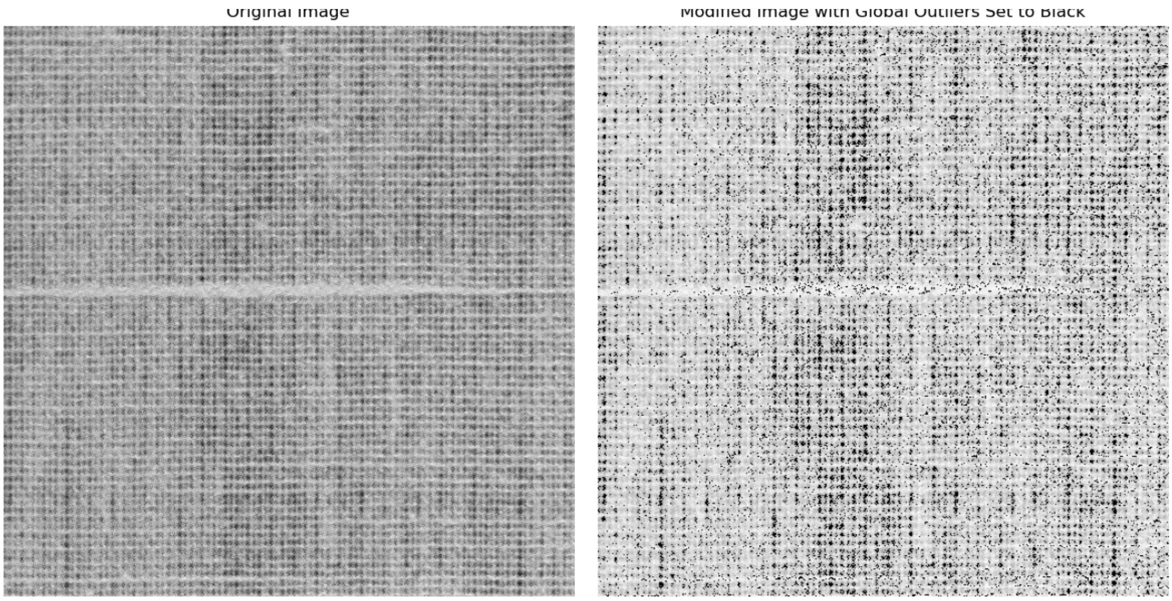
Below are the results of method 1 using 0.001 probability limits.





Below are the results of method 1 using 0.05 probability limits. As can be seen, defects are better detected using limits of 0.05 probability.

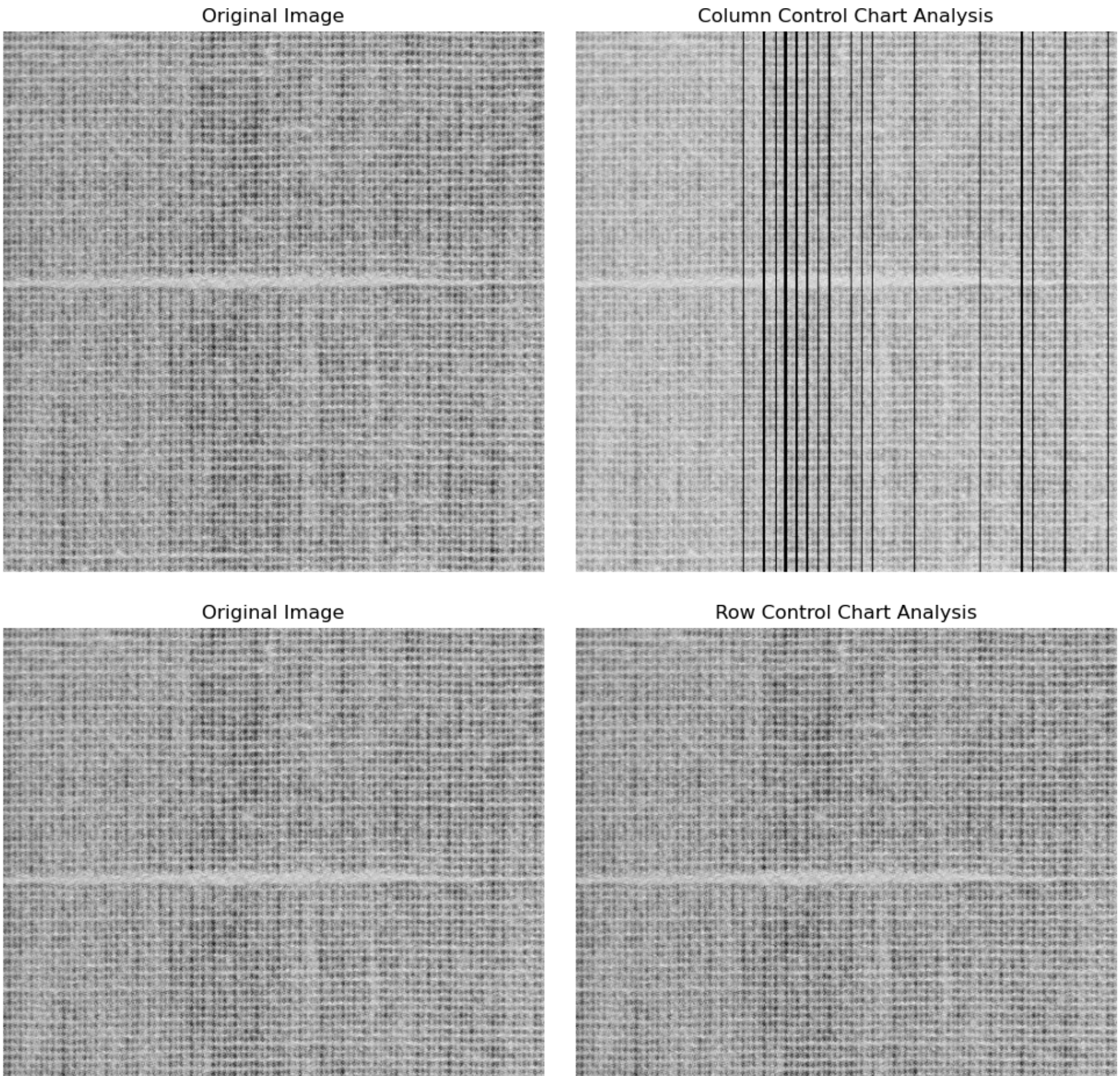




Method 2: Control Chart Perspective

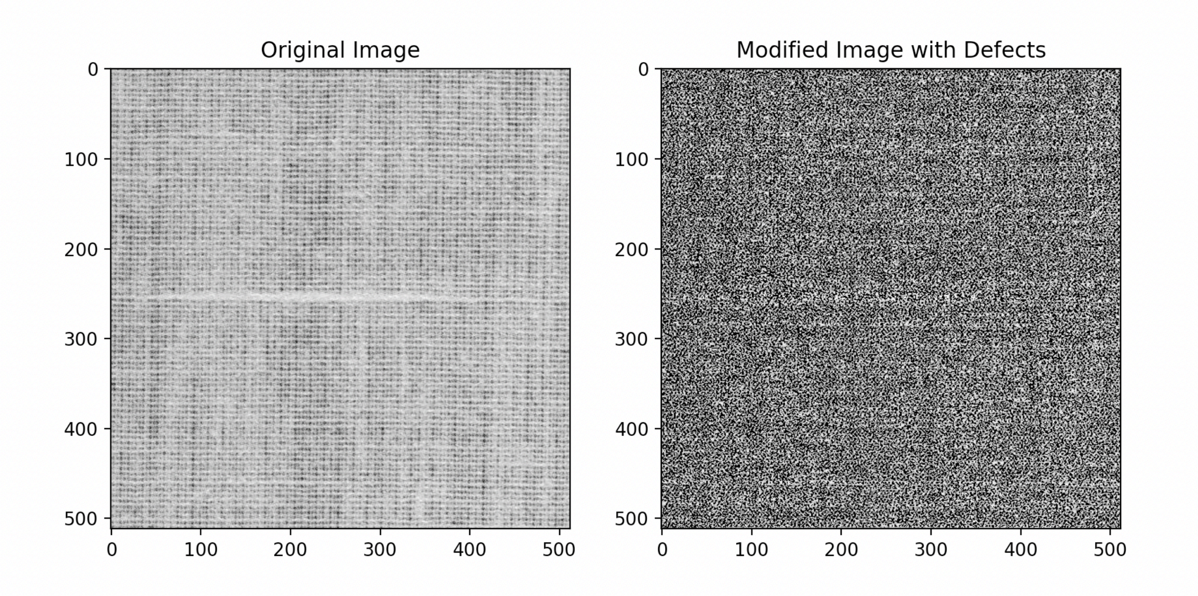
This method creates a control chart for pixel intensity values across rows and columns. Control limits are established, and patterns within these charts are analyzed for signs of defects. We established control charts for rows and columns individually. We observed that although we can see the column defects clearly, row detection does not work the way it is intended to.

Row Mean Control Limits: [153.91, 217.76]
Row Variance Control Limits: [-95.79, 1080.76]
Column Mean Control Limits: [155.13, 216.54]
Column Variance Control Limits: [121.87, 880.10]

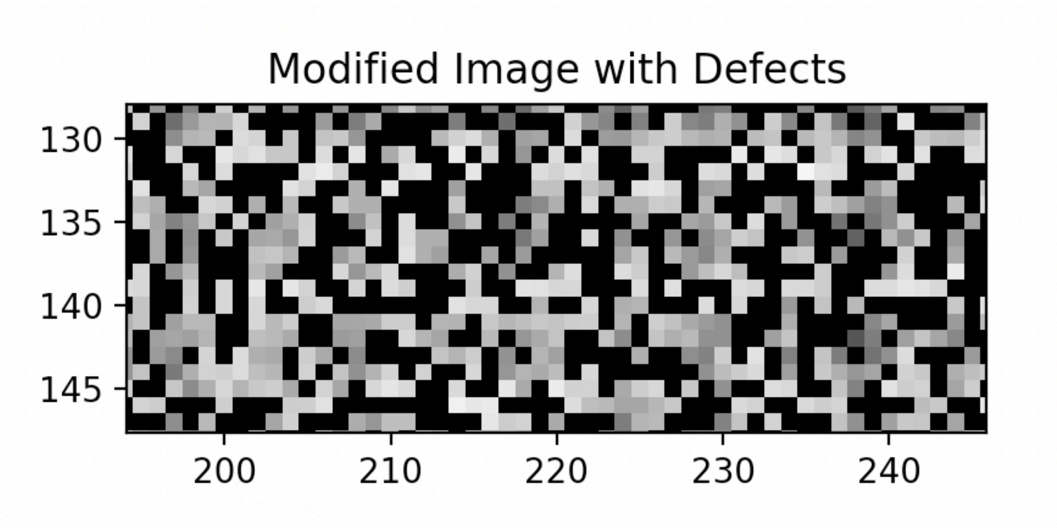


Method 3: Our Proposal

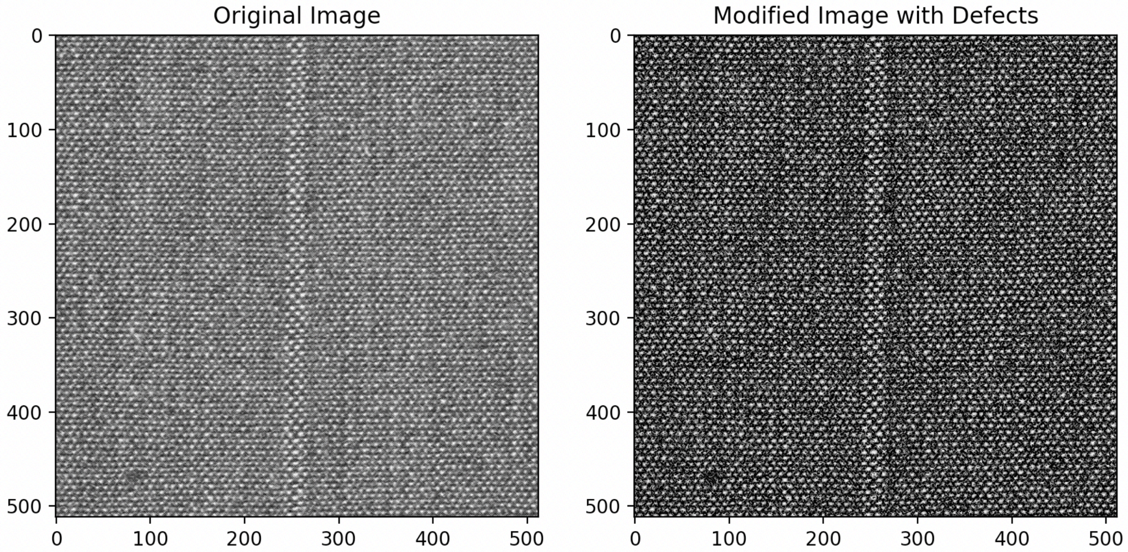
We use LBP method to detect defects, and we use whole pixel values in the picture. For the whole image, the model cannot visualize the defect exactly but we can analyse it more in detail. Following there are some image examples we used to analyse.

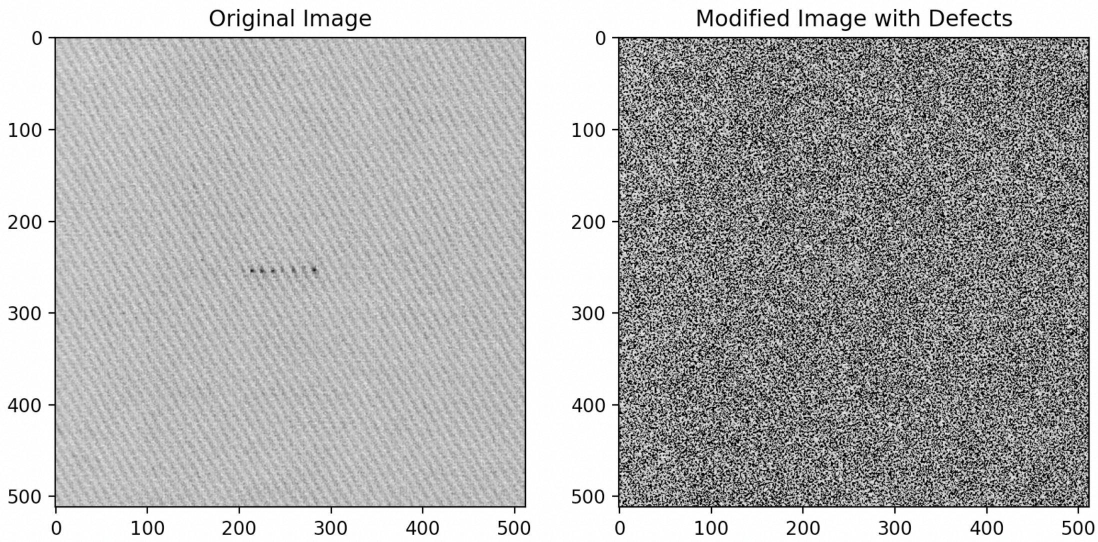


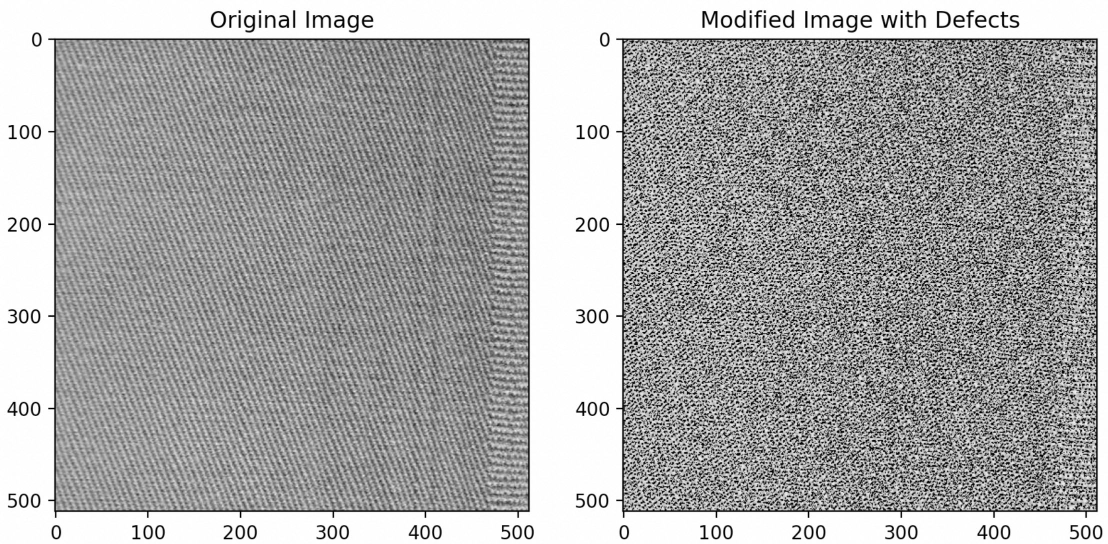
When we look at more closer to the modified image we can see the defect points in more detail. So we can conclude that we can use this method if we want to analyse minor detailed pictures.

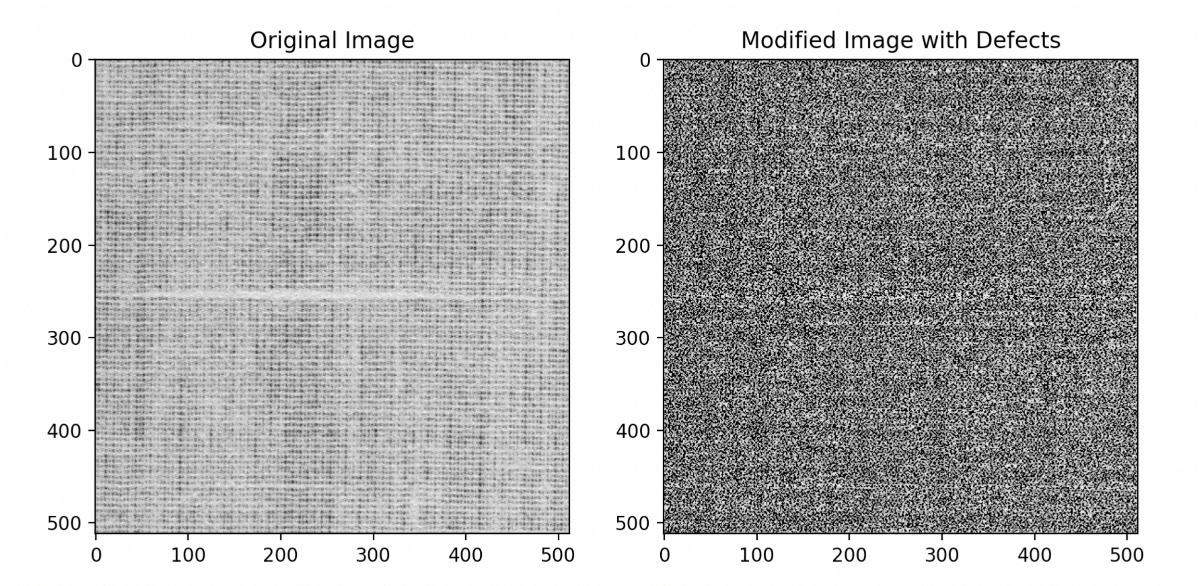


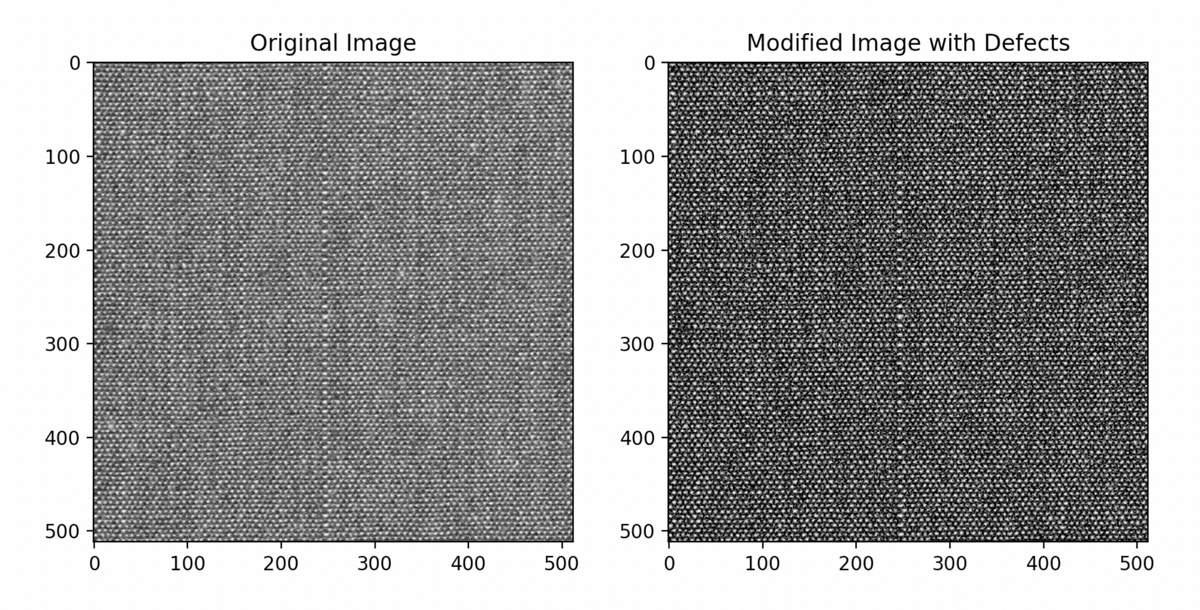
We also apply this method to the other pictures. There are some other images with original and modified versions as follows:


Original Image
Modified Image with Defects


Original Image
Modified Image with Defects


Original Image
Modified Image with Defects


Original Image
Modified Image with Defects
0
100
200
300
400
500


Original Image
Modified Image with Defects
0
100
200
300
400
500

5. Conclusions and Future Work

Summarize your findings and comments regarding your approach. What are possible extensions to have a better approach?

1. Statistical Data Analysis Approach: This method involves analyzing the distribution of pixel values across the entire image or within specific patches. For whole images, it looks for global outliers which can signify defects but may miss local patterns. In the patch-based variation, the analysis is more localized, focusing on smaller areas (like 51x51 pixel windows). One limitation is its treatment of each patch in isolation, potentially overlooking larger-scale patterns.

2. Control Chart Perspective: Adapted from traditional manufacturing process control, this approach analyzes pixel values along rows and columns of an image. It's effective in identifying systematic deviations and patterns such as consistent changes across a row or column, which can indicate defects.

3. Local Binary Pattern (LBP) Method: LBP offers a texture-based approach, focusing on the local spatial patterns of pixel intensity. It's particularly useful for textured surfaces where the relationship between neighboring pixels is crucial for understanding the image's structure. By analyzing the LBP histograms, it's possible to detect anomalies in texture. However, LBP primarily captures local textural features and might require integration with other methods for a comprehensive analysis.

Possible Extensions:

- **Autocorrelation**: Both methods have their limitations in addressing autocorrelation. The patch-based statistical data analysis approach offers some improvement over the global approach by considering local relationships within windows but may still miss larger-scale patterns. The control chart method is better at understanding how pixels are related in a line because it looks at the sequence of pixel values. But, like the statistical method, it doesn't fully consider the two-dimensional relationships between pixels, especially in images with complex textures. To do this better, the method would need some adjustments.

- **Multi-scale Analysis**: Analyzing images at multiple scales, by varying patch sizes or using pyramidal representations, can help detect defects that manifest at different resolutions.

- **Dynamic Thresholding in Control Charts:** Implementing adaptive or dynamic control limits that adjust based on local image characteristics can make the control chart method more robust, especially for images with varying textures and intensities.