# IE 423 Quality Engineering

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## PROJECT PART 3

## QUALITY CONTROL ON IMAGES


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## INTRODUCTION

*(Image 25 selected as a group image)*

Linen, obtained from the fibers of the flax plant, is a very valuable textile product that stands out especially in hot climates with its absorbency, coolness and freshness. On the other hand, flax production is a very labor-intensive process and it is vital to monitor these processes as the quality of the flax affects the quality of the final product and to preserve these outstanding qualities of flax. Monitoring helps detect and correct deviations or defects that may arise during production. By using images in this monitoring process, the quality control process becomes both more effective and faster. Traditional auditing methods can be time consuming and human errors may occur during this auditing process. Since linen tissues are complex tissues, it is very difficult for the human eye to distinguish defects in linen consistently. Therefore, automation of visual inspection becomes almost mandatory during the production of materials with complex structures such as linen. In other words, the motivations for using visuals to detect errors in linen manufacturing can be listed as follows:

- Efficiency: Increase the efficiency of the process by using images in the quality control process.
- Accuracy: Increase the accuracy of the defect detection process by leveraging image processing techniques.
- Consistency: Ensure consistent quality in linen by minimizing variations introduced during the production process.
- Timeliness: Speed up the identification and resolution of defects that arise in production to meet production timelines.

## BACKGROUND INFORMATION

Linen process monitoring begins with the production of linen and continues during its use. The aim of this process is to ensure optimum use, cleanliness, quality and sustainability during the life cycle of linen. Technological developments related to this process are continuing. The currently used methods and emerging new trends are as follows:

1. **Inventory Control:** Real-time tracking is made possible by radio-frequency identification (RFID) tags inserted into linens, which guard against loss, theft, and misplaced goods. According to studies, using RFID reduces linen losses by 15% to 20%.

2. **Hygiene Monitoring:** There is a risk of bacterial growth and contamination on linen. These risks can be evaluated and prevented by using UV light sensors and temperature measurement systems. This encourages proactive sanitation measures that protect customers' well-being.

3. **Predictive Maintenance:** By analyzing equipment data, machine learning algorithms are used to schedule preventive maintenance and forecast potential malfunctions. This lessens downtime and extends the life of the equipment.

4. **Sustainability Tracking:** Tools for life cycle assessments track how much resources are used and how using linen affects the environment. This guides environmentally friendly disposal and procurement procedures.

**Emerging Trends**

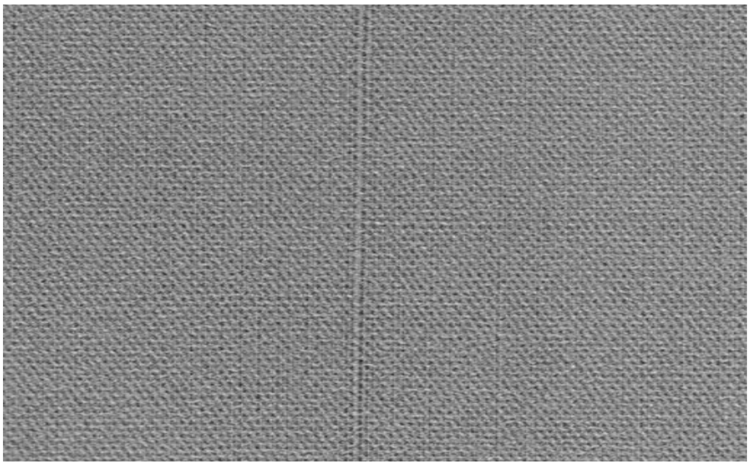
1. **Internet of Things (IoT) Integration:** Real-time data analysis, preventative maintenance, and remote management of linen processes are made easier by connecting monitoring systems to cloud platforms.

2. **Artificial intelligence (AI):** In order to optimize cleaning cycles and enable preventive maintenance, machine learning algorithms are being used to analyze process data and forecast potential problems.

## APPROACH

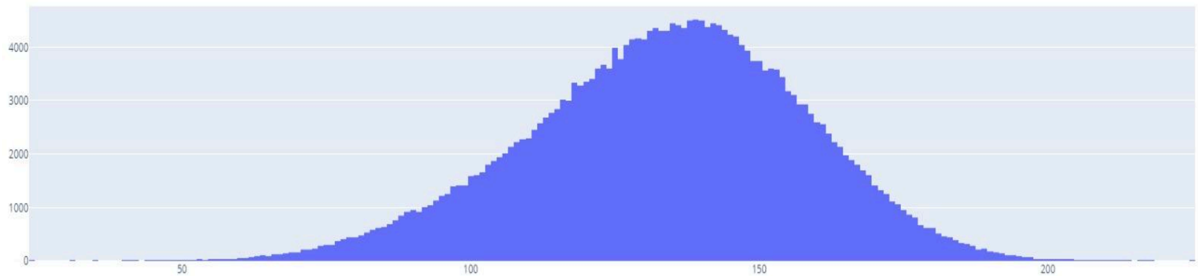
Baseline Defect Detection Approach from a Statistical Data Analysis Perspective

Parallel to the potential steps of the baseline defect detection approach from a statistical data analysis perspective, we have transformed the main image into a grayscale image as a first stage.

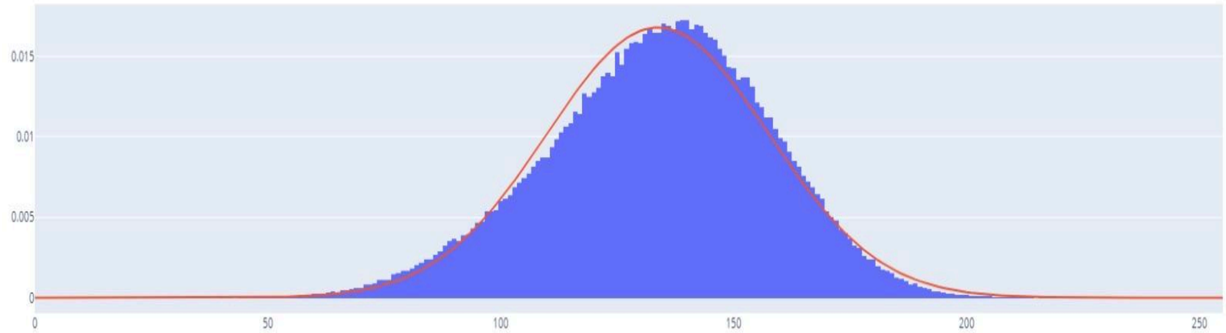


*Grayscale image*

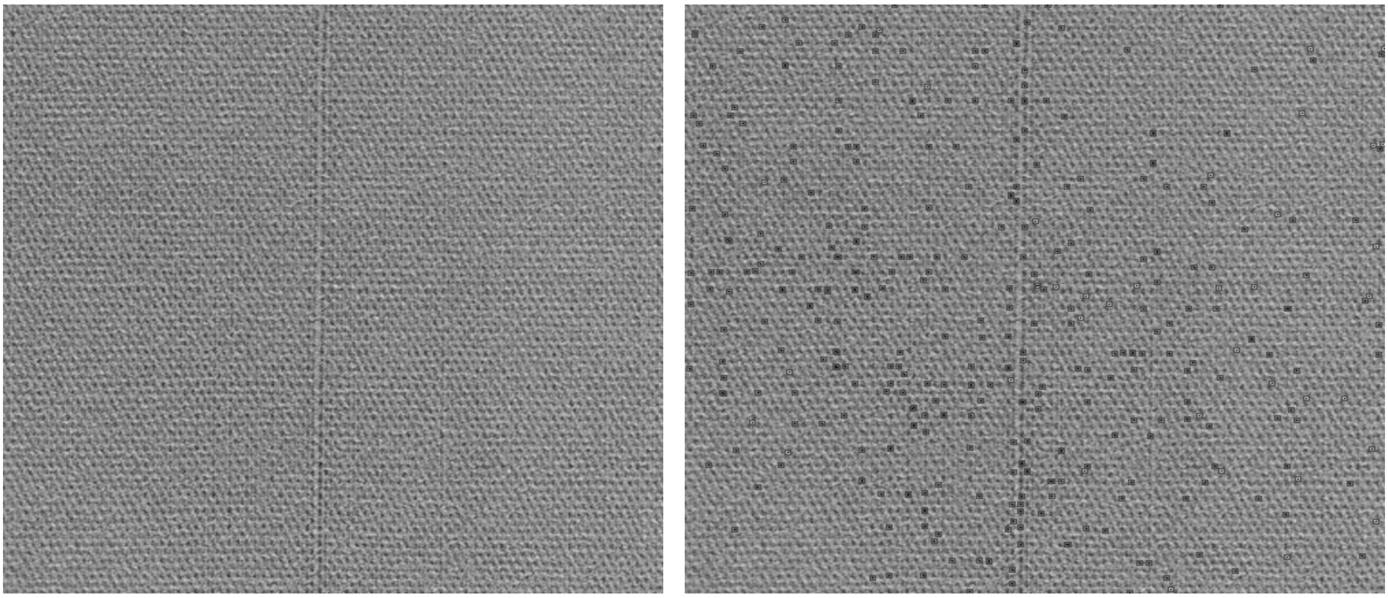
Then, the resulting image provided us basically a matrix where each matrix entry shows the intensity (brightness) level. After this stage, in order to find the pixel value distribution of the grayscale image, we draw the histogram of all pixel values in the image and have obtained the following histogram.




The obtained histogram clearly indicated that the pixel values had a distribution very close to a normal distribution. Therefore, assuming that the pixel value distribution follows a normal distribution, we calculated the mean, standard deviation, and range of the existing data. Then, we have obtained a probability density function (pdf) of a normal distribution that fits the data based on these parameters.The similarity between the obtained probability density function (pdf) and the actual data is illustrated in the following figure.



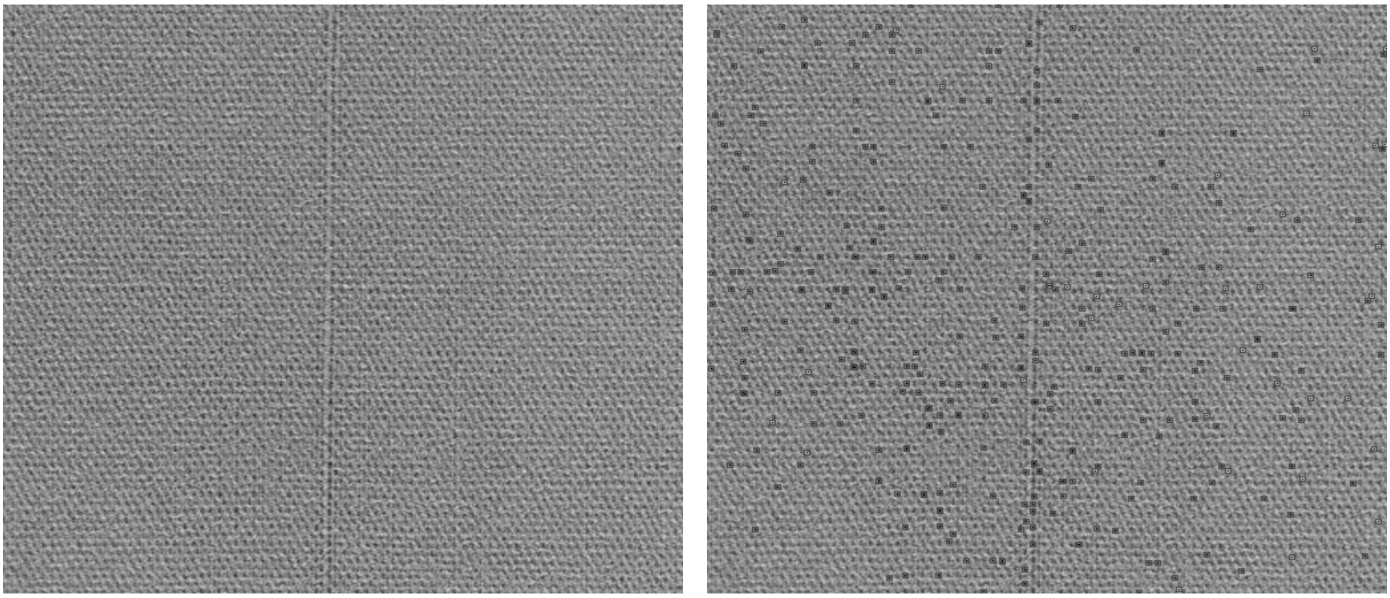

After we assume pixel values follow the normal distribution and its parameters are equal to what we have estimated, we have identified the pixels that are out of the 0.001 probability limits. Accordingly, we have found upper control limit (UCL) and lower control limit (LCL) that leave 0.001 of the observations on the smaller and larger side of the distribution respectively. Then, we have identified these pixels by making these pixels black colored (value of pixels = 0). These black pixels that are outside the UCL and LCL are marked with a rectangular box in the image below.



*Original & Overall based approach*

The pixels outside the probability limits of 0.001 are those that fall outside the upper and lower control limits within the specified intensity levels ranging from 0 to 256. Therefore, considering the average brightness of the total image, pixels appearing very bright (bigger than UCL) and very dark (lower than LCL) are classified as outliers and marked within the rectangular box.

In the next stage, it is required to perform the same operation on the 51x51 patches of images. In order to do that we need to consider each 51x51 window and provide an appropriate probability distribution that fits well to the shape. Assuming that the pixel value distribution of each window follows a normal distribution, we calculated the mean and standard deviation of each window. Then, we have obtained a probability density function (pdf) of a normal distribution that fits the data based on these parameters. After that we have found UCL and LCL that leave 0.001 of the observations on the smaller and larger side of the distribution respectively. At the end, we have identified out of control pixels by making these pixels black and marking them with a rectangular box.

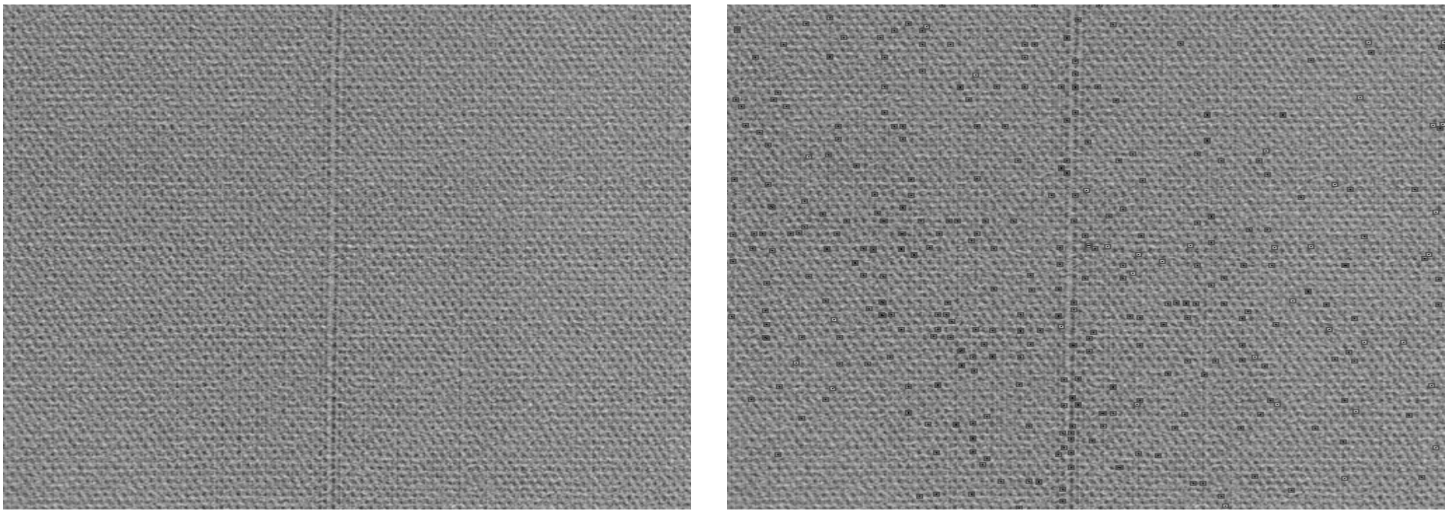


*Original & 51x51 window based approach*

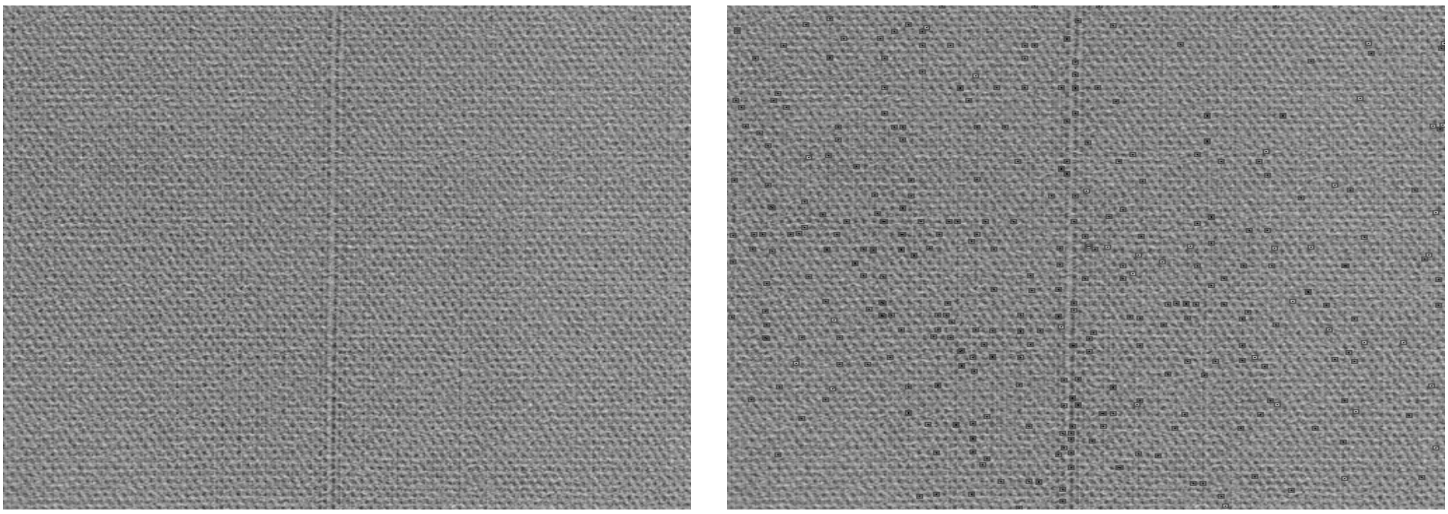
In images with 51x51 sized regional patterns, this method proves to be more successful compared to the previous approach and provides a model with fewer errors based on pixels in each region. Since this approach determines out-of-control pixels by considering the mean and variance of each window, it selects pixels that are very bright or very dark relative to mean brightness of each window. However, it is inadequate for defect detection in images containing different patterns, as in our example.

A Simple Defect Detection Approach from a Control Chart Perspective

In the simple defect detection approach from a control chart perspective part, it is required to find out out-of-control pixel values considering the each row and each column of the matrix. Accordingly, we have determined mean and variances of each column and each row as a first step. Then, we have applied 3-sigma control limit approach to find upper control limit (UCL) and lower control limit (LCL) by summing mean and 3 times standart deviation of each column/row. After constructing an appropriate chart for monitoring the mean and variance, we have identified pixels that are out of control. We have specified them by making black colored (value of pixels = 0). Also, these black pixels that are outside the UCL and LCL are marked with a rectangular box in the images below.



*Original & Row based approach*



*Original & Column based approach*

In images with vertical or horizontal patterns, this method proves to be more successful compared to the previous approach and provides a model with fewer Type 1 and Type 2 errors based on pixels in each row/column. Since this approach determines out-of-control pixels by considering the mean and variance of each row/column, it selects pixels that are very bright or very dark relative to each row/column. However, it is still inadequate for defect detection in images containing two-dimensional patterns, as in our example.

<u>Our Approach</u>

Regular control charts built as in the simple strategy assume that pixel values are independent of each other. However, the linen image we are working on possesses a textured appearance, meaning that pixel values are correlated. In other words, when we use regular control charts built as in the simple strategy for our image, we encounter an autocorrelation problem. However, we have devised a strategy to eliminate this autocorrelation problem in defect detection in our approach.

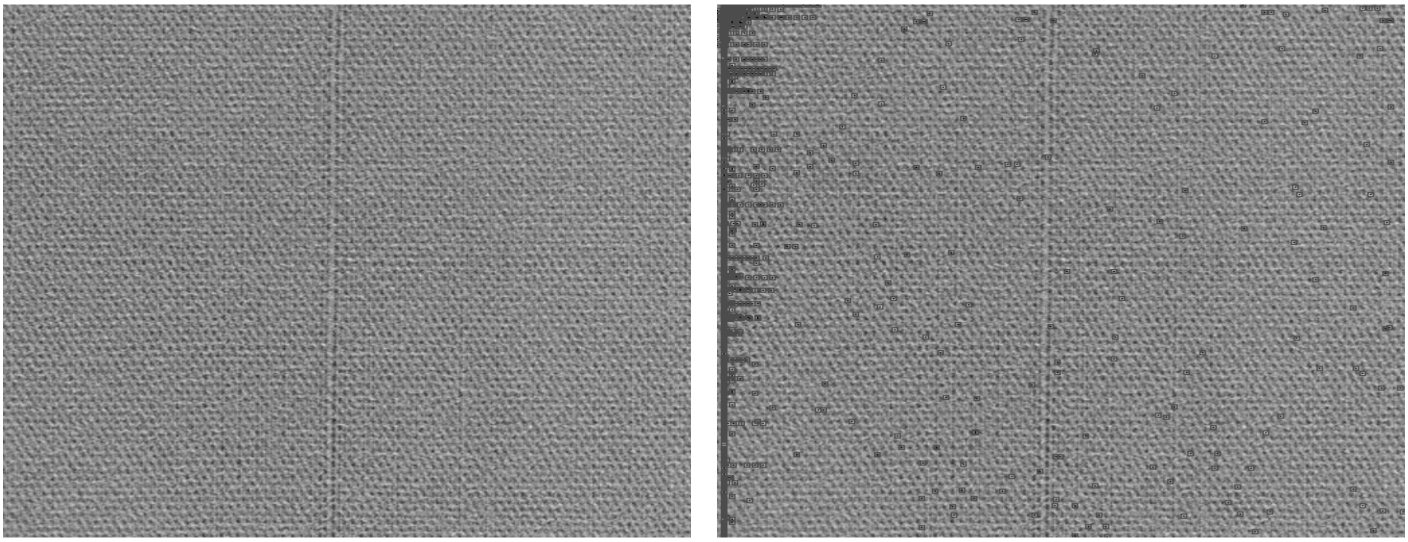
In our model, we have created an unique ARIMA model for each row using the 'autoarima' function. Subsequently, we compared the predictions generated by these ARIMA models with our actual data. In these comparisons, we have calculated the difference in intensity of pixels between the actual data and the model output in each row, creating a 'residual' list. To determine the parameters of this list, we computed the mean and standard deviation of the data within the list. Lastly, using the residual parameters, we established our control limits as Mean(residual) ± 3*Standard Deviation(residual). We then checked pixels the residual amount exceeding these control limits to zero (black) for the corresponding pixels.

## RESULTS

We applied the ARIMA model that we created to our image and analyzed the resulting defect detection outcomes. The obtained results did not exhibit a sufficient accuracy for defect detection and produced clustered outcomes in specific regions. Although the created model, utilizing residual parameters, allowed for more comprehensive comparisons compared to previous methods, the error rate in the visual examination of objects with textures similar to those in our sample image was high. Possible reasons for this could include:

- Not applying the ARIMA model separately to columns
- Not evaluating column and row control limits together
- Not appropriately determining residual control limits
- Overfitting

Chosen pixels by our model that are outside the UCL and LCL are marked with a rectangular box in the images below.



*Original & Our Model*

The model, which we tried to eliminate autocorrelation through the ARIMA model, did not yield satisfactory results in the other five images as well. Therefore, comparisons for the other five images have not been included in the report.

## CONCLUSIONS AND FUTURE WORK:

After examining the models created using overall image, 51x51 windows, columns and rows it is inferred that 2D inspections and multiple control charts are necessary to detect defections of textured objects as in the linen example. While our model generated using residual parameters facilitated more extensive comparisons than previous approaches, there was a notable high error rates. However, under the conditions where the suggested corrections and improvements are implemented in the report, this approach will yield reliable results.

## WHAT ARE POSSIBLE EXTENSIONS TO HAVE A BETTER APPROACH?

As a result of the research we conducted from online resources to develop our method, we thought that getting rid of autocorrelation in two-dimensional data and performing a statistical analysis would give better results. As a result of our research, we learned that methods such as 'Gaussian filtering' and 'spatial correlation' can be applied for this, but we could not put it into code. However, we can say that if we could add these methods to the code and get a result, we would see an improvement over our current result.

**Gaussian Filtering:** Gaussian filtering is similar to using a bell-shaped brush to softly blur a signal or image. A mathematical function is employed to reduce undesired noise and maintain crucial information. Consider a weight matrix that resembles a bell curve and is centered around a pixel. The environment surrounding each pixel affects its new value, with closer neighbors having a larger impact. By adjusting the "spread" of this bell curve, we control the amount of blurring, reducing noise without losing too much fine detail. This makes Gaussian filtering a powerful tool for image denoising, softening features, enhancing edges, and even analyzing images at different scales. It's a delicate balance, though, as too much smoothing obscures important details, so picking the ideal amount is essential.

**Spatial Correlation:** Spatial correlation analysis reveals the hidden relationships in our environment by analyzing how values of a variable, such as temperature or crime rates, tend to cluster together across different geographic locations. From forecasting disease outbreaks to improving urban planning, this potent tool, akin to a statistical GPS, aids in our understanding of the non-random patterns found in nature. Spatial correlation helps us make sense of the world around us, create precise models, and eventually reveal the mysteries woven throughout its fabric by measuring the degree and kind of relationship between neighboring points.

## REFERENCES

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