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Case Study

Detection of Piston Ring Deficiency in The Assembly of Automotive Ball Joint and Tie Rod End Parts

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ABSTRACT

In today's intensely competitive environment, businesses strive to optimize production efficiency to reduce costs, increase profitability, and ensure customer satisfaction. This focus on efficiency and quality enables businesses to operate more effectively, gain a competitive advantage in the market, and move towards sustainable growth. This study uses image processing techniques to detect missing segments in the assembly of ball joints automatically. In the automotive industry, performing quality control of critical components before assembly and detecting and classifying the defective ones is essential. Many quality control methods can be applied with existing technologies. This paper proposes an automatic real-time control based on image processing techniques to detect ball joint missing segments, a common defect in the automotive industry. In the company, operators perform defect detection by visual inspection. In this system, production continues in cases where the operator cannot detect the defect. This system aims to detect the errors made by the operator during the assembly operations and provide instant feedback. The developed system uses OpenCV library algorithms that are highly accurate in detecting defects in manual assembly processes so that missing components are removed from the production chain, and production quality is significantly improved. Accuracy is over 94% when identifying missing segments, about 30% better than traditional methods. In tests, 1200 ball joints were run through the system, resulting in 1150 defects being correctly identified and removed from the production line. Accuracy is high thanks to the application of various image processing techniques such as grayscale conversion, edge detection, and shape recognition. This also provides real-time feedback to the operator so the system can reduce detection and response time from 15 seconds to 5 seconds. This increases production speed and reduces the error rate in manual assembly processes by 20%. This paper also highlights the potential of image processing technology in manufacturing. It will contribute to improved quality control mechanisms to increase the reliability and efficiency of production lines in the automotive industry.

Keywords: *Image Processing, Quality Control, OpenCV-based system, Automatic Defect Detection, Automotive Industry*

Otomotiv Rotil ve Rotbaşı Parçalarının Montajında Sekman Eksikliğinin Tespiti

ÖZ

Günümüzün yoğun rekabet ortamında, işletmeler, maliyetleri düşürmek, kârlılığı artırmak ve müşteri memnuniyetini sağlamak için üretim verimliliğini optimize etmeye çalışmaktadır. Verimlilik ve kalite konusundaki bu odaklanma, işletmelerin daha etkin çalışmasını, pazarda rekabet avantajı elde etmesini ve

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sürdürülebilir büyüme yolunda ilerlemesini sağlar. Bu çalışma; rotil ve rot başı parçalarının montajında segman eksikliğinin görüntü işleme teknikleriyle otomatik tespiti üzerinedir. Otomotiv sektöründe kritik bileşenlerin montaj öncesinde kalite kontrollerinin yapılması ve hatalı olanlarının tespit edilip tasnif edilmesi önemlidir. Mevcut teknolojiler ile birçok kalite kontrol yöntemi uygulanabilmektedir. Bu makalede, firmada karşılaşılan bir hata olan rotil ve rot başı parçalarının montajında eksik segmanları tespit etmek için görüntü işleme tekniklerine dayalı gerçek zamanlı otomatik kontrol sistemi önerilmektedir. Firmada operatörler hata tespitini göz ile kontrol ederek yapmaktadırlar. Böyle bir sistemde operatörün hatayı tespit edemediği durumlarda hatalı olan ürünler montaj hattından hatalı bir şekilde geçmektedir. Bu çalışmada, görüntü işlemeye dayalı bu sistem ile montaj operasyonlarının yapıldığı süreçte operatör tarafından yapılan bu tip hataların tespit edilip operatöre anlık geri bildirim sağlanması amaçlanmıştır. Geliştirilen sistem, manuel montaj süreçlerindeki kusurları tespit etmede yüksek doğrulukla çalışan OpenCV kütüphanesi algoritmalarını kullanmaktadır; bu sayede eksik bileşenler üretim zincirinden çıkarılmakta ve üretim kalitesini önemli ölçüde iyileştirilmektedir. Yaklaşık %30 daha iyi bir oranla, geleneksel yöntemlerle yapıldığı gibi eksik segmanları tanımlarken de doğruluk oranı %94'in üzerindedir. Yapılan testlerde 1200 rotil ve rot başı parçası sistemden geçirilmiş ve sonuçta 1150 adet kusur doğru bir şekilde bulunarak üretim hattından çıkarılmıştır. Gri tonlama dönüştürme, kenar algılama ve şekil tanıma gibi çeşitli görüntü işleme tekniklerinin uygulanması ile doğruluk oranı yüksektir. Bu aynı zamanda operatöre gerçek zamanlı geri bildirim sunmakta; dolayısıyla sistem algılama ve yanıt süresini 15 saniyeden 5 saniyeye düşürmektedir. Bu artış sadece üretim hızını artırmak değil, aynı zamanda manuel montaj süreçlerindeki hata oranını da %20 oranında azaltmaktadır. Bu makale aynı zamanda görüntü işleme teknolojisinin üretimdeki potansiyelini de vurgulamaktadır. Ayrıca otomotiv endüstrisindeki üretim hatlarının güvenilirliğini ve etkinliğini arttırmak için geliştirilmiş kalite kontrol mekanizmalarına katkıda bulunacaktır.

Anahtar Kelimeler: *Görüntü İşleme, Kalite Kontrol, OpenCV tabanlı sistem, Otomatik Hata Tespiti, Otomotiv Endüstrisi*
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I. INTRODUCTION

Quality control in manufacturing processes has become a cornerstone of production efficiency and product reliability, especially in high-precision industries such as the automotive industry. In recent years, the advancement of image processing technologies and artificial intelligence applications has enabled the development of new methodologies for detecting assembly defects [1, 2]. Systems based on the OpenCV library have attracted attention with their real-time image processing and object recognition capabilities [3]. These systems offer essential steps in automatically detecting and correcting assembly defects, thus playing important roles in increasing production line efficiency and reducing costs. Considering these technological advances, the current study presents a system to detect the missing piston ring in ball joints, a shared assembly defect in the automotive industry. Previous studies have demonstrated the potential of machine learning and deep learning techniques in detecting assembly defects [4]. Image-based quality control systems in aerospace manufacturing provide an example to illustrate the effectiveness and applicability of image-based quality control techniques in the aerospace industry. The case study evaluates how image-based quality control is integrated and utilized and results in a specific aerospace component manufacturing process. [5]. Color-based machine vision systems in textile manufacturing, evaluating the applicability and effectiveness of color-based image processing techniques in the textile industry. It examines different color-based quality control systems' design, implementation, and performance. [6] There are examples of color-based machine vision techniques for defect detection in plastics manufacturing. These examples compare the effectiveness and applicability of color-based image processing techniques in the plastics industry. It analyzes different color-based defect detection systems' performance, advantages, and limitations. [7]

Quality control in manufacturing has become crucial for ensuring production efficiency and product reliability, particularly in high-precision industries like automotive manufacturing. Recent advancements in image processing technologies and artificial intelligence have led to the development of new methods for detecting assembly defects. Systems based on the OpenCV library have gained attention for their real-time image processing and object recognition capabilities. These systems play a vital role in automatically detecting and correcting assembly defects, thus increasing production line efficiency and reducing costs. One specific application is the detection of missing piston rings in ball joints, a shared assembly defect in the automotive industry. Machine learning and deep learning techniques have shown potential in detecting assembly defects. In aerospace manufacturing, image-based quality control has proven effective in evaluating and improving specific components' manufacturing processes. Similarly, in textile manufacturing, color-based machine vision systems have been assessed for their effectiveness in quality control. Another notable area is defect detection in plastics manufacturing, where color-based machine vision techniques have been compared for their efficacy and applicability. Color-based machine vision systems have also been discussed in metal fabrication, industrial products, electronics manufacturing, food manufacturing, and pharmaceutical manufacturing. These discussions often focus on evaluating the design, implementation, and performance of color-based defect detection systems across different industrial sectors. In summary, image processing and machine vision technologies, particularly those based on the OpenCV library, have significantly enhanced quality control processes across various manufacturing industries, ultimately improving production efficiency and product reliability. Some color-based machine vision systems are applied for defect detection in metal fabrication. They focus on designing, implementing, and optimizing color-based image processing systems to detect color defects in metal products.[8] Color-based machine vision systems have also been applied in metal fabrication industrial products, electronics manufacturing, food manufacturing, and pharmaceutical manufacturing. These applications typically involve designing, implementing, and optimizing color-based image processing systems. The goal is to detect defects specific to each industry. For instance, in metal fabrication, these systems focus on detecting color defects to identify flaws in metal products. In electronics manufacturing, they are employed to detect defects in electronic products. The use of color-based machine vision systems extends to food and pharmaceutical manufacturing. They help detect color defects in food products. Additionally, they ensure the quality of pharmaceutical products. These systems are designed and implemented to meet specific quality control needs. Each industry demonstrates the versatility and effectiveness of color-based image processing techniques. In the automotive industry, the combination of OpenCV library and convolutional neural networks (CNN) has been used for real-time defect detection. They integrate deep learning techniques with image processing algorithms. These systems achieve higher accuracy. They also improve efficiency in defect detection on the production line. The application of such systems highlights a practical approach to real-time quality control. Overall, image processing and machine vision technologies, particularly those based on the OpenCV library, have significantly enhanced quality control processes. This improvement spans various manufacturing industries. These technologies contribute to improved production efficiency and product reliability. They enable automatic and accurate defect detection. This study focuses on a real-time and exact image processing system developed using OpenCV and Python programming language. The system can quickly and effectively detect missing piston rings in automotive assembly lines, thus minimizing errors in production processes and maximizing product quality. This study aims to make a significant contribution that increases the applicability of image processing and machine learning techniques in industrial manufacturing processes and brings a new perspective to research in these fields. In this context, by conducting a comparative analysis with similar studies in the literature, we will discuss the developed system's advantages and potential development areas in detail and provide a basis for future research.

II. MATERIAL AND METHOD

A. DETECTION OF QUALITY DEFECTS IN BALL JOINT AND TIE ROD END PARTS

A ball joint is a rotating component in the steering mechanism of vehicles. The lower ball joints are critical parts that affect the vehicle's steering capability by allowing the vehicle's front wheels to turn. These parts' quality and correct assembly directly affect steering system stability and the vehicle's steering performance. Therefore, any defects in the ball joints must be detected and remedied. This study uses image processing techniques to detect one of the assembly defects in ball joints, namely, missing a circlip. Using a setup consisting of a camera, Wi-Fi network, and PC systems, it is aimed to detect and eliminate the up and down piston ring deficiencies in ball joints by the operator on the assembly line. The company's customer feedback stated that the piston rings need to be installed in 1-2 out of 500-750 parts. This situation is considered a serious problem by the company regarding customer satisfaction. Python programming language and OpenCV library were used for image processing. This system aims to increase operational efficiency and maximize product quality by detecting defective parts in real-time. In particular, the flexibility of the OpenCV library enables precise detection of missing components. The algorithm provides real-time processing of images, reading each frame from the stream and converting it into HSV color space. A mask is then created based on a specific range of blue colors, and contour detection is performed on this mask. Rectangles are drawn around the detected blue objects, and descriptive text is written to display each processed frame on the screen. By processing the images in real-time, an audible warning system next to the assembly line is activated when defective products are detected. This situation allows operators to intervene quickly and correct defective products before they leave the production line. This study highlights the importance of image processing techniques in industrial production processes and shows how critical real-time detection is in quality control processes. Future studies aim to obtain more precise results using deep learning techniques and illumination optimization.

A. 1. Image Processing with OpenCV

This system combines the Python programming language's power and the OpenCV library's flexibility to bring a new dimension to quality control processes in the manufacturing industry. This system can be developed and implemented quickly thanks to Python's easy-to-read and extensive library support. The OpenCV library's image processing algorithms enable precise detection of missing components. This study used OpenCV to discriminate between color and shape in images. The images were converted from RGB format to HSV format for color discrimination. The HSV format separates colors into hue, saturation, and brightness components, making color perception more consistent and accurate. For example, blue piston rings in the ball joints were detected by creating a mask sensitive to blue. This masking process distinguished blue segments by considering a specific range of blue tones (e.g., 89<tone<121). This masking process distinguished blue segments by considering a particular range of blue tones (e.g., 89 < tone < 121). The defined range ensures that only the hues falling within the blue spectrum are considered, effectively filtering out other colors that might be present in the image. This selective filtering is crucial for accurately identifying the blue piston rings amidst potentially noisy backgrounds. Moreover, the saturation and value thresholds are set to enhance the reliability of detection. By ensuring that the saturation is higher than the value, the method prioritizes vivid blue tones, which are less likely to be confused with other objects or artifacts in the image. This approach reduces the risk of false positives and improves the precision of the detection system. The binary thresholding step further refines the image by creating a clear binary mask. This mask isolates the blue regions, allowing for precise measurement and analysis of the area occupied by the blue segments. Consequently, this systematic approach enhances the robustness and accuracy of the missing piston ring detection system, ensuring that only relevant features are considered during the verification process. This way, accurate information about the absence or presence of blue segments was obtained. The flexibility of OpenCV provides an ideal platform for implementing image processing algorithms. This condition enables real-time detection and intervention of defective parts on the production line, improving product quality and maximizing operational efficiency.

Figure 1. *Representation of the piston rings in the tie rod end*

The OpenCV library can perform many operations, such as edge detection and color object motion detection. In the current study, a distinction was made between color and shape.

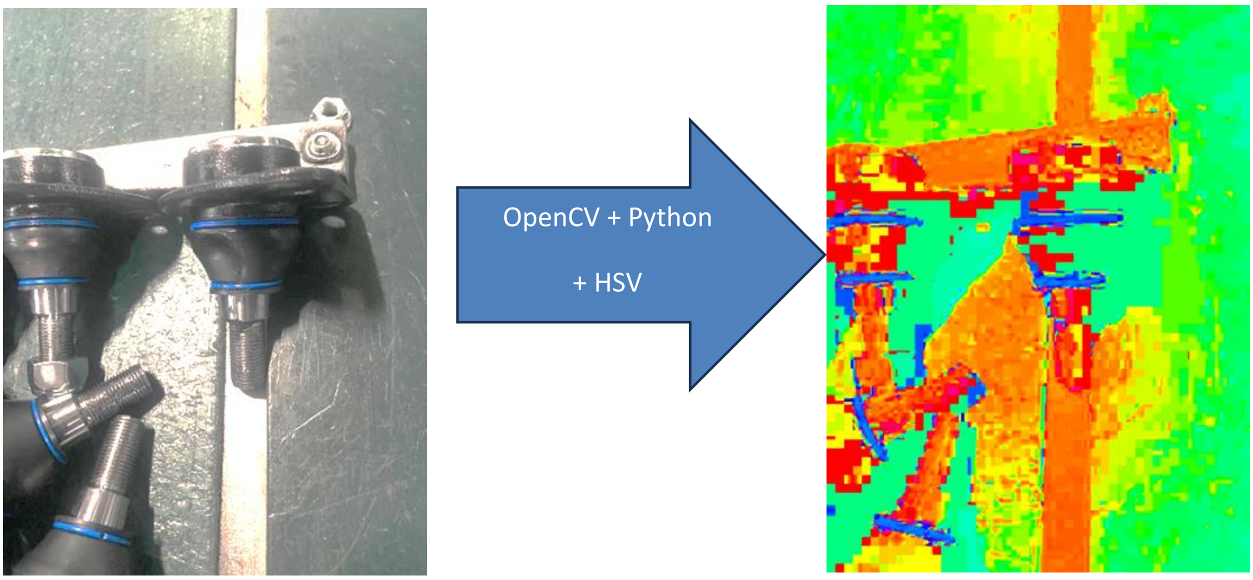

Figure 2. *Image of ball joint part images converted from RGB to HSV*

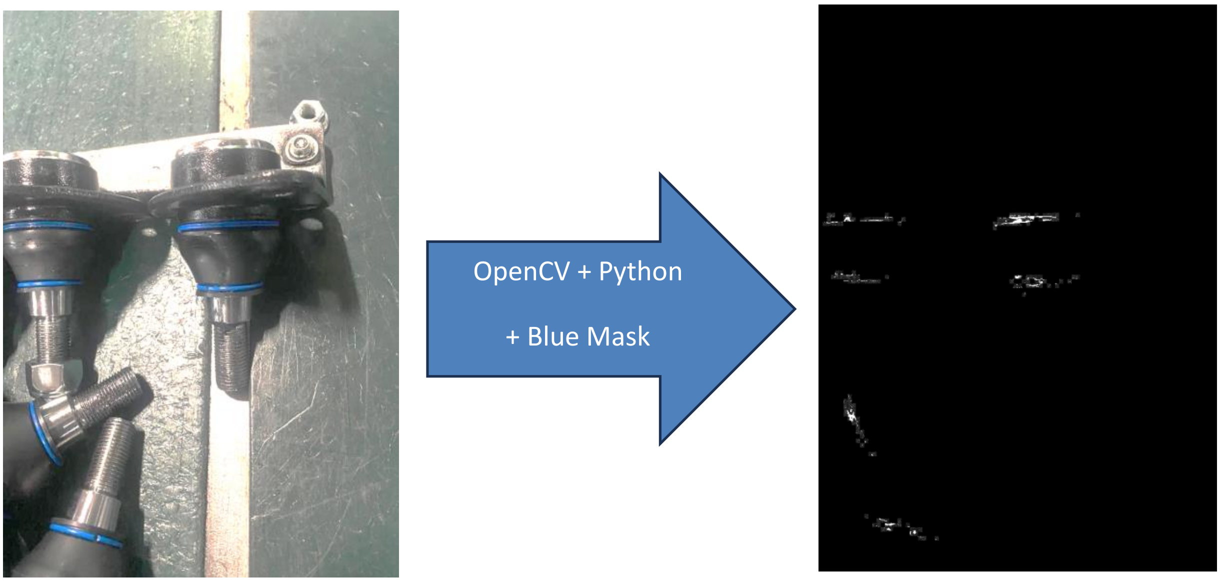

Figure 3. *Image with ball joints with a blue mask of 89<TON<121*

The image with the ball joints taken with the camera in Figure 2 is transformed into HSV. In this image, some regions are blue with no blue piston rings. For these, the blue tone range is set to 89<ton<121. In this way, the blue piston ring can be distinguished. The application of the blue mask in this range is shown in Figure 3. Several formulas and transformations are used for RGB HSV transformation. The RGB (Red, Green, Blue) values of the image are separated by 255 to change the range from 0...255 to 0...1:

R '= R / 255 (1)
G '= G / 255 (2)
B '= B / 255 (3)
Cmax = max (R ', G ', B ') (4)
Cmin = min (R ', G ', B ') (5)
Δ = Cmax – Cmin (6)

Tone calculation is:

$$H = \begin{cases} 0^\circ, & \Delta = 0 \\ 60^\circ \times \left(\frac{G'-B'}{\Delta} \mod 6\right), & C_{\max} = R' \\ 60^\circ \times \left(\frac{B'-R'}{\Delta} + 2\right), & C_{\max} = G' \\ 60^\circ \times \left(\frac{R'-G'}{\Delta} + 4\right), & C_{\max} = B' \end{cases} \tag{7}$$

Saturation value calculation:

$$S = \begin{cases} 0, & C_{\max} = 0 \\ \frac{\Delta}{C_{\max}}, & C_{\max} \neq 0 \end{cases} \tag{8}$$

Value calculation below:

V = C_max (9)

RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value) color spaces are commonly used in image processing and computer vision. These color spaces represent colors differently, allowing color-related operations to be performed more effectively. While RGB space represents colors with a combination of red, green, and blue components, HSV space represents colors with three components: hue, saturation, and luminance. These formulations are used to provide transformations between color spaces. These formulations transform from RGB space to HSV space and vice versa. The OpenCV library offers a wide range of functions to perform these transformations. These functions make switching between color spaces in image processing applications easier and increase their image processing ability. For example, to detect the color of a particular object in an image or to perform color-based object detection, a transformation from RGB color space to HSV color space can be performed. This transformation allows colors to be more accurately distinguished and processed. Also, HSV space can often be a more appropriate choice when analyzing colors because it represents colors in a way that is closer to human perception. The RGB and HSV conversion functions available in the OpenCV library are essential for performing various color-related tasks in image processing applications. These functions can be used in color-based object detection, color segmentation, color matching, and many other image-processing algorithms. Hence, these transformation functions allow for the successful performance of color-related analyses in image processing and computer vision projects. The RGB HSV transform is provided in the OpenCV library because of these formulations running in the background.

A. 2. Defective Product Detection

The acquired images are processed on a computer (PC) in real time. This processing operation can be done using image processing algorithms, which enable the detection of defective products. If a product is defective, the computer immediately detects and processes this information. A buzzer system located next to the assembly line is then activated. A PC buzzer or similar sound output device realizes the buzzer. When a defective product is detected, a signal triggered by the computer is sent to the PC buzzer. The PC buzzer informs the operators about the defective product by emitting a specified warning tone or signal. This buzzer system allows operators to intervene quickly and facilitates the removal of defective products from the assembly line. It provides a fast feedback mechanism for real-time product inspection and enables operators to act more efficiently, increasing productivity on the production line. In addition, the audible warning system helps to quickly identify defective products and prevent disruptions on the production line. In this way, the quality control process on the assembly line becomes more reliable, and the company's product quality and customer satisfaction increase.

A. 3. Detection Method

Several verifications are essential for ensuring accuracy when developing a detection system for missing piston ring products using OpenCV. The system relies on specific parameters to identify the presence or absence of the piston ring. One of the critical verifications involves analyzing the area size, which is calculated as the total area minus the sum of the blue area pixels. This means that the system identifies regions within the image that correspond to the expected location of the piston ring and then subtracts the pixels that fall within the defined blue color range. The selection of the blue color range, specifically with hue values between 89 and 121, is a critical aspect of the missing segment detection process in image processing applications. This specific range is meticulously chosen to optimize the detection accuracy and reliability of the system. The parameters for selecting this range are not arbitrary but are determined through careful consideration of several factors, including the masking color, the camera angle, and the segment's real color as captured by the camera. Each of these factors plays a significant role in ensuring that the system operates efficiently and accurately under various conditions. Firstly, the concept of masking color is fundamental in image processing. Masking refers to the process of isolating certain colors or regions in an image to facilitate more accurate analysis. In this context, the chosen blue color range of 89 to 121 is likely selected to maximize the contrast between the segments of interest and the background or other objects in the image. This high contrast is crucial for the detection system to effectively differentiate the segments from their surroundings. By isolating the blue hues within this specific range, the system can filter out extraneous information and focus solely on the relevant segments, thereby enhancing the precision of the detection process. Secondly, the angle at which the camera captures the image significantly influences the perceived color of objects. Variations in camera angle can cause changes in lighting and shading, which in turn affect the hue values recorded by the camera. The range of 89 to 121 is selected to account for these variations and ensure that the blue segments are consistently detected regardless of the camera angle. This adaptability is crucial for maintaining the robustness of the detection system across different imaging conditions. By considering the potential variations in camera angle, the system can reliably identify the blue segments even when the viewing perspective changes. Thirdly, the real color of the segment captured by the camera must be accurately represented within the selected hue range. The colors captured by a camera can differ from their true colors due to factors such as lighting conditions, camera sensor characteristics, and environmental influences. The hue range of 89 to 121 is chosen based on empirical observations and experimental data to best match the true color of the segments as they appear in the camera images. This ensures that the detected color closely corresponds to the actual color of the segments, minimizing false detections and improving the overall accuracy of the system. Additionally, the selection of this specific hue range may be supported by prior experimental results and domain-specific knowledge. Through a series of controlled experiments and iterative testing, it was determined that the hue values between 89 and 121 consistently yield the best results for segment detection in the given application. This data-driven approach ensures that the chosen color range is not only theoretically sound but also practically validated, providing a reliable basis for the detection system.

In conclusion, the specified blue color range of 89 to 121 is a carefully considered parameter in the missing segment detection system. It addresses key factors such as masking color, camera angle, and the real color as captured by the camera, all of which are essential for accurate and reliable detection. The meticulous selection process ensures that the system can effectively isolate and identify the relevant segments, thereby enhancing the overall efficiency and robustness of the image processing application. This thoughtful approach underscores the importance of considering multiple variables in the design and implementation of advanced detection systems. Hue is one of the components of the HSV (Hue, Saturation, Value) color model, which is often used in image processing because it separates color information (hue) from intensity information (value), making it easier to segment images based on color. The saturation and value components are also considered, with the condition that the saturation must be greater than the value. This constraint ensures that the detected blue color is vivid and not washed out, essential for reliable detection. Thresholding is another vital verification step. In this context, thresholding creates a binary image where the blue regions are marked with a value of 1, and all other areas are marked with 0. This binary image then isolates the blue regions corresponding to the piston ring. The thresholding function Iblue(x,y)I_{\text{blue}}(x,y)Iblue(x,y) outputs one if a pixel at coordinates (x,y) falls within the blue color range and 0 otherwise. This process helps create a clear distinction between the areas of interest (the blue regions) and the rest of the image, facilitating more accurate detection and analysis. Using these verifications—calculating the area size, defining the blue color range, and applying thresholding—the system can effectively identify whether the piston ring is present or missing. This method leverages the distinct blue color properties and ensures that only regions with the specified hue, saturation, and value characteristics are considered. Consequently, it minimizes the likelihood of false detections and enhances the reliability of the piston ring detection system.

To summarize, the detection system for missing piston rings using OpenCV incorporates several verification steps:

1. **Area Size Calculation**: Subtracting the sum of blue area pixels from the total area to identify the region of interest.
2. **Blue Color Range Specification**: To detect vivid blue regions, set the hue range between 89 and 121, with the condition that saturation is greater than the value.
3. **Thresholding**: Isolating the areas of interest by creating a binary image in which blue regions are marked as one and others as 0 isolates them.

These verifications are critical for accurately and reliably detecting missing piston rings in the product detection system.

The verifications to be used for the missing piston ring product detection system with OpenCV are as follows:

$$Area\ size = Area - \sum \quad Blue\ Area\ Pixels$$

Blue Color Range = 89<Hue<121, Other Values: Saturation> Valuer

Thresholding= I_blue (x,y)-{1,0 if it fits within the blue color range,0 for other cases

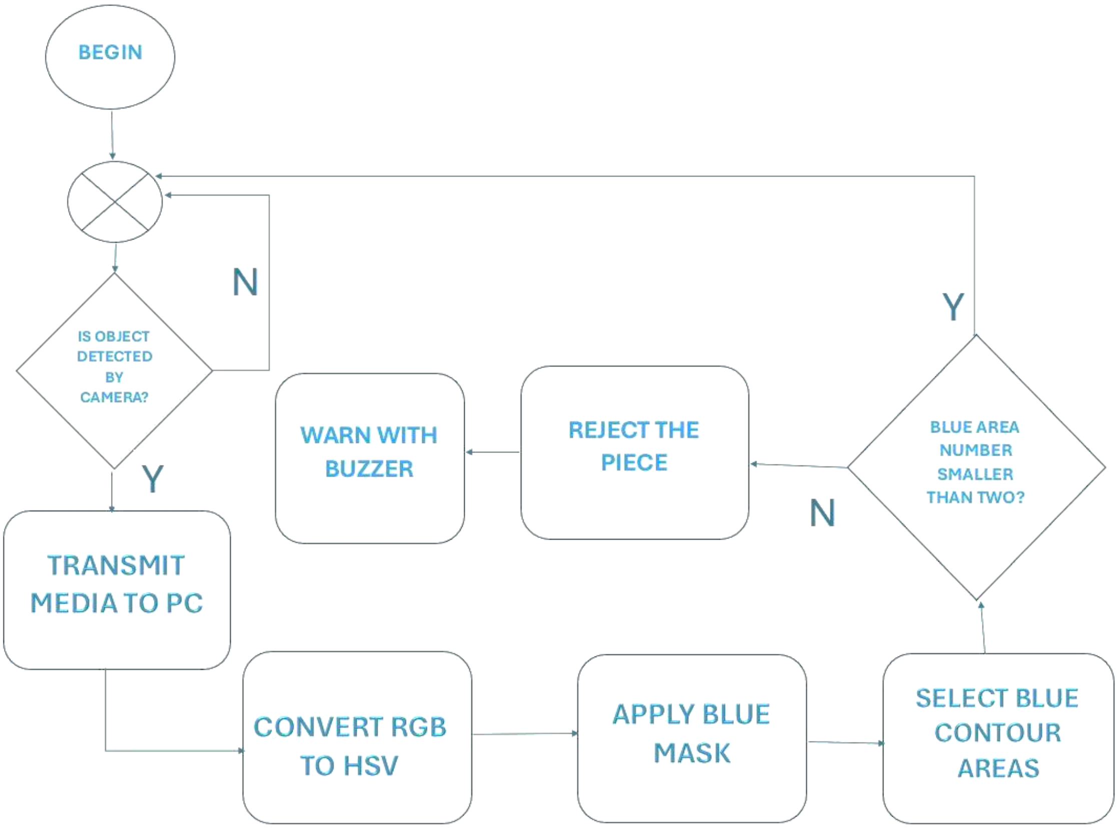

Figure 4. *Flowchart of the missing piston ring detection system*

A flowchart of the disappeared piston ring detection system is given in Figure 4. This flowchart shows the system's working algorithm.

III. EXPERIMENTAL STUDIES

Attempting to detect the condition of piston rings, a series of eight tests were conducted. The primary objective was to detect if some rings were missing, and the results of such tests were compared with findings obtained through visual inspection. The accuracy percentages resulting from these tests are represented below based on evaluations of two hundred and fifty pieces moving on a continuously flowing conveyor. These tests were more accessible as an IP camera had been installed over the conveyor belt, and the footage was quickly taken accordingly. The camera operated at a transfer rate of 25 FPS and offered a very in-depth and continuous monitoring process. Image processing and analysis were done using the Python-OpenCV library, and the percentage accuracy can be tabulated below: These percentages indicate the system's efficiency in recognizing the absence of piston rings—information critical to the quality and performance of the conveyor belt operation. From this fact, it is paramount to state that the present study does not work with a predefined dataset but functions with a Rule-Based System. Therefore, if a Machine Learning system is included in further research attempts, there is room to improve the accuracy and reliability of the detection with adequate strength and vigor. The current system is configured to continuously monitor the conveyor belt and offer an immediate warning in case of an error. This warning could be on a screen close to an operator or adjuster, or it might be audible. Real-time feedback like this is necessary to keep the production line efficient and accurate because any discrepancy in the conveyor's performance has enormous implications.

Each part that goes through the conveyor belt is susceptible to being pushed out in three to four minutes. As this process is critical, the single and double piston rings have been intentionally shifted in the tests by letting them move towards the system to test its capability to detect flaws. All these tests and comparing the results with the findings of a visual test conducted by human operators took time. System design and operation rely on eliminating human errors to improve the general reliability of the inspection process. Detecting absent piston rings is automated and, thus, eliminates as much dependence on manual checks, which are typically prone to omissions and variations. Real-time error notification enforces the correction of errors within the set timelines, subsequently eliminating the possibility of parts with errors flowing down the line. Figure 5 presents a schematic diagram of the sample system. This figure provides an overall view of the system's several components and their relationships, with particular attention to the IP camera, the conveyor belt, and the error notification interaction. In total, acquaintance with the system's structure and functioning can be beneficial in finding value in this diagram. In short, eight tests to assess piston rings' states proved that the Python-OpenCV-based system can detect ring absence correctly. The monitoring is continuous through an IP camera that works at 25 FPS, and the Rule-Based System provides a substantial foundation on which further advancements could be applied by using Machine Learning. More importantly, the system can issue error notifications, which can be both visual and audible, instantaneously, which further underlines its contribution toward maintaining both the integrity and productivity of the production process. As development goes on, improvements using the techniques of Machine Learning are expected to bring even more accuracy and reliability to the system, thus leading to robust and dependable solutions for inspection in this environment.

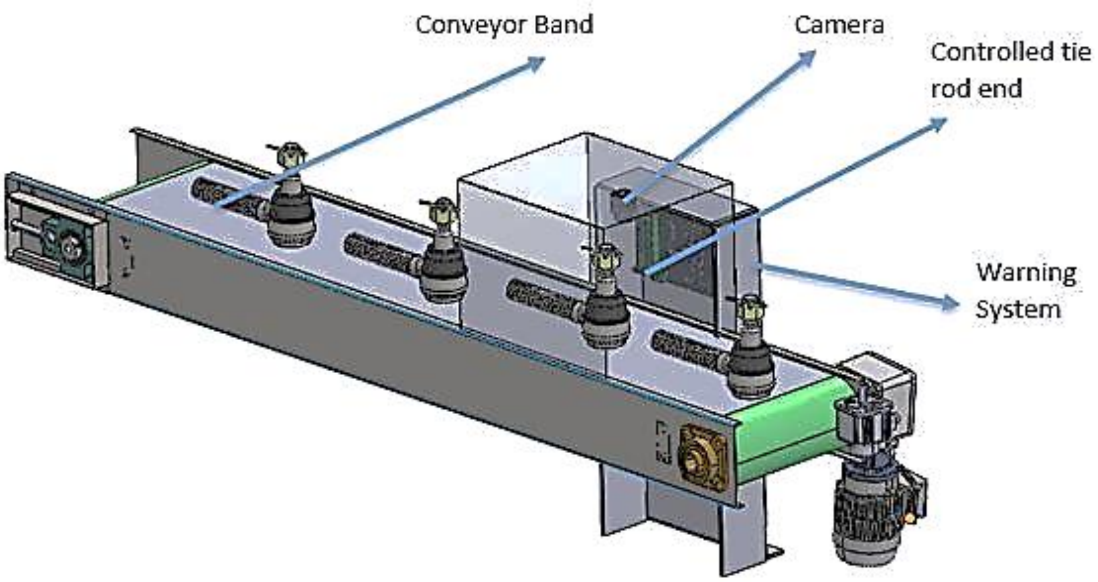

Figure 5. *A single IP camera takes the image from the part on the rotating conveyor and transmits it to the computer. The computer decides whether there is a defective product or not.*

***Table 1**. The numbers are given in the above table. Each test was performed for fifty pieces, and the number of correct detections of the algorithm was given.*

	NO SMALL SEGMENT	NO BIG SEGMENT	WITHOUT BOTH RINGS
1. Test	47	48	50
2. Test	46	48	49
3. Test	46	47	49
4. Test	49	48	48
5. Test	46	48	48
6. Test	47	49	48
7. Test	46	49	49
8. Test	47	48	48

Table 1 depicts the results of running an algorithm for detecting some segments in different tests. Each test contained fifty pieces, and the table tells us how many correct detections were obtained for three conditions: Without a Small Segment, Without a Big Segment, and Both Rings. The table shows eight tests, each giving specific results for this counting under these conditions. Regarding the "No Small Segment" condition, the proper detections vary from 46 to 49 in eight tests. The highest number was 49 proper detections during the fourth test. The most frequent number of detections, 46, appears four times. This ensures that the algorithm works very solidly but shows slightly fluctuating results. "No Big Segment" is the only condition where an algorithm detection count falls between 47 and 49. The highest obtained is 49, which happened on the sixth and seventh tests. A count of 48 arises more commonly, appearing six times. This shows that the algorithm can be reliable enough to detect the absence of significant segments. This demonstrates the highest detection counts of all to be 48 to 50, which is the "Without Both Rings" condition. A perfect detection count of 50 is measured in test number one, and the detection count of 48 comes up most frequently- five times- all of which indicates that the algorithm is particularly well-outfitted for detecting the lack of both rings. Comparatively, the algorithm best performs with the "Without Both Rings" condition. It shows a perfect detection rate in the first test and maintains a high detection count in all tests. Under the "No Big Segment" condition, the performance is good, with a slight but consistent drop in some tests. The "No Small Segment" condition showed the highest variability, so the algorithm perhaps is more challenged at detecting the lack of small segments than large segments or both rings. Data seems to indicate in a general way that it is a reliable algorithm since detection rates are consistently high across conditions. Differences in detection counts are trivial, meaning performance is stable, with small fluctuations without influence. Performance is most consistent in the "No Big Segment" and "Without Both Rings" conditions, where detection counts are rarely at the low end of the scale. A slightly lower and less stable detection rate within the "No Small Segment" condition indicates a possible area for improvement in the algorithm. The latter could provide more consistent overall performance conditions by improving the sensitivity to small segments. The data suggests that the algorithm in its present form is highly effective for situations where more significant portions lack either element (rings), and future refinements could be made to develop the performance of the more minor elements. Overall, the abstract gives good insight into the capabilities of detection by algorithm across conditions. This algorithm is accurate and remarkably consistent, especially when more significant portions lack rings and elements. The relatively small variation in detection performance for "No Small Segment" indicates room for refinement to reach close-to-ideal detection performance in all these test conditions. This data hints at the strengths but points explicitly to places where a focused improvement effort could raise the bar around the overall performance. The data in the table underscores the fact that high detection rates are well preserved for this algorithm, primarily when larger or more complex segment combinations are missing. Here, we have evidence that the algorithm has learned the changes of a more substantial nature excellently. However, these drops for the smaller segments reflect some degree of optimization that remains necessary. These small, critical details are focused on and bring the algorithm's performance up to an even higher level. The constant high performance under the "Without Both Rings" condition indicates that the algorithm is fit for tasks that demand the identification of several missing elements. Very likely, robustness is, in turn, a very likely sign that it might be applied in various practical scenarios for which both precision and reliability count. Meanwhile, the slightly variable good performance under "No Small Segment" reminds us that even good algorithms are never done. In that sense, these results of the experiments represent valuable guidance for the developer to make focused improvements so that the algorithm can deal with the broadest possible variety of challenging tasks and conditions. The table provides an all-embracing insight into the capabilities and deficiencies within an algorithm. It is an excellent algorithm with excellent performance and reliability in cases of highly accurate detection, especially in complex scenarios. With these minor inconsistencies considered during the detection of smaller segments, developers can rest assured that it will operate perfectly under all conditions, making it an even more valuable tool in its application domain.

Figure 6. *In the picture given in (a), the product is defective because it has a single segment; in (b), it is defective because it has no segment; in (c), it is correct. It has two segments: in (d), it is not very accurate because it has only a tiny segment; in (e), it has double segments. In (f), there are no rings at all. Therefore, it is a defective product.*

Figure 6 shows some examples of the tests performed. The presence of two segments indicates that the product is correct. The presence of a single segment suggests that the product is defective. The absence of any segments is another type of error.

As a result of the experiments, approximately 47 out of 50 ball joints were found to have no segments, with an accuracy of more than 94%.

V.CONCLUSION

In this study, a missing component detection system was developed for real-time quality control in the manufacturing industry. In this system, defective products are passed through a conveyor belt, and image processing techniques are used to detect missing segments in ball joints and tie rod ends. An IP camera was mounted on the conveyor belt. This camera operated at a transfer rate of 25 FPS and the parts passing through the conveyor were continuously recorded. These recordings were analyzed in a computer environment using image processing techniques and the Python-OpenCV library. As a result of this examination, clear images of the elements were taken, and sensitivity was increased as much as possible. Inferences were made according to the results obtained and the number of photographs was increased to detect missing parts. Thus, the accuracy rate was increased to over 94% using the Python-OpenCV library. Increasing the camera resolution used during this study, correcting the lighting conditions, and using a more powerful processor can increase the accuracy rate. This increases efficiency by providing real-time feedback to the operator performing this work, reducing the detection and response time of the system by 66.6%, thus increasing the production speed and reducing the error rate in manual assembly processes by 20%, also, in terms of efficiency and precision.

A. SUGGESTIONS AND FUTURE STUDIES

There are some suggestions to improve the study: Firstly, we used a single blue color range and threshold to examine the ball joint and tie rod end pieces. Trying out different color ranges and thresholds could enhance the accuracy of the detection process. Secondly, while this study relied on image processing techniques, incorporating deep learning could boost the accuracy and reliability of our results. Deep learning models have a remarkable ability to learn and generalize from large datasets, which could lead to better performance in recognizing and classifying the components we're studying. Thirdly, transferring the image to a PC for processing slowed down the study. If we optimize the algorithm and process it directly on the system using powerful microcontrollers, we could significantly speed up the workflow and improve overall performance. Lastly, utilizing advanced preprocessing techniques—such as morphological operations, noise reduction, and edge detection algorithms—with higher-quality images, could greatly enhance the study's performance. These steps would improve image clarity and feature extraction, resulting in more accurate and reliable outcomes.

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