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Improving Quality Inspections with Image Analysis and Artificial Intelligence

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Abstract: This study delves into the pivotal role of artificial intelligence (AI) and image processing techniques in revolutionizing quality control processes across diverse industries. The modern landscape of manufacturing and quality assurance demands advanced methodologies that go beyond human capability, and AI-powered image analysis has emerged as a transformative solution. In this research, we explore the integration of machine learning, computer vision, and image processing algorithms to enhance the accuracy, efficiency, and comprehensiveness of quality control procedures. The study begins by elucidating the theoretical foundations of image processing and AI, highlighting their synergy and applicability in quality control. It examines the pivotal components of this technology, including deep learning, convolutional neural networks (CNNs), and object recognition algorithms. We also investigate the practical challenges and considerations associated with implementing AI-driven image processing systems in industrial settings, such as data acquisition, hardware, and real-time processing. A central focus of this research is the evaluation of AI's capacity to inspect and analyze images, patterns, and anomalies across various sectors, from automotive and electronics to pharmaceuticals and food processing. We present case studies and empirical results demonstrating the significant improvements in defect detection, yield enhancement, and production efficiency achieved by integrating AI-powered image analysis. In conclusion, this study underscores the transformative potential of AI and image processing techniques in quality control, offering a glimpse into the future of manufacturing and production. The integration of AI and image analysis not only accelerates defect detection but also ensures consistent product quality, ultimately strengthening competitiveness and customer satisfaction.

1. Introduction

Quality control has been a cornerstone of manufacturing and production processes for decades, ensuring that products meet predefined standards and specifications. Traditional quality control methods, primarily reliant on human inspection, while effective to a certain extent, are laborintensive, subjective, and often susceptible to errors. In today's fast-paced and increasingly complex industrial landscape, there is a growing demand for more efficient, reliable, and comprehensive quality control solutions. The integration of artificial intelligence (AI) and image processing techniques has emerged as a transformative force in the realm of quality control. Leveraging machine learning, computer vision, and advanced image analysis algorithms, AI systems are capable of automating, enhancing, and, in some cases, redefining quality control procedures. This revolution is not limited to a specific industry but spans a broad spectrum, from automotive and electronics to pharmaceuticals and food processing.

The primary objective of this study is to explore the multifaceted implications of AI-powered image processing in the context of quality control. By integrating AI and image analysis into quality assurance workflows, industries are poised to achieve unprecedented levels of precision, efficiency, and cost-effectiveness. The time is ripe to investigate the theoretical foundations, practical implementations, challenges, and transformative potential of this dynamic technological convergence. This study begins by establishing the theoretical underpinnings of AI and image processing in quality control. It unravels the synergy between AI and computer vision, detailing the core components of AI systems, including neural networks, deep learning, and convolutional neural networks (CNNs). We explore how these components enable machines to recognize, classify, and analyze visual data, thus facilitating automated quality assessments. We delve into real-world applications of AI and image processing in quality control across various industries. Case studies and empirical evidence demonstrate the tangible benefits, such as enhanced defect detection, yield optimization, and increased production efficiency. These examples highlight how AI-driven image analysis can transcend the limitations of human inspection, identifying subtle defects or irregularities that might elude the human eye. The adoption of AI and image processing in quality control is not without its challenges. This study addresses practical considerations, including data acquisition, hardware requirements, and real-time processing constraints. We also discuss issues of data privacy, ethical considerations, and compliance with regulatory standards, as these are paramount in the integration of AI technologies into quality assurance workflows. As AI and image processing redefine the landscape of quality control, it is essential to explore their broader implications. This includes not only efficiency gains and cost savings but also their impact on traditional quality control workflows and workforce dynamics. The integration of AI systems necessitates a rethinking of roles and responsibilities in quality assurance.

In conclusion, the introduction of AI and image processing in quality control represents a significant paradigm shift in manufacturing and production. This study aims to illuminate the path forward, providing insights into how industries can harness the power of AI and image analysis to ensure consistent product quality, improve competitiveness, and enhance customer satisfaction. This study organized into five sections. A literature review of the image processing in section 2. Section 3 presents the methodology and Section 4 covers implementation and last section covers the conclusion.

2. Literature Survey

Improving quality inspections with image analysis and artificial intelligence (AI) is an emerging and rapidly growing field. A Some of the researchers discussed the feature construction methods for food quality inspections. They use of deep learning techniques for quality control in manufacturing systems, particularly for defect detection in images [1, 2]. Lee et al. explore insights into computer vision applications for quality control in manufacturing processes, offering case studies and practical approaches [3]. Seong et al. explore the use of machine learning, including deep learning, for computer vision tasks, which are critical for quality inspections [4]. Some of the scientists discusse the use of image analysis and machine learning for quality control in the care in oncology [5-7]. Chow et al. explore a computer vision system for detecting surface defects with deep learning in concrete structure, which is crucial for quality control in the civil infrastructure [8]. Wang et al. used the Aı techniques to improve and enhance the patient care quality [9]. Wang et al. applied the deep learning methods to early deterction and prediction of gastric cancer [10]. Li et al. focuse on the application of deep learning for defect detection in X-ray images, which is critical for non-destructive testing in manufacturing [11]. Ardebili et al. used the artificial intelligence in dam water level detection [12]. Naiki et al. provide a comprehensive review of deep learning methods applied to quality inspection tasks, covering various industries [13]. Zhong et al. used the AI algortihms the analysis of quality properties of botanical drugs [14]. Bendaouia et al. used the real time montoring with ConvLSTM in flotation monitoting techniques for froth inspection [15]. Rozanec et al. discussed the visual quality control with industry 4.0 [16]. They developed the automatic visual inspector.

In summary, improving quality inspections with image analysis and AI is essential for enhancing product quality, reducing costs, and maintaining competitiveness in today's fast-paced and data-driven industrial landscape. The ability to provide consistent, accurate, and scalable quality control is a key driver for the adoption of AI in manufacturing and related fields.

3. Image Processing

Images (photographs, drawings, etc.) can be queried based on their color distribution, texture structure, regional shape, outline coherence, or objective classification [17]. As part of this system, applications such as comparing all images for image matching or randomized review are quite costly.

Unlike image enhancement and image restoration, image segmentation is a problem related to image analysis and is the process of preparing an image for the display and recognition stages of image processing. In this sense, image segmentation can be defined as dividing an image into meaningful regions, each of which contains different features. These features can be, for example, similar luminances in the image, which can represent objects in different regions of the image (in Fig. 1).

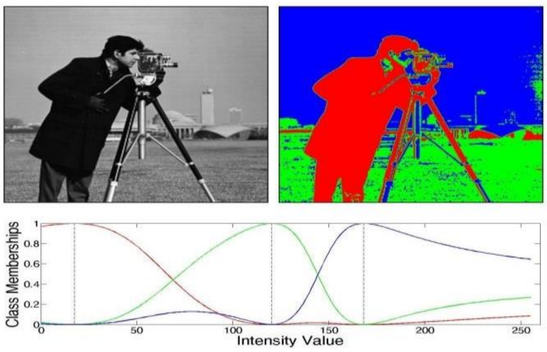


Figure 1: Image Segmentation (https://www.fiverr.com/haroonshakeel/do-image-classification-segmentation-and-object-detection)

The identification of object particles with similar brightness within an image can be used for classification and identification purposes. In general, segmentation algorithms for gray-scale images are designed based on one of two basic properties of gray level values. These properties are related to the discontinuity and similarity in the gray level values within the image [18].

3.1 Similarity Measure

Image similarity is assessed on two levels: the first level involves region-level evaluation, which quantifies the dissimilarity between two regions based on their low-level characteristics. The second level pertains to image-level comparison, which gauges the overall resemblance between two images, even if they contain differing numbers of regions. Many researchers commonly utilize a Minkowski-type metric to establish the distance between regions [19-21]. For instance, if we have two regions represented by p-dimensional vectors (x_1, x_2,...,x_p) and (y_1, y_2,...,y_p), respectively, the Minkowski metric can be expressed as:

$$d(X,Y) = \left(\sum_{i=1}^{p} |x_i - y_i|^r \right)^{1/r} \quad (1)$$

Notably, when r equals 2, it corresponds to the familiar Euclidean distance (L_2 distance), and when r is set to 1, it becomes the Manhattan distance (L_1 distance). A commonly employed variation involves the weighted Minkowski distance function, which incorporates weights to emphasize specific features, and it can be expressed as:

$$d(X,Y) = \left(\sum_{i=1}^{p} w_i |x_i - y_i|^r \right)^{1/r} \quad (2)$$

Represents the weights assigned to different features.

3.2 MPEG-7 Visual Descriptors

The Moving Picture Experts Group (MPEG) has introduced a range of visual descriptors within their MPEG-7 standard. These descriptors are designed to be computationally efficient for acquisition and comparison while optimizing memory storage requirements. An overview of these features can be found in references [22, 23, 24, 25]. The MPEG initiative has a strong focus on features that are both affordable to obtain and compare, and it places a high emphasis on memory optimization.

We utilized this reference implementation in our framework for experiments involving these features. We employed the comparison measures as proposed by the MPEG standard and as implemented in the reference implementation.

MPEG 7: Scalable Color Descriptor The scalable color descriptor is essentially a color histogram in the HSV color space encoded using a Haar transform. It possesses a binary representation that can be scaled concerning bin numbers and bit accuracy representation over a wide range of data rates.

MPEG 7: Color Layout Descriptor The color layout descriptor efficiently represents the spatial distribution of color in visual signals in a highly compact form.

MPEG 7: Edge Histogram The edge histogram descriptor characterizes the spatial distribution of five types of edges, including four directional edges and one non-directional edge.

3.3 Correlation Analysis of Features

The method presented here takes a different approach. It doesn't necessitate training data but rather analyzes the correlations between the features themselves. Instead of automatically selecting a set of features, it provides the user with information to assist in selecting an appropriate set of features. Automatic methods for feature selection have been proposed in the past [26, 27]. However, these automatic methods have limitations. They don't directly explain why certain features are chosen, can be challenging to manipulate from a user's perspective, and often require labeled training data. To assess the correlation between different features, we examine the correlations between the distances (d(q, X)) obtained for each feature when comparing a query (q) to each image (X) in the database. For each pair of a query image (q) and a database image (X), we construct a vector (d_1(q, X), d_2(q, X), ..., d_m(q, X), ..., d_M(q, X)), where d_m(q, X) represents the distance between the query image (q) and the database image (X) for the mth feature. We then calculate the correlation between these dm values across all q in the set (q_1, ..., q_l, ..., q_L) and all X in the set [X_1, ..., X_n, ..., X_N]. The M by M covariance matrix R is computed by considering all N database images and all L query images. The matrix is calculated as follows:

$$\mu_i = \frac{1}{NL}\sum_{n=1}^{N}\sum\nolimits_{l=1}^{L}\left(d_i(q_i,X_n)-\mu_i\right).\left(d_j\left(q_{ij},X_n\right)-\mu_i\right) \tag{3}$$

With

$$\mu_i = \frac{1}{NL}\sum_{n=1}^{N}\sum_{l=1}^{L}\left(d_i(q_i,X_n)\right) \tag{4}$$

3.4 Edge Detection

Edge detection is a widely used technique in image processing. Its purpose is to detect or highlight the edges of objects or structures in an image (in Fig.2). Edges are sharp transitions between different pixels of an object or structural element.

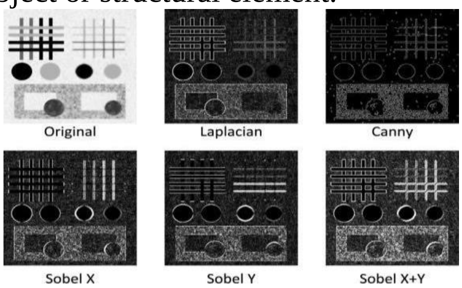


Figure 2: Example of Edge Determination Application

Edge detection finds edge regions by detecting abrupt changes in intensity or color values in an image. This is accomplished using image processing algorithms and filters. Edge detection algorithms use differences in pixel values and intensity gradient to determine the location of edges. There are several different types of edge detection algorithms, including:

1) Gradient-based Edge Detection: This method uses the gradient in pixel values. Usually gradient filters such as Prewitt, Sobel filter are used.

2) Laplace Based Edge Detection: This method uses the second derivative of the pixel values in the image. Where there are edges, the pixel values change drastically. It is implemented using Laplacian filters or LoG (Laplacian of Gaussian) filter.

3) Canny Edge Detection: This method uses a Gaussian filter to reduce noise and then calculates the gradient in pixel values. It then generates a clear edge map by attenuating or removing weak edges using a given threshold value.

Edge detection is an important step in many image processing applications such as object detection, image segmentation, image compression and object tracking.

3.5 OpenCV Library

OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine vision library. Computer vision is a discipline that deals with and analyzes the digital world of illumination. OpenCV provides a set of functions, executions and tools to perform a variety of such operations. The OpenCV library consists of five basic components. These components are shown in Figure 3.

The main purpose of OpenCV is to enable developers to enhance their applications by offering different operations on images. Below are some of the key features and components of OpenCV:

Image Processing: OpenCV provides processing to perform a number of operations on images. These operations include basic operations such as resizing, rotation, cropping, brightness and contrast adjustment.

Image Filtering: OpenCV can be used to playback images. Filters such as blur, sharpen, edge adjustment and noise limit can be applied.

Object Detection and Recognition: OpenCV provides a range of work and functions for object detection and recognition. It is possible to detect and run detection using unattended machine computer models.

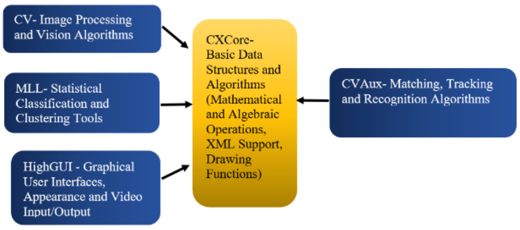


Figure 3: OpenCV Components

Face Recognition: OpenCV offers variety and purpose for face recognition. Operations such as face detection, face recognition and facial feature detection can be performed.

Camera and Video Processing: OpenCV can be used to perform operations on cameras and video streams. It can take frames from video streams, perform operations such as motion output, object detection, etc.

OpenCV can be used with many programming languages such as C++, Python, Java as well as Windows, Linux, macOS. It is a popular library with a large user community and resource support for image processing frameworks.The OpenCV library is licensed under the BSD license. In this license, which is known as the freest of the free licenses, the person who receives the code has the freedom to use it as they wish. This library, which is free for academic and commercial use, can be used on different platforms such as Windows, Linux, MacOS X. Developed in Intel's image processing laboratories and optimized for speed, the OpenCV Library was developed for real-time applications. With USB 2.0 technology, real-time applications can now be run even on a standard computer. All these developments have led to the use of this library in many areas from toy making to industrial production [28].

4. Case Study

In the plant, a 24 meter long profile is produced after the extrusion process in the presses. A sample is then taken from this profile for examination. This sample is examined by an employee. This employee is a quality control officer. We list the activities carried out by this officer during the inspection: dimensional control, wall thickness control, deviation from perpendicularity control, bump control, functional working parts control, plastering trace control, etc. on the sample. Sometimes the quality employee is even indecisive in some controls and talks to the production supervisor. During this time, as the human performs these activities, both time is lost and sometimes faulty products may pass the control.

Stage 1: Examining the Existing System: In the current system, each press line has one person in charge of quality control. These people take samples during profile production and make examinations. As a result of these examinations, the quality control officer decides whether the profile is within the desired tolerance range. As a result, he gives approval for the profile to be sent to the next process location. If he does not give approval, the profile is tried to be brought to the desired feature. The scrapped profile is a kind of fail. Apart from the press lines, there is a Quality Control officer in every line of every department in the factory. Thus, we ensure that our quality is extremely high by conducting inspections at every stage of production. In this case, we apply the Total Quality Philosophy in our business (in Table 1).

Stage 2: Identifying Problems or Areas for Improvement: There are 3 options in front of us to determine the area where the problem will be applied. These are; Kanuni Press, Orhan Press, Fatih Press. We decided to use the AHP method to choose between these 3 press lines. As a result, the AHP study we performed is as follows (in Table 2):

Table 1: Feature of Presses

FEATURE / PRESS NAME	Kanuni Press	Orhan Press	Fatih Press
Tonnage	16500	15300	25300
Cold Saw	Manuel	Manuel	Automatic
Failure Frequency	15 day	17 day	11 day
Scrap	5%	%3.5	%2.5

Table 2: Comparison of (a) Tonage Characteristics (b) Cold Saw Feature (c) Failure Feature (d) Tonnage Characteristics

a

TONAGE	Kanuni Press	Orhan Press	Fatih Press	Normalization-Press-Kanuni	Normalization-Press-Orhan	Normalization-Press-Fatih	Total
Kanuni Press	1	3	1/5	0,1579	0,3333	0,1429	0,2114
Orhan Press	1/3	1	1/5	0,0526	0,1111	0,1429	0,1022
Fatih Press	5	5	1	0,7895	0,5556	0,7143	0,6864
Total	6,33	9,00	1,4				

b

COLD SAW	Kanuni Press	Orhan Press	Fatih Press	Normalization-Press-Kanuni	Normalization-Press-Orhan	Normalization-Press-Fatih	Total
Kanuni Press	1	1	7	0,4667	0,4667	0,4667	0,4667
Orhan Press	1	1	7	0,4667	0,4667	0,4667	0,4667
Fatih Press	1/7	1/7	1	0,0667	0,0667	0,0667	0,0667
Total	2,143	2,143	15				

c

FAILURE	Kanuni Press	Orhan Press	Fatih Press	Normalization-Press-Kanuni	Normalization-Press-Orhan	Normalization-Press-Fatih	Total
Kanuni Press	1	3	1/3	0,2308	0,3333	0,2174	0,2605
Orhan Press	1/3	1	1/5	0,0769	0,1111	0,1304	0,1062
Fatih Press	3	5	1	0,6923	0,5556	0,6522	0,6333
Total	4,33	9	1,53				

d

TONAGE	Kanuni Press	Orhan Press	Fatih Press	Normalization-Press-Kanuni	Normalization-Press-Orhan	Normalization-Press-Fatih	Total
Kanuni Press	1	3	5	0,6522	0,6923	0,5556	0,6333
Orhan Press	1/3	1	3	0,2174	0,2308	0,3333	0,2605
Fatih Press	1/5	1/3	1	0,1304	0,0769	0,1111	0,1062
Total	1,53	4,33	9				

We scored the features we identified according to the degree of impact on the number of defective products of the presses. We determined 1 to be ineffective and 9 to be very effective. As a result, we scored 50.78% and since Kanuni Press tends to produce more defective products, we determined the line of Kanuni Press as our work area for our design project. We determined our work area as Kanuni Press. Then we decided to conduct a time study on this press line (in Fig. 4). Thus, we concentrated our work in this area by determining the activities that we spend too much time. The summary of the time study we conducted is as follows (in Table 3):

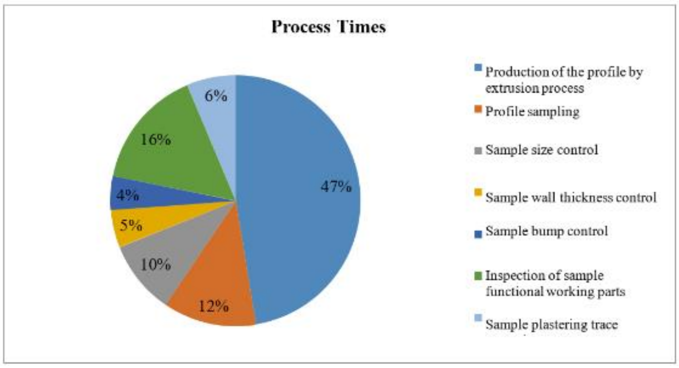


Figure 4: Pie Chart of Activities and Processing Times for Time Study

Table 3: (a) Comparison of each other (b) Attributes Weight

a

FEATURE	Kanuni Press	Orhan Press	Fatih Press	Normalization-Press-Kanuni	Normalization-Press-Orhan	Normalization-Press-Fatih	Kanuni Press	Orhan Press	Total
Tonage	1	1/5	1/3	1/7	0,0625	0,0441	0,0455	0,0789	0,057755
Cold Saw	5	1	3	1/3	0,3125	0,2206	0,4091	0,1842	0,281597
Failure Frequency	3	1/3	1	1/3	0,1875	0,0735	0,1364	0,1842	0,145401
Scraw	7	3	3	1	0,4375	0,6618	0,4091	0,5526	0,515247
Total	16	4,53	7,33	1,8095					

b

Alternative	Tonage	Cold Saw	Failure Frequency	Scraw	Criteria	WEIGHT
Kanuni Press	0,2114	0,4667	0,2605	0,6333	Tonage	0,0578
Orhan Press	0,1022	0,4667	0,1062	0,2605	Cold Saw	0,2816
Fatih Press	0,6864	0,0667	0,6333	0,1062	Failure Frequency	0,1454
					Scraw	0,5152

From Table 4 and Figure 5, we derived the data. We can see the activities we performed and the time when we check the manual control phase, as well as the percentage of these activities in production. We can say the press line directly affects the quality of product.

Table 4: Ranking of Attribute Values

ALTERNATIVE	SCORE	PERCENTAGE
Kanuni Press	0,5078	50,78%
Orhan Press	0,2870	28,70%
Fatih Press	0,2052	20,52%

Table 5: Table of Activities and Processing Times for Time Study

Activities	Process Times (sn)
Production of the profile by extrusion process	165
Taking samples from the profile	42
Sample size control	33
Sample wall thickness control	17
Sample camber control	15
Control of sample functional working parts	54
Sample coating trace control	22
Total	**348**

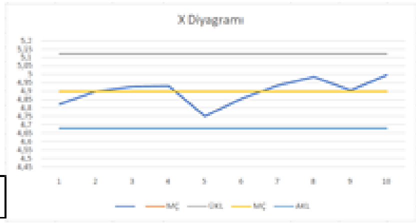
Stage 3: Analyzing the Number of Defects in Parts: We also wanted to examine the Kanuni Press line from a quality perspective. For this, we chose the wall thickness control, which is also applied manually. We measured the wall thickness of the part by sampling the process 10 times, 5 units each time (in Table 6).

Table 6: Piece Wall Thickness Measurement and X-R Values Table

Örnek No	Ölçüm Değerleri					R Değerleri				X Değerleri				
	X1	X2	X3	X4	X5	R	ÜKL	MÇ	AKL	Ortalama	Ortalamaların Ortalaması	ÜKL	MÇ	AKL
1	4,86	4,55	4,81	4,85	5,03	0,48	0,81005	0,38	0	4,82	4,8992	5,12019	4,8992	4,67821
2	5,02	5,05	4,72	4,89	4,81	0,33	0,81005	0,38	0	4,898	4,8992	5,12019	4,8992	4,67821
3	4,88	4,98	4,95	4,74	5,08	0,34	0,81005	0,38	0	4,926	4,8992	5,12019	4,8992	4,67821
4	5,03	4,91	4,97	4,79	4,95	0,24	0,81005	0,38	0	4,93	4,8992	5,12019	4,8992	4,67821
5	4,87	4,12	4,89	4,88	4,99	0,87	0,81005	0,38	0	4,75	4,8992	5,12019	4,8992	4,67821
6	4,89	5,01	5,03	5,09	4,25	0,84	0,81005	0,38	0	4,854	4,8992	5,12019	4,8992	4,67821
7	4,96	4,92	4,95	4,94	4,89	0,07	0,81005	0,38	0	4,932	4,8992	5,12019	4,8992	4,67821
8	5,01	5,02	4,89	4,97	5,03	0,14	0,81005	0,38	0	4,984	4,8992	5,12019	4,8992	4,67821
9	4,78	4,88	4,91	4,88	5,07	0,29	0,81005	0,38	0	4,904	4,8992	5,12019	4,8992	4,67821
10	4,89	5,12	5,09	4,95	4,92	0,23	0,81005	0,38	0	4,994	4,8992	5,12019	4,8992	4,67821
					R ortalama	0,38			X ortalama	4,8992				
A2	0,577													
D4	2,115													
D3	0													

Then we determined the control limits of our part by creating X and R diagrams with these data. The figure 5-a shows the X diagram of our part. As can be seen from the graph, the production of our part continues within the control limits. Below, in Figure 5-b, is the R diagram of our part. The

a



b

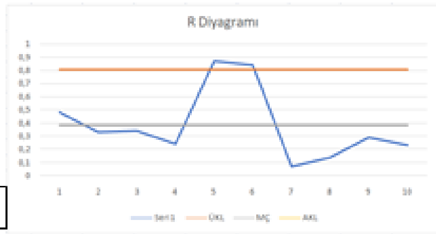


Figure 5: (a) X Diagram (b) R Diagram

R control chart shows the deviations from homogeneity. When we examine the graph, we see that parts 5 and 6 are above the control limits. This shows that the distribution of mass has changed over time. We should investigate the reasons for these separately. As can be seen from here, in the manual control, we noticed that there were defects in 2 parts even in the sample of 5 units. If we had missed these, perhaps these defects would not have been noticed until packaging and would have been noticed at the final stage. With this result, we have once again realized how useful our quality control project with artificial intelligence will be for production.

Stage 4: Interpretation of Data: When we examined the current system, we saw that after the profile was produced, we manually took samples and the quality control officer examined them. Then we used the AHP method to determine which press line we would work on. When we examined the results, we decided that Kanuni Press needed more improvement and since it caused more defective products, we decided that this should be the area of our design work. Then we decided to conduct a time study on this press line. Finally, we took 10 samples of 5 units in the existing system and recorded the values we found as a result of manual wall thickness measurement. Then we created a quality diagram using these values. Thus, we determined features such as whether the process is under control or not, how many defective products are produced. As a result of all these, we decided to implement 'Image Processing with Artificial Intelligence' on the Kanuni Press line.

Stage 5: Develop a Model and Source Code to Solve the Problem: At this stage, a picture of a sample was used that it covers the production phase. The suggested model source code includes the grayscale, edge detection and image processing. The gaussian_filter function takes the input image and creates a Gaussian filter kernel with the kernel size and sigma value specified with cv2.getGaussianKernel. The image is filtered with the cv2.filter2D function (in Fig. 6).

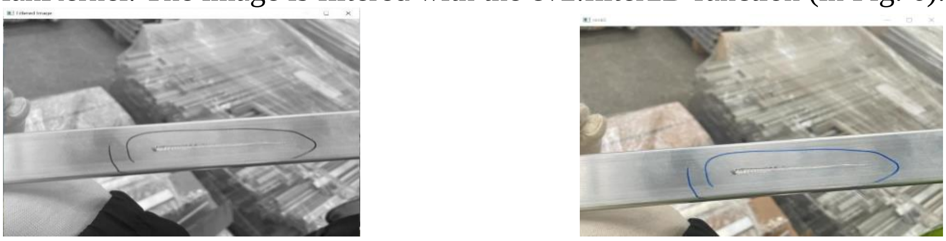


Figure 6: (a) Original Image (b) Applied Gauss Filter

Stage 6: Edge Finding: Applying Laplace, Sobel and Canny Filters

The developed program source code used the Laplace filter from the OpenCV library. The laplace_filter function takes the input image and applies the Laplace filter with cv2.Laplacian. It converts the filtered image to an absolute value with the np.absolute function and normalizes it to the range 0-255 with the np.uint8 function. As a result, after running the codes, the Figure 6.a original image was displayed. The Sobel filter used from the OpenCV library. The sobel_filter function takes the input image and applies the Sobel filter with cv2.Sobel. The sobel_x and sobel_y variables apply the Sobel filter to calculate the x and y line borders. We use these two borders to calculate the size of the border. Finally, it is normalized to the range 0-255 with the np.uint8 function. After running the codes, the following image was displayed. The canny_edge_detection function takes the input image and applies the Canny edge detection filter with cv2.Canny. It detects edges according to the thresholds set by the two threshold values threshold1 and threshold2. After running the code, the following image was displayed in Figure 7 and Figure 8. In our study, the real sample image was made suitable for the image processing program by filtering and edge detection applications. For this reason, we completed the statistical analysis part by examining the specific values of the pixels of the images. To find the values of the pixels, we first need to turn the images into a histogram. Then we found the mean, standard deviation, min-max data of this histogram. According to the t test results in Table 7, the average pixel number of a real sample image is 145.51. The average pixel number of the image obtained as a result of 4 filter processes applied with gray scale and edge detection applications was calculated as 24.15 with a standard deviation of 58.40. As a hypothesis question, there is no difference between the standard deviation of the pixel difference between the filtered image and the original image, while creating the hypothesis Ho, there is a difference if the opposite hypothesis is H1.

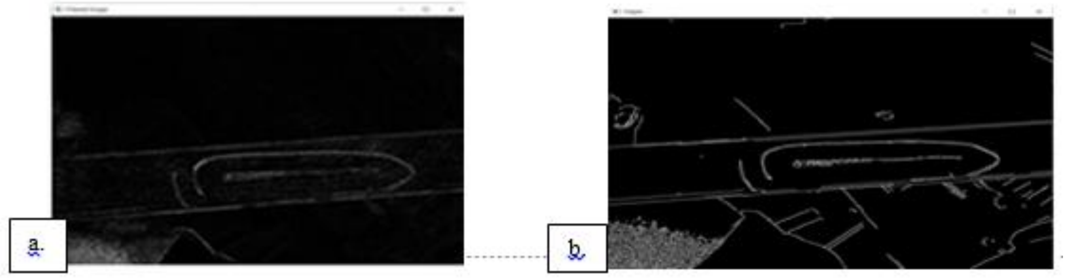


Figure 7: (a) Laplace filter (b) Canny filter applied to the image

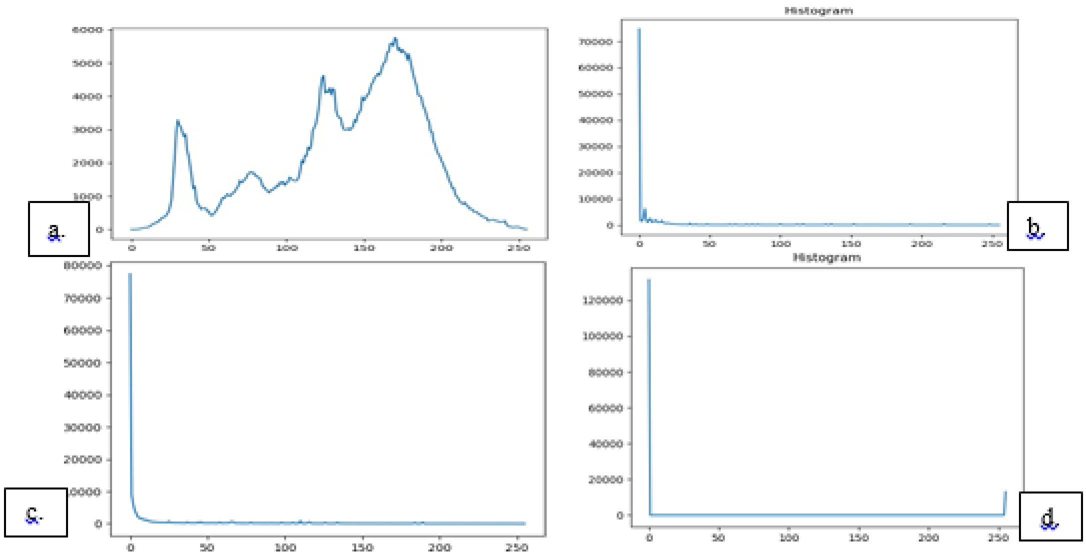


Figure 8: (a) Pixel histogram of real sample image (b) Pixel histogram with Sobel filter applied (c)) Pixel histogram with Laplace filter applied (d) Pixel histogram with Canny filter applied

Table 7: Statistical Analysis

	Original Image	Laplace Filter	Sobel Filter	Canny Filter	Total Filter
Total Number of Pixels	Too much	144597	144597	144597	144597
Average Pixel Number	145.51	19.68	29.79	22.99	24.15
Standard Deviation	51.42	43.28	58.88	73.05	58.40
Lowest Pixel Value	0	0	0	0	
Highest Pixel Value	255	255	255	255	255

Hypotheses H0: μ=24,15 H1: $\mu \neq$24,15

$n=21, \bar{x}=145{,}51, \quad S=58{,}40 \quad , \quad v=4-1=3, \quad S\bar{x} = \frac{s}{n-1} = \frac{58{,}40}{\sqrt{3}} = 33{,}72$

In aluminum profile cutting, the use of artificial intelligence can optimize the quality control process. For example, it may be possible to check the accuracy of profile cut dimensions and cut quality using artificial intelligence algorithms. Using image analytic methods, these algorithms can measure the dimensions and shape of the cut profile and evaluate the cut quality. In addition, artificial intelligence systems, using machine learning methods, can detect and prevent the types of errors that may occur during the cutting process. This improves cutting quality, reduces error rates and increases production efficiency. As a result, we made the error more visible with machine learning with the programs we wrote for each filter, which we applied to the photograph taken of the real sample. We increased the detectability of the error.

5. Conclusion

Improving manufacturing quality through AI-enhanced image processing is a promising and innovative approach that has the potential to revolutionize the manufacturing industry. In this conclusion, we will summarize the key points and benefits of using AI in image processing for manufacturing quality improvement and discuss some future directions and considerations. AI-enhanced image processing offers a significant advantage in terms of accuracy and consistency. It can identify defects or anomalies in real-time, reducing the margin of error associated with human inspection. This leads to higher product quality and reduced waste. AI can process images much faster than humans, which accelerates the manufacturing process. It allows for 24/7 monitoring, eliminating bottlenecks and increasing production efficiency. Implementing AI in image processing can lead to cost savings by reducing the need for manual inspections and rework. This not only lowers labor costs but also minimizes the cost of defective products reaching the market

The future of AI-enhanced image processing in manufacturing holds great promise. Advancements in AI algorithms, hardware, and data collection technologies will likely lead to even more accurate and efficient systems. In conclusion, AI-enhanced image processing is a transformative technology that can significantly improve manufacturing quality by enhancing accuracy, speed, efficiency, and cost-effectiveness. As AI continues to evolve, it will play a central role in shaping the future of manufacturing, ensuring higher quality products, increased efficiency, and reduced waste.

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