IE423 - QUALITY ENGINEERING

Project Part 3

A COMPREHENSIVE ANALYSIS REGARDING QUALITY CONTROL ON LINEN IMAGES

Group 16

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Introduction

Linen is a textile made from flax plant fibers and it is eminent for its absorbency and freshness especially in hot conditions. Since its manufacturing process is complicated and demanding, monitoring of the linen processing and ensuring its quality is very important. Using images for the detection of defects in linen manufacturing is essential since it helps maintaining high standards which are expected for linen products. Image based inspection methods bring many advantages such as increased precision, efficiency and overall detection ability.

Background Information

For materials with textures like linen, automation of visual inspection has received a lot of attention in the field of quality control. Efficient texture analysis tools and complex image capturing systems are needed for this strategy. Although they are not commonly used, these systems help manufacturers to ensure proper quality of linen that they produce. They do this by spotting defects that are very difficult to detect with traditional inspection methods. According to the literature, there has been a growing trend towards sophisticated image processing techniques into the manufacturing processes. The main goal is to improve the consistency of quality and dependability of the final product

Approaches

Approach 1: Baseline Defect Detection Approach from a Statistical Data Analysis Perspective

In this method, we look at how bright or dark the pixels are in our linen images. We draw a chart to see how many pixels have similar brightness levels. Then, we guess which type of chart fits well with our observations, like whether it's a normal chart or something else. After that, we figure out some numbers that describe our chart, like the average brightness and the range. We then find pixels that are kind of unusual, not like the others, and change their color to black. We do this not only for the whole image but also for smaller parts of it. We want to see if we can find and fix defects in the linen.

We plotted pixel values to histogram with respect to their probability values. After we plotted proportions of the data, we see that pixel values are distributed approximately normal.

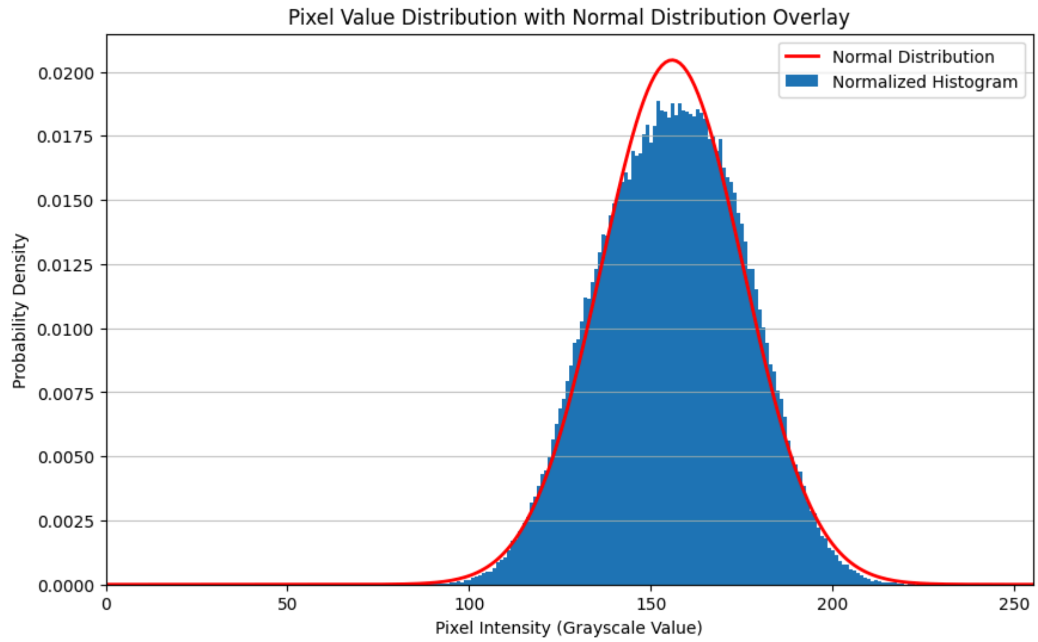

Figure 1: Proportions of Pixel Brightness Values over the whole picture

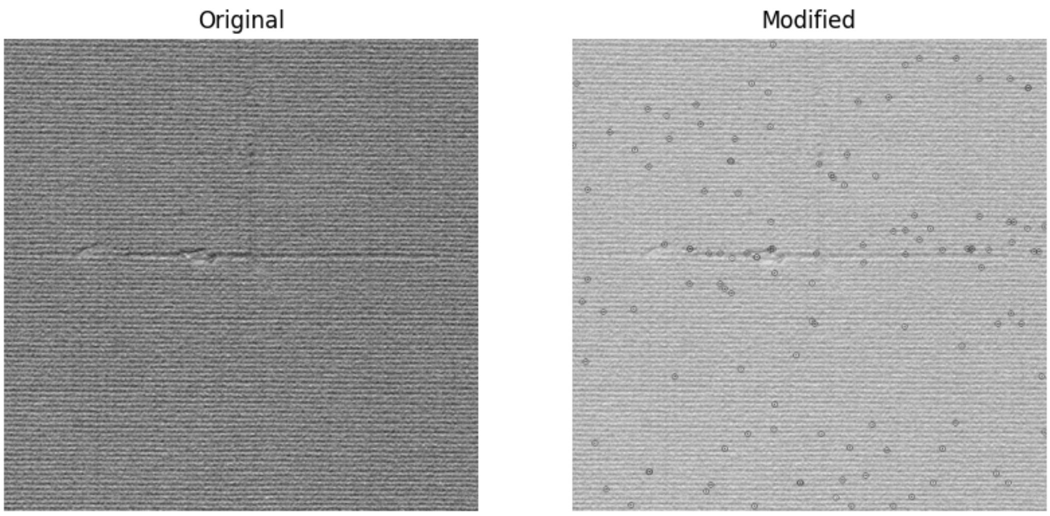

Figure 2: Detected and labeled outliers of the whole image.

Then, we performed outlier analysis over the whole data and painted them into black. We also labeled them into circles.

After we carried our analysis over the whole picture, we divided (512x512) pixel picture into (51x51) pixel 100 pictures. Then, again we performed outlier analysis and labeled them also. Below, it can be seen original photo and the labeled one.

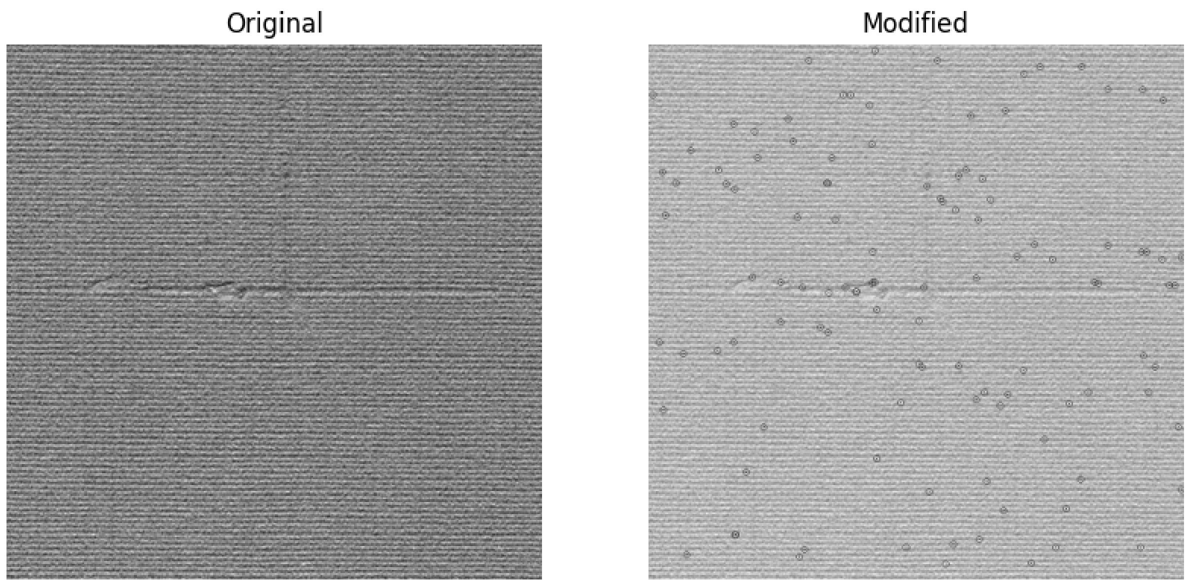

Figure 3: Detected and labeled outliers of the 51x51 divided image.

Approach 2: Simple Defect Detection Approach from a Control Chart Perspective

In this way, we're checking if the brightness of our linen pixels is consistent not just overall, but also in each row and column. We make charts for each row to see if the average brightness stays the same, and we do the same for columns. If we find pixels that are not following the usual pattern, we make them black. We want to see if there are parts of the linen image that don't match the rest in terms of brightness. This helps us find and deal with defects in a simpler way.

In the pictures below, mean and variances of the brightness values of Rows can be seen. We observed a series pattern in the mean.

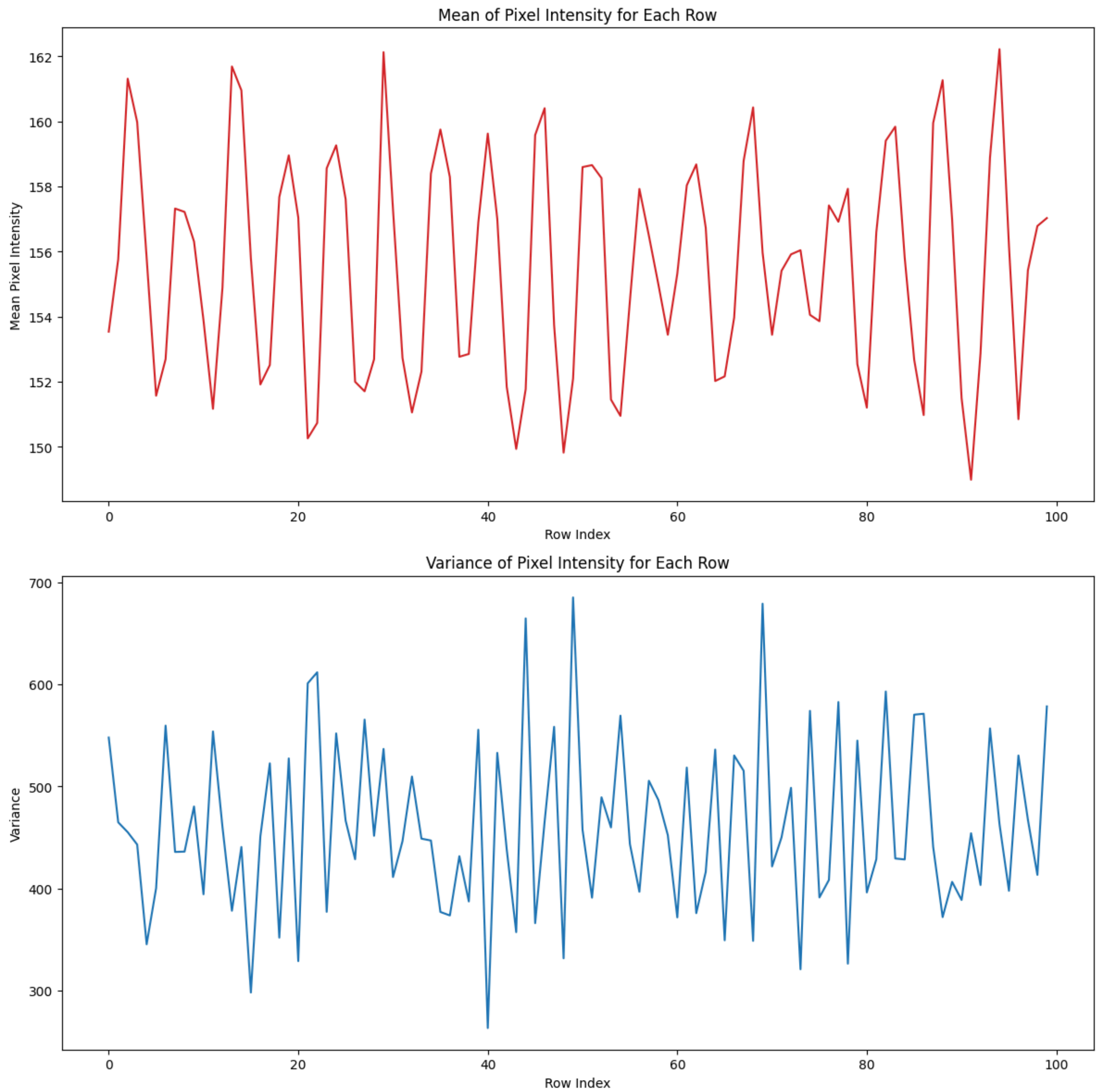

Figure 4: Mean and Variances of the Brightness Values in Rows

Based on these graphs, we concluded outlier analysis and labeled outlier pixels in circles. It can be seen that most of the outliers placed horizontal edges of the Image.

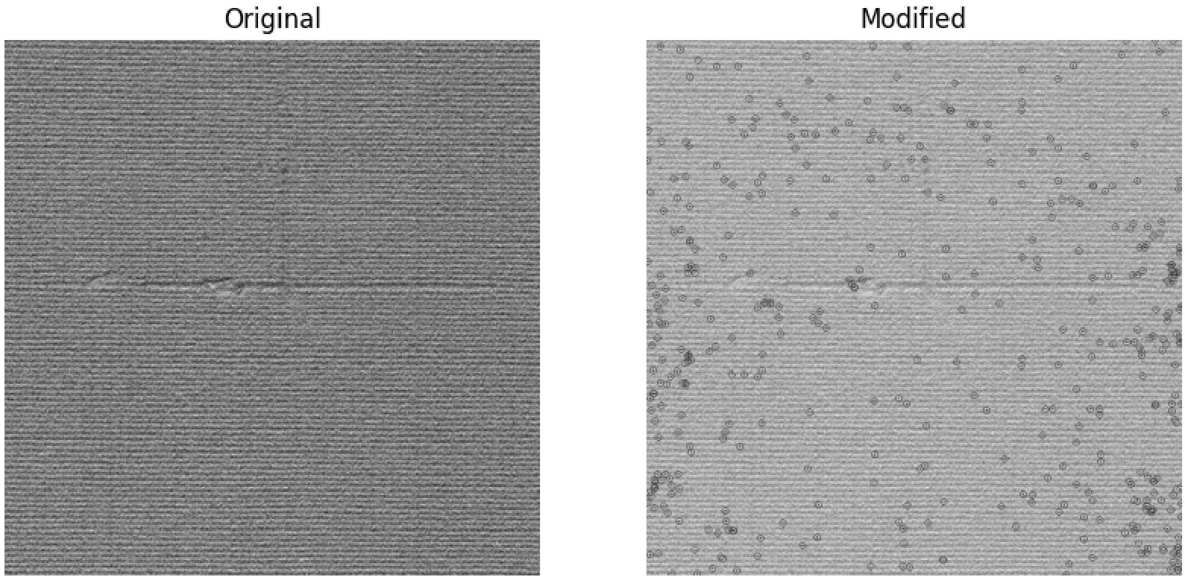

Figure 5: Detected and labeled outliers of the Rows.

In the pictures below, mean and variances of the brightness values of Columns can be seen.

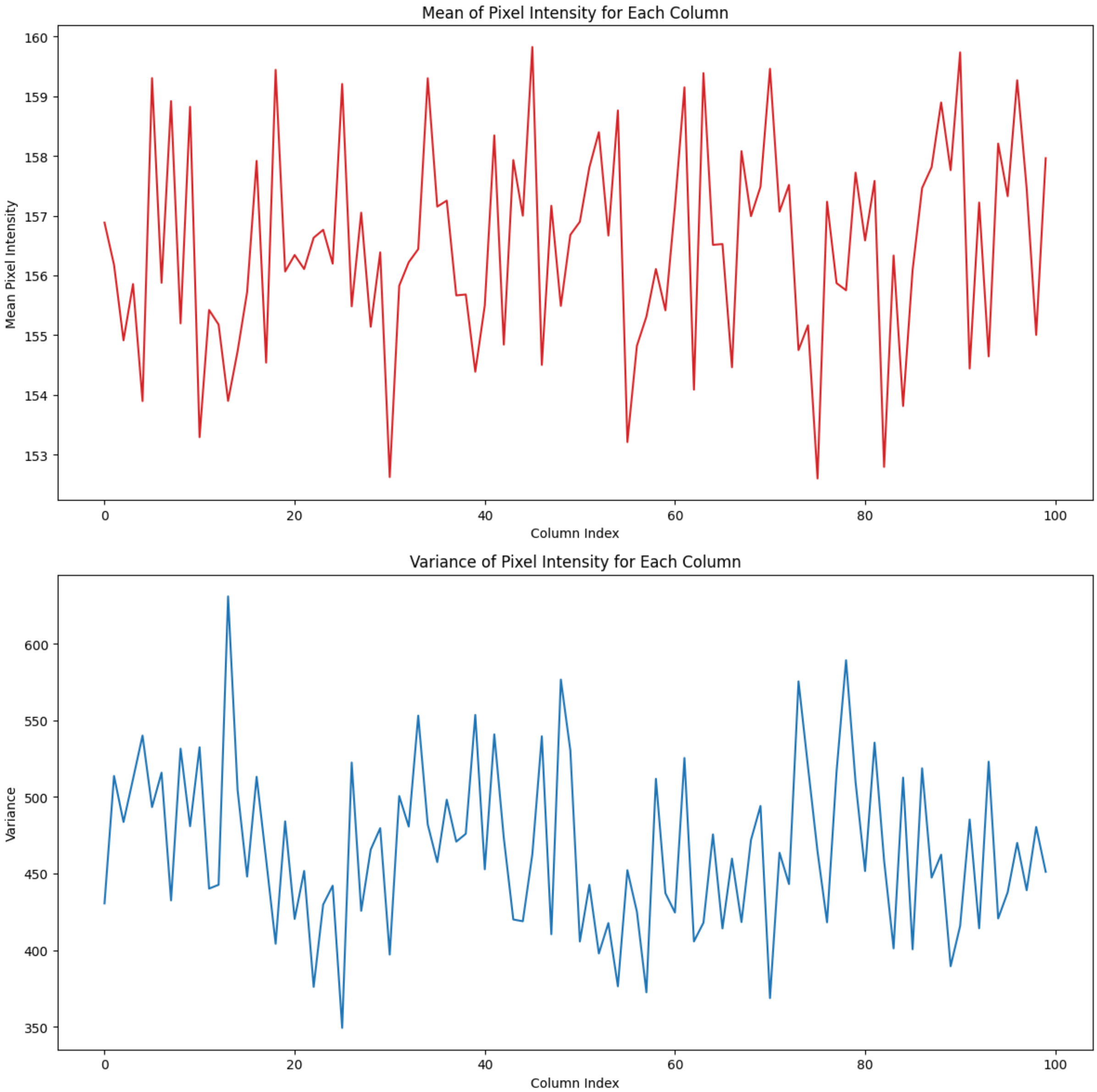

Figure 6: Mean and Variances of the Brightness Values in Columns

Based on these graphs, we concluded outlier analysis and labeled outlier pixels in circles for analysis of Columns.

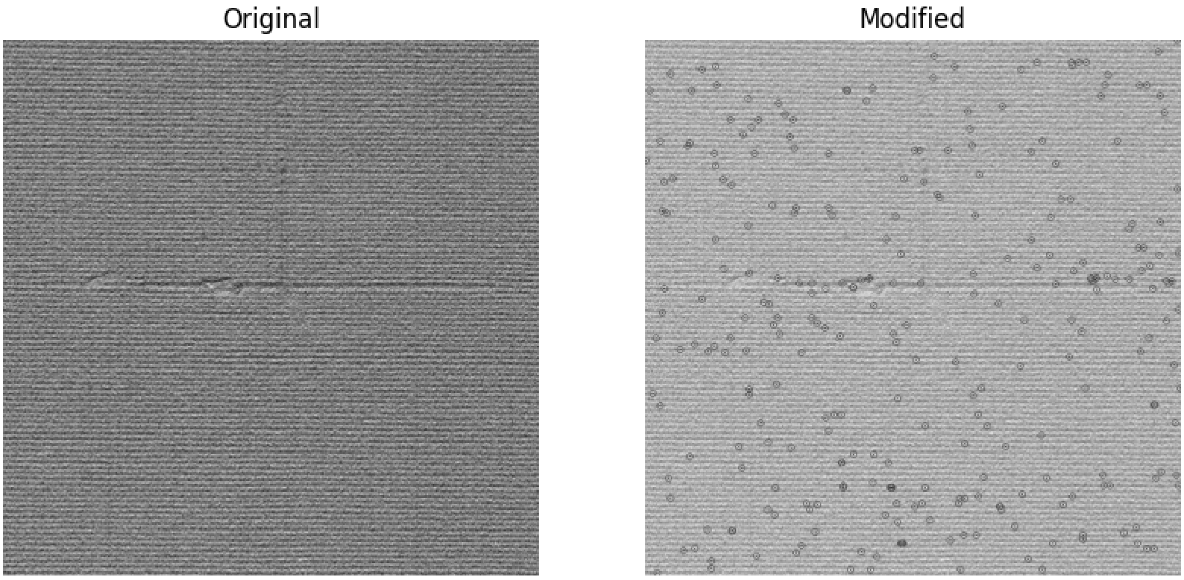

Figure 7: Detected and labeled outliers of the Columns.

Approach 3: Our Proposal

Our approach to image analysis begins with the computation of pixel value averages across the rows and columns of grayscale fabric images, followed by an autocorrelation analysis of these averages. The objective is to identify the series relationship (lag) between pixels. Once this lag is determined, we utilize a window size of 51x51 pixels for each pixel, selecting specific pixels based on the lag values and examining their distribution to detect statistically abnormal pixels (outliers). These outliers are then visually distinguished by marking them in black, and isolated outliers—those without adjacent outlier pixels—are filtered out to prevent the detection of random noise. This comprehensive methodology successfully integrates the principles of statistical process control into two-dimensional image analysis. The use of both global (based on overall residuals) and local (row-wise and column-wise control charts) approaches allows for an extensive examination of the images. This innovative method is considered a significant advancement in quality control and defect detection within textured images, offering a robust framework that overcomes the limitations of traditional SPC methods by considering the spatial relationships between pixel values.

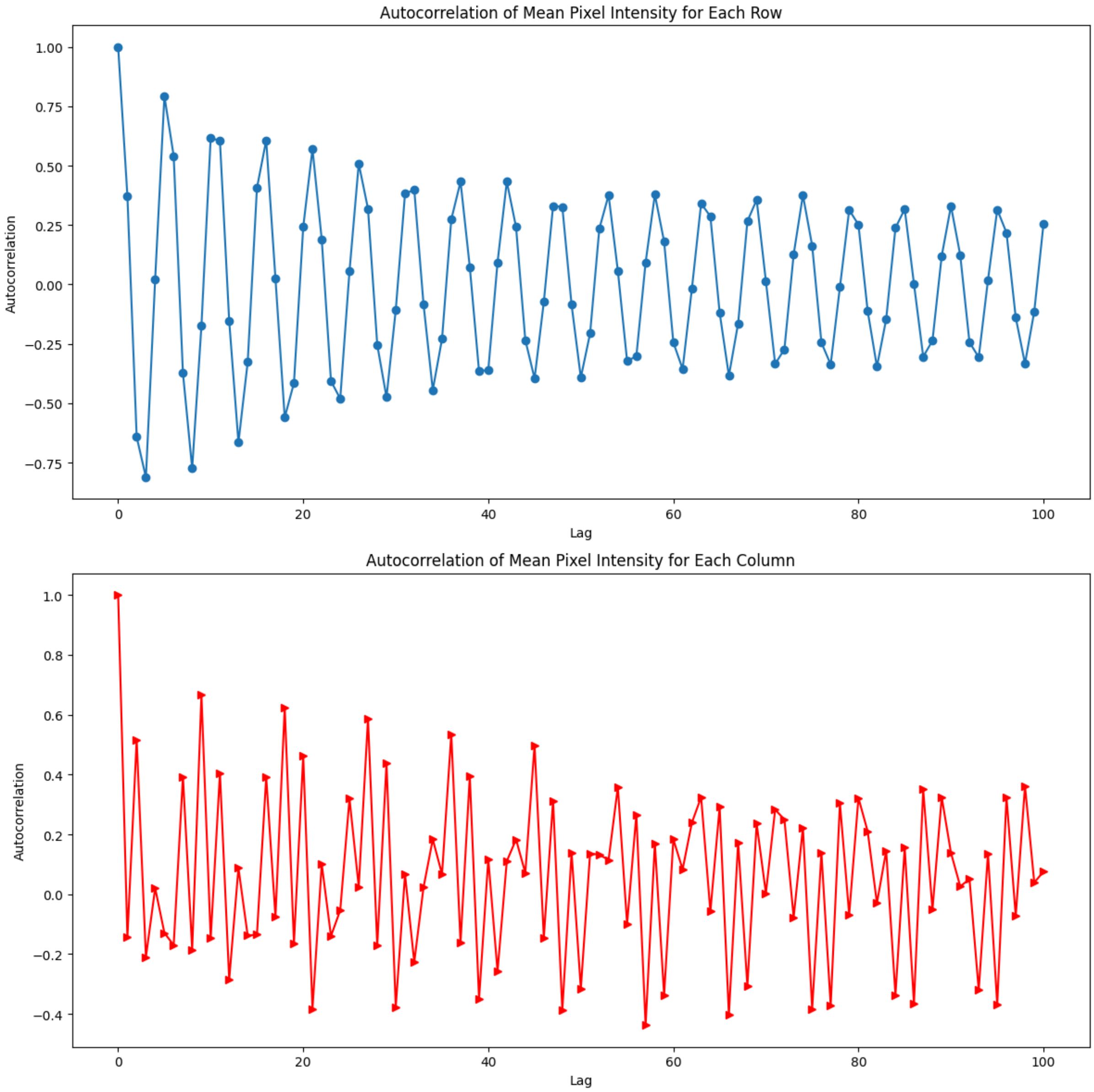

Figure 8 : Autocorrelation graphics of Mean Pixel Intensity for Row and Columns

In our proposal, we analyzed autocorrelated pixel values. We saw a pattern and continued our research over this pattern. Then, based on this pattern we concluded outlier analysis and obtained modified image where detected defects are labeled. Original and Defect-Detected Images are below.

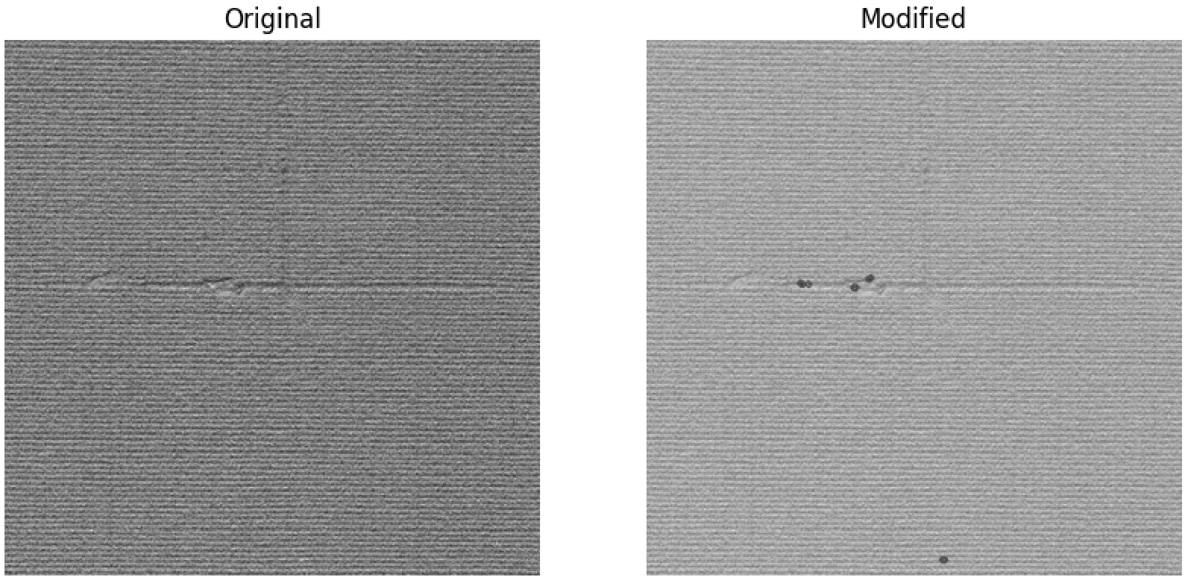

Figure 9: Detected and labeled outliers based on Autocorrelation Outlier Detection.

Comparison

To assess our proposal on alternative images, we generated 100 random integers between 2 and 196 and selected the first 5 available images (172, 6, 116, 191, 59). We applied our proposed method to these five images. The original and modified images are presented below.

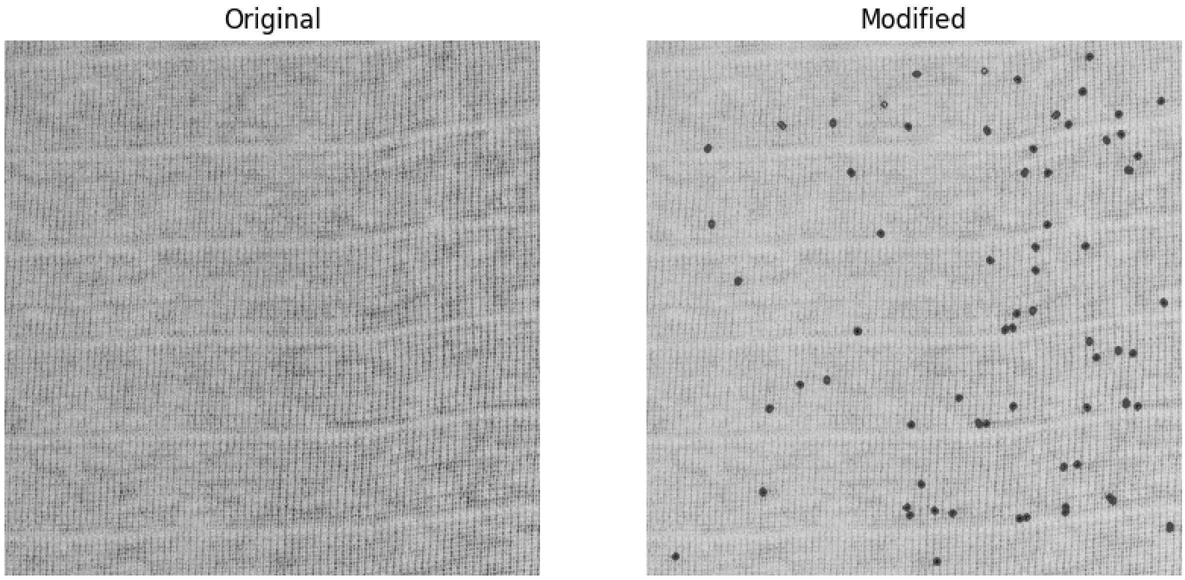

Figure 10: Original image 172 and modified image showing out-of-control pixels

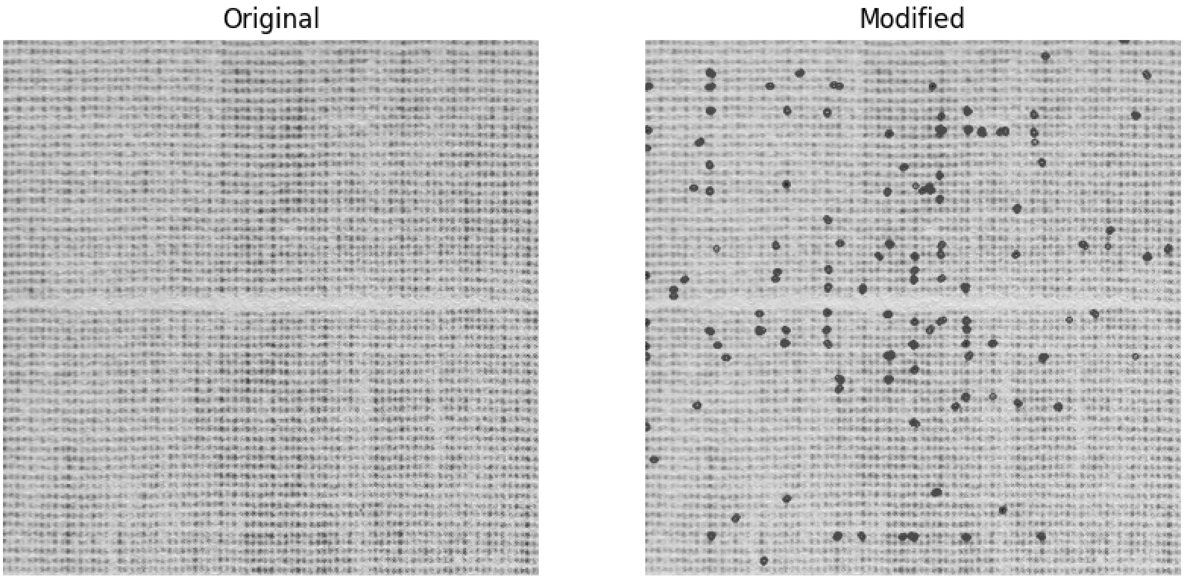

Figure 11: Original image 6 and modified image showing out-of-control pixels

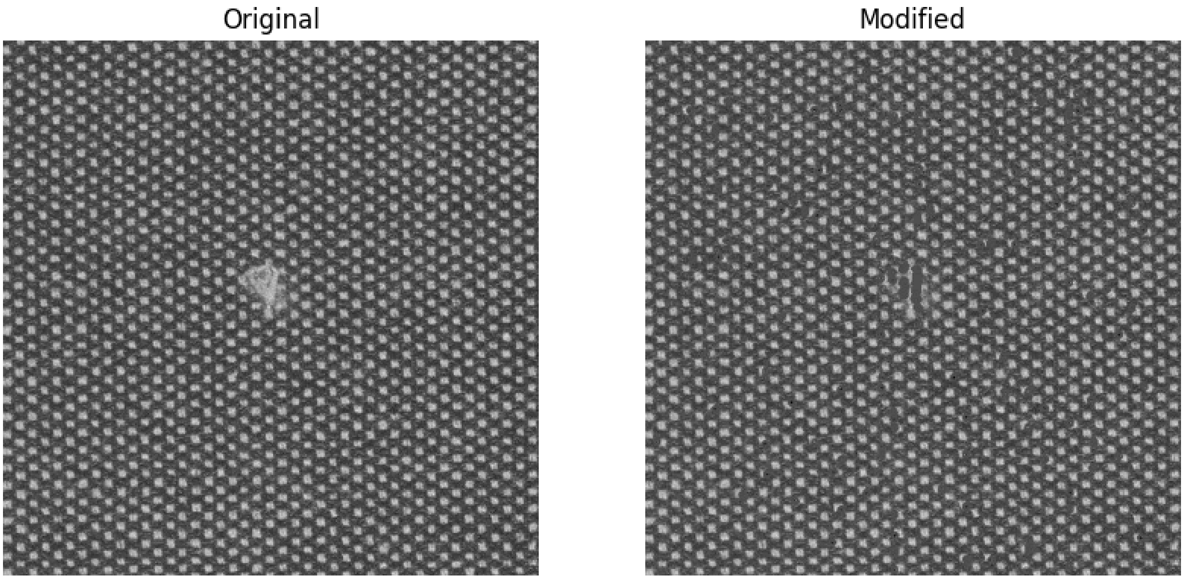

Figure 12: Original image 0116 and modified image showing out-of-control pixels

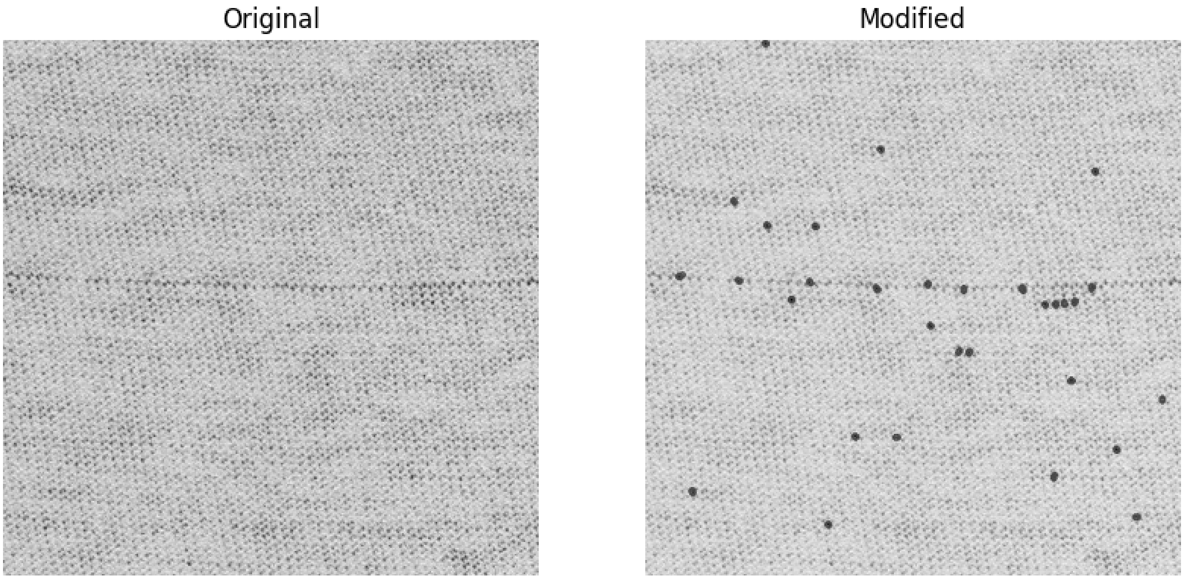

Figure 13: Original image 191 and modified image showing out-of-control pixels

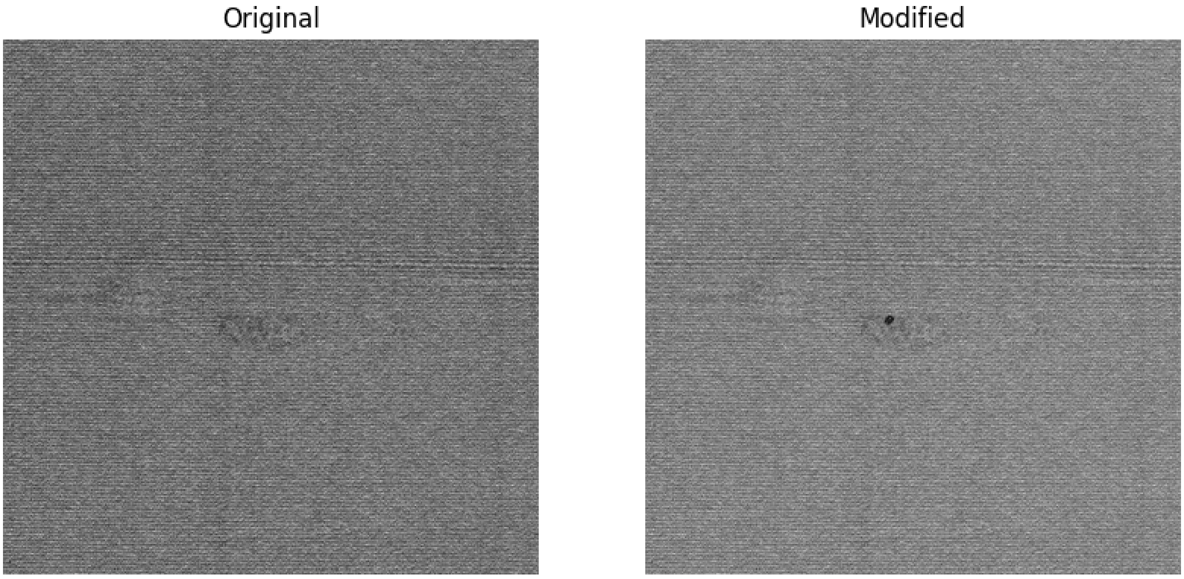

Figure 14: Original image 59 and modified image showing out-of-control pixels

Conclusion

Future Work

Looking ahead, there are ways to make our linen defect-detection project even better. One thing we could explore is finding new ways to understand how pixels in the linen images relate to each other, especially when they form patterns like textures. Right now, our methods assume pixels are kind of independent, but we know that's not exactly true for textured images. So, a better approach might involve figuring out how pixels are connected in these linen pictures. Also, we could test different methods to set the rules for finding defects. Right now, we use some fixed rules, but maybe there are smarter ways to decide what's normal and what's not. It's like finding a better game plan to catch the defects and improve the quality of our linen images. These are the kind of things we could look into for making our project even more effective in the future.

Results

To detect defects and anomalies in a Linen Sample, we practiced two different Approaches [Approach 1&2] and developed a new approach which is based on Autocorrelation values of brightness among rows and columns. Although Approach 1 & Approach 2 provided some anomalies,we observed that not all the detected anomalies are not necessarily a defect. In other words, not all the defects provided by Approach 1 & 2 are not anomalies and these two approaches marked normal pixels as anomalies.

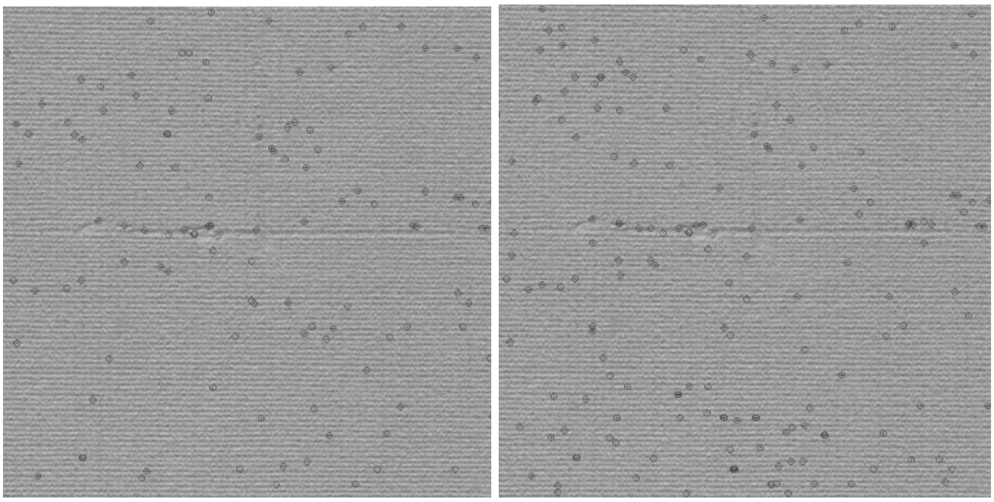

Figure 15: Modified Images from Approach 1(left) & 2(right)

However our proposal, which examines autocorrelation relationships among columns and rows provided a better scene. Although it provided less defects, all the defects that Proposal Approach provided were real defects.

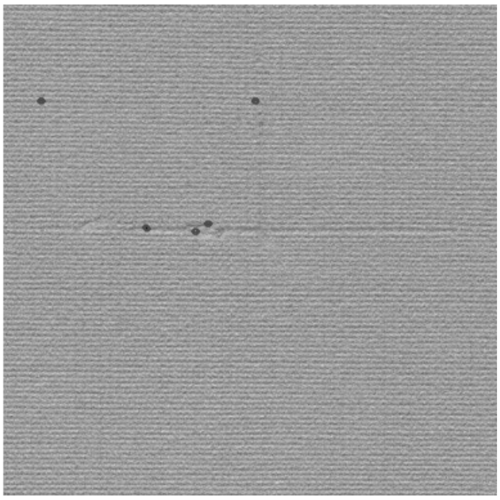

Figure 16: Modified Image from proposed Approach.

Discussion

We can see that Approaches 1 and 2 generated more data points compared to Proposed Approach. To measure the reliability of Approaches, we examined pictures by eyeballing. In result, although Approaches 1&2 provided more data points, they actually marked some of the 'no-defect' pixels as 'defect' pixels. On the other hand, the Proposed Approach marked some of the 'defect' pixels correctly, however, it couldn't manage to mark all the 'defect' pixels. We can see that in Approach 1 & 2, we observed Type-1 error and in Proposed Approach, we observed Type-2 Error, if we consider markings as 'Reject' and not-markings as 'Accept'.

All three of the approaches can be utilized as a starting approach for the further studies in 'Defect Detection in Image Samples'. Next approaches may include 'Randomization of Work Samples (that is, randomly chosen parts of rows, columns, or matrices)', Changing Image Parameters (Not only taking brightness as single input but using all three RGB components, or filters) and many more.

Lastly, Anomaly Detection is a highly popular topic especially if Anomaly is searched in Images. Deep Learning is a highly valued and frequently used method to detect anomalies in an Image. Relevant Deep Learning methods can give powerful results if utilized accordingly.