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Production Line Piston Position Control Based on Image Processing

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Abstract: This study presents a real-time vision-based system for detecting the open and closed positions of pneumatic pistons in industrial production lines without using physical sensors. Conventional magnetic and inductive sensors are often affected by cable damage, environmental contamination, vibration, and temperature variations, which can cause unplanned downtime and increased maintenance costs. To address these limitations, a camera-based monitoring approach is proposed as a reliable and low-maintenance alternative.The main objective of this work is to develop a low-cost, robust, and easily integrable sensorless position-detection system using deep learning–based object detection. A dataset consisting of 250 RGB images was collected from a production-like test platform and annotated into two classes representing open and closed piston states. The dataset was split into training and testing sets with ratios of 80% and 20%, respectively.A YOLOv8 object detection model was fine-tuned using transfer learning and deployed on a Raspberry Pi 4B for real-time operation. To improve reliability, a high confidence threshold and a frame-based stability filter requiring consistent predictions across multiple frames were applied. Detected piston states were converted into digital control signals via GPIO outputs.Experimental results show that the proposed system achieves over 97% detection accuracy with a processing latency of 25–40 ms per frame on embedded hardware. The stability filter effectively reduces false state transitions, ensuring reliable output. The results indicate that the proposed approach provides a practical visual backup solution for sensor failures and a scalable alternative for new production line designs.

Keywords: İmage Processing, Piston Position Detection, Deep Learning, YOLO, Raspberry Pi

Introduction

Automation systems in industrial production lines are of critical importance to ensure that processes operate efficiently, reliably, and continuously. One of the key components of these systems is piston sensors that detect the open/closed positions of clamps. These sensors, which are widely used today, play a fundamental role in ensuring the safe operation of production lines. However, in practice, these sensors have significant disadvantages. In particular, welding spatter adhering to sensor surfaces, prolonged exposure to high temperatures, and mechanical wear over time frequently cause sensor failures.

Sensor failures do not only increase part replacement costs. In many cases, these sensors are installed in hard-to-reach areas of the production line. Therefore, maintenance or replacement operations require the complete shutdown of the line. Such unplanned downtimes disrupt the production process, lead to labor losses, and reduce overall operational efficiency. In addition, production losses during downtime may cause delays in customer deliveries, imbalances in inventory management, and a decrease in competitiveness. Consequently, piston sensor failures represent not only a technical issue but also a critical problem in terms of cost, labor, and production continuity.

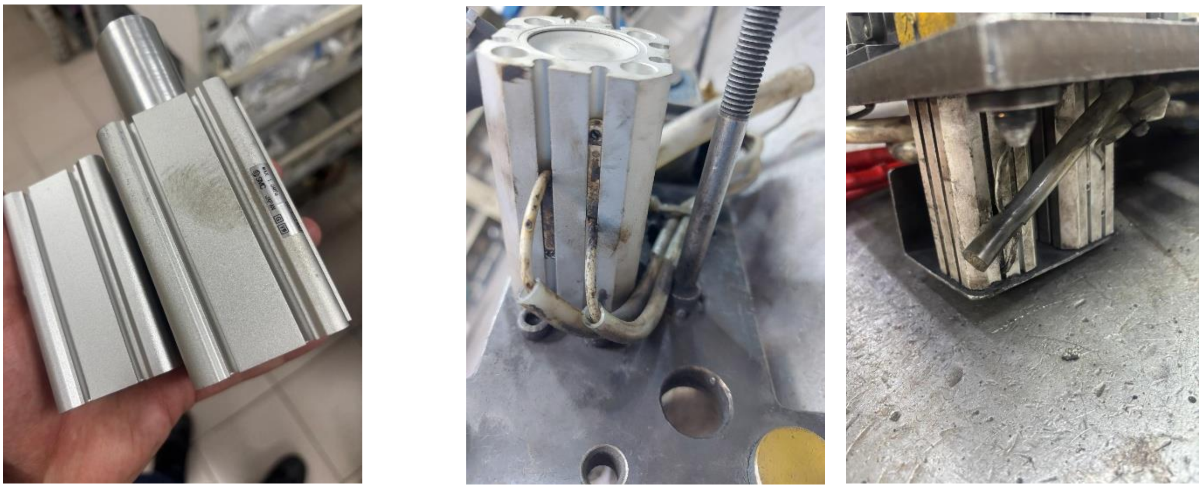

Figure 1. piston and piston sensor

In this study, a camera-based image processing method is proposed to eliminate these disadvantages. The proposed system monitors clamp positions in a contactless manner using industrial cameras and appropriate lighting equipment. With the help of image processing algorithms, the open or closed state of the clamp is detected, and the obtained information is transmitted directly to the production line as a digital signal. In this way, the need for maintenance and replacement of physical sensors is eliminated, resulting in a reliable and long-lasting system that is not affected by environmental factors.

The most important advantage of the camera-based image processing system is that it does not require physical contact and is resistant to environmental conditions. Factors such as high temperature, welding spatter, oily surfaces, or vibration severely affect sensors, whereas they do not significantly impact camera performance. Furthermore, since the proposed system can capture images from different angles, it offers multi-level verification and minimizes the risk of incorrect detection. In addition, the same infrastructure can later be used not only for open/closed position detection but also for early fault warning mechanisms and quality control applications.

During the testing phase of the study, the system will be installed on a prototype production line, and performance measurements will be conducted under various scenarios. The accuracy of open/closed clamp detection, system response time, and ease of integration into the production line will be evaluated. The aim is to demonstrate the feasibility of a lower-cost, more reliable, and maintenance-free alternative compared to conventional sensors.

In conclusion, this study aims to prevent maintenance costs, labor losses, and production downtimes caused by piston sensors. The camera-based image processing method stands out not only as a technical innovation but also as a strategic solution in terms of cost optimization, production continuity, and industrial efficiency. In the future, it is planned to monitor more complex moving parts using artificial intelligence–supported algorithms and to easily integrate the system into different production lines.

In order to prevent frequent failures of piston sensors used in the production line due to high temperature and welding spatter, several studies were carried out using 3D printing technology. Within this scope, special protective parts were designed to shield the sensors from environmental effects and were produced using different filament materials. These protective structures were tested in the field, and their performance was evaluated. However, two main problems were encountered during the trials.

In the study titled "Research on a Small Target Detection Method for Industrial Safety Helmets Based on Improved YOLOv8" (Zhang, 2023), the problem of automatically detecting the use of safety helmets by personnel working in industrial environments was addressed. Considering the difficulties in detecting small targets, architectural improvements were applied to the YOLOv8 architecture, and the model was trained using helmet images with different colors, sizes, and viewing angles. The obtained results showed that even small targets could be detected with high accuracy. However, the study revealed that the detection results remained only at the level of visual reporting and did not present an integrated structure with industrial control systems.

In the study "Real-Time Students' Safety Helmet-Wearing Detection Based on Convolutional Neural Network" (Fang, 2020), the aim was to detect in real time whether students wear safety helmets in educational and workshop environments. A lightweight model suitable for embedded systems was developed using the YOLOv3-Tiny architecture, and high accuracy was achieved under normal lighting conditions. However, a decrease in performance was reported under low-light conditions. This situation clearly demonstrates the effect of environmental conditions on image-based detection systems.

In the study titled "Detection of Protective Eyewear Usage Using Image Processing Methods" (Yılmaz, 2021), the automatic inspection of protective eyewear usage within the scope of occupational safety was targeted. Experiments were conducted on images obtained under different positions and lighting conditions using a YOLOv4-based object detection model, and high accuracy rates were achieved. The study shows that image-based systems can serve as an alternative to manual inspections in occupational safety applications. However, the transfer of detection results to field control mechanisms was not addressed in this study.

In the study "Detection of Elements of Personal Safety for the Prevention of Accidents at Work with Convolutional Neural Networks" (Rubio-Romero, 2020), the problem of detecting multiple personal protective equipment elements simultaneously was examined. Using CNN-based models, it was shown that equipment such as helmets and safety glasses could be detected with high accuracy. This study highlights the importance of multi-object detection for industrial safety; however, it does not present an integrated control structure with industrial automation systems.

In the study titled "Eye Recognition System to Prevent Accidents on the Road" (Mandal, 2018), the aim was to detect risky conditions such as loss of attention and drowsiness by analyzing drivers' eye states. Using VGG-based convolutional neural networks, stable results were obtained under different lighting conditions. This study demonstrates the effectiveness of image-based detection systems in safety-critical applications. However, the system only generates warnings and does not include a physical control mechanism.

In the study "Current Software Technology in Physiotherapy and Rehabilitation: Image Processing Technique" (Kaya, 2019), it was shown that image processing methods can be used for analyzing human movements and monitoring rehabilitation processes. The study demonstrates that image-based systems provide reliable results in monitoring and state analysis. However, this approach is not related to the control of industrial mechanical systems.

In the agricultural field, the studies "Detection of Vine Leaf Mite Damage Using Image Processing Techniques" (Çelik, 2020) and "Classification of Apple Varieties Using Image Processing Techniques" (Karaca, 2018) show that image processing and deep learning methods can produce successful results in classification and disease detection problems. These studies demonstrate the adaptability of image-based approaches to different fields; however, they do not include real-time control requirements.

a-)Sensorless Detection, Industrial Inspection, and Embedded System Studies

In the study "A High Precision YOLO Model for Surface Defect Detection Based on PyConv and CISBA" (Liu, 2022), attention mechanisms and multi-scale convolution structures were applied to the YOLO architecture in order to detect small defects on metal surfaces without sensors. The results showed that small and low-contrast defects could be detected with high accuracy. This study demonstrates the effectiveness of sensorless image-based inspection in industrial quality control applications.

In the study "Metal Surface Defect Detection Using SLF-YOLO Enhanced YOLOv8" (Wang, 2023), the YOLOv8 architecture was optimized to operate on embedded systems, and real-time detection of metal surface defects was achieved. Similarly, the studies "Surface Defect Detection of Industrial Components Based on YOLOv5" (Sun, 2021) and "YOLO-RFF: An Industrial Defect Detection Method Based on Expanded Field of Feeling and Feature Fusion" (Zhou, 2022) showed that high performance could be achieved in surface defect detection using different YOLO-based architectures.

Focusing on embedded systems, the study "Edge AI for Industrial Visual Inspection: YOLOv8-Based Embedded Solution" (Rossi, 2023) demonstrated that YOLOv8-based models can be executed in real time on platforms such as Raspberry Pi. The study "Applications of Artificial Intelligence-Based Image Processing Techniques on Unmanned Aerial Vehicles" (Aydın, 2021) showed that image-based detection can be used in real time on autonomous and mobile systems. In addition, the review study "Computer Vision and

Image Processing: A Paper Review" (Sharma, 2020) comprehensively summarizes general trends in the fields of image processing and computer vision.

When these studies are evaluated together, it is clearly seen that sensorless image-based detection approaches are applicable in industrial inspection and embedded systems. However, the majority of studies in the literature focus on static objects or surfaces, while dynamic problems such as position verification of moving pneumatic systems are addressed to a limited extent.

First, the parts produced by 3D printing restricted the visibility of the sensor light, preventing the sensors from performing their function properly. Second, the filament materials used did not exhibit sufficient durability under production line conditions. In particular, exposure to high temperature and welding spatter caused deformation, melting, and loss of functionality. As a result, this protection-based approach did not provide a sustainable long-term solution and was found to be impractical.

The obtained results showed that 3D printer–based solutions are insufficient for such harsh industrial environments. Therefore, it was concluded that instead of protecting piston sensors, it is necessary to focus on alternative methods such as camera-based image processing systems.

b-)Camera Angle Adjustment and Image Acquisition

In this study, real-time images were captured from a computer camera using the OpenCV library. The purpose of the code is to provide a live preview in order to correctly adjust the camera angle and position. The default camera was opened using the cv2.VideoCapture(0) command, and the connection status was checked with the isOpened() function. When the camera was successfully opened, a window named "Camera Preview" was created, and the image was continuously displayed on the screen.

Within the loop, each frame was read, resized to a resolution of 640×480 using the resize() function, and displayed using the imshow() function. This allowed the user to view the camera's perspective in real time and physically adjust its position or angle. The application was terminated by pressing the ESC key, after which the camera connection was released using the release() command and all windows were closed with destroyAllWindows(). In this way, a practical preview tool was created using OpenCV to test the camera angle and ensure proper image positioning.

In this study, a specified number of images were captured using the OpenCV library and saved to a designated folder. The purpose of the code is to perform automatic image capture to test camera angles or to create a dataset for model training. First, the required libraries (cv2, os, time) were included in the program. The directory for saving images was defined using the save_path variable, and the existence of the folder was checked with the os.makedirs() command. If the folder did not exist, it was created automatically.

The default camera was initialized using cv2.VideoCapture(0), and the connection was verified using the isOpened() function. After the camera was opened, a 7-second preparation time was given to the user using time.sleep(7). Then, a while loop was started to capture 50 images (maxFrames = 50). Each frame was read using the read() function, resized to 640×480, and displayed on the screen using imshow(). At the same time, each image was saved to the specified folder using cv2.imwrite() with incrementing file names such as p4_0.jpg, p4_1.jpg, and p4_2.jpg.

A 0.5-second (500 ms) delay was applied between each frame, and the user could terminate the process early by pressing the ESC key. After the loop was completed, the camera connection was released, and all windows were closed using destroyAllWindows(). As a result, this code performs automatic image capture and saving at short intervals using OpenCV, which is highly useful for data collection or camera angle adjustment.

In this study, for two sensors, 50 images were captured for each of the following combinations: both sensors open, both sensors closed, right sensor closed and left sensor open, and left sensor closed and right sensor open.

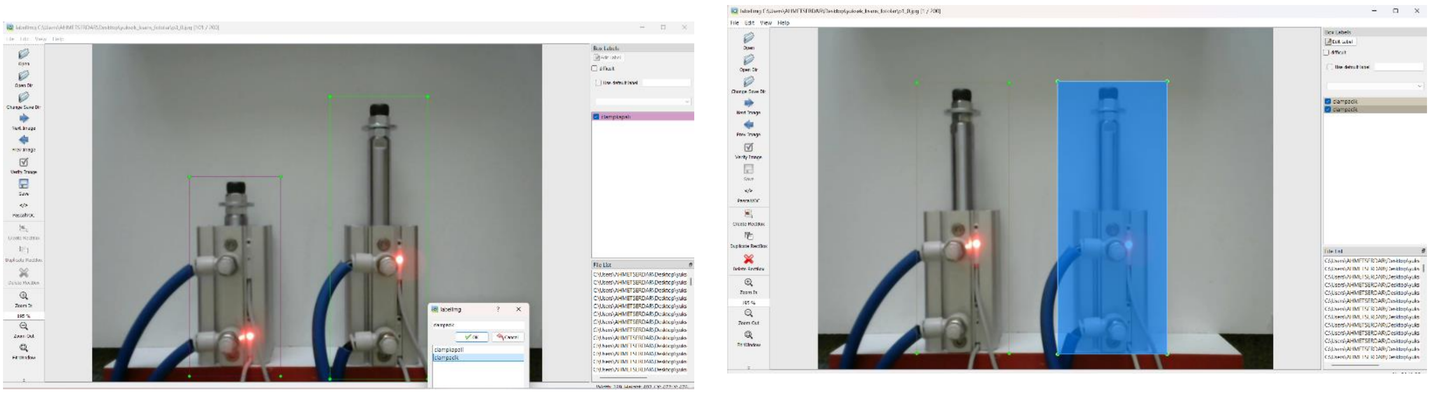

Figure 2. Image Labeling Using LabelImg

c-)Purpose of Writing the Code

This code was written to run on a Raspberry Pi and to activate LEDs according to the forward and backward positions of the piston. Different LEDs are activated depending on the piston position.

In this study, two pneumatic pistons (left and right) with “clampopen” and “clampclosed” states were detected in real time using a Raspberry Pi, the YOLOv8 object detection model, and the OpenCV library. Based on these detections, the GPIO pins were automatically controlled.

The main objective is to detect the piston positions from camera images and correctly activate the output pins on the Raspberry Pi, enabling physical interaction with the system state.

Methodology

Three main libraries are used in the code:

ultralytics.YOLO: Loads the YOLOv8 model trained with the “clampopen” and “clampclosed” classes and performs predictions.

cv2 (OpenCV): Captures images from the camera and displays bounding boxes and text on the screen.

RPi.GPIO: Used to control the digital pins of the Raspberry Pi.

a-)Model and Camera Settings

model = YOLO("/home/pi/piston_model/best.pt")
cap = cv2.VideoCapture(0)

The trained YOLO model is loaded from its directory.
The camera connected to the Raspberry Pi is initialized using VideoCapture(0) to continuously capture images.
The model detects whether the pistons are in open or closed positions in each frame.

b-)System Parameters

CONF_THRESHOLD = 0.90

Detections with a confidence value below 90% are ignored.

STABILITY_FRAMES = 5

The same state must be detected consecutively for 5 frames.
This stability filter prevents false transitions and vibration-related detection errors.

c-) GPIO Pin Definitions

Four output pins are defined in the code:

Piston	State	GPIO Pin
Left	Forward	17
Left	Backward	18
Right	Forward	27
Right	Backward	22

All pins are initially set to LOW (inactive).
The BCM numbering standard is used for GPIO pin configuration.

d-)Image Processing and Object Detection

In each loop iteration, a frame is captured from the camera and divided into left and right regions to distinguish the pistons.
The YOLO model processes the frame and returns piston labels:
clampopen → piston forward (green bounding box)
clampclosed → piston backward (red bounding box)

Based on the model output, the piston states are defined as: “LEFTCLAMPFORWARD”, “LEFTCLAMPBACKWARD”, “RIGHTCLAMPFORWARD”, and “RIGHTCLAMPBACKWARD”.

e-)Stability and State Confirmation

For each piston, the last detected state is temporarily stored.
If the same state is detected for 5 consecutive frames, it is confirmed as a valid state.

This process ensures that unstable or temporary detection errors do not affect the GPIO outputs.

f-)GPIO Control

According to the confirmed state, the corresponding GPIO pins are activated:
Left piston forward → GPIO17 HIGH, GPIO18 LOW
Left piston backward → GPIO18 HIGH, GPIO17 LOW
Right piston forward → GPIO27 HIGH, GPIO22 LOW
Right piston backward → GPIO22 HIGH, GPIO27 LOW
During intermediate or temporary detections, all pins are set to LOW to prevent incorrect signal transmission.

g-)Visual Interface

In the OpenCV window:
Piston bounding boxes are color-coded (green or red).
State labels (e.g., "LEFTCLAMPFORWARD") are displayed in yellow text.
When the user presses the ESC key, the system stops safely.

h-)Program Termination

Using the finally block, regardless of whether the program stops due to an error or manual interruption:
All GPIO pins are set to LOW.
GPIO resources are released using GPIO.cleanup().
The camera connection is closed and all windows are destroyed.

This system is a vision-based piston position monitoring and control mechanism running on a Raspberry Pi. With the YOLOv8 model, the open/closed positions of pistons are automatically detected, GPIO pins are activated accordingly, and visual recognition and physical control operate in an integrated manner.

Result and Discussion

In this section, the results of the experimental studies carried out for sensorless detection of the open and closed positions of pneumatic clamps using image processing and deep learning–based methods are presented, and the obtained findings are discussed in detail. The experimental evaluations were conducted in terms of model accuracy, stability, real-time operability, and industrial applicability. In order to evaluate the accuracy and industrial feasibility of the developed image processing–based sensorless clamp position detection system, comparative tests were performed with the piston sensors currently used in the production line. During these tests, the sensor indicator lamp representing the physical sensor detecting the forward movement of the pneumatic piston and the clamp position outputs obtained from the image processing–based system were monitored simultaneously.

In the experiments, it was observed that when the piston reached the forward position, the sensor lamp became active, and at the same time, the image processing–based system detected the clamp position as “forward/open.” Similarly, when the piston moved to the backward position, the sensor lamp became inactive, and the image processing–based system simultaneously detected the “backward/closed” state. This synchronization demonstrates that the image processing–based approach can produce results consistent with physical sensors.

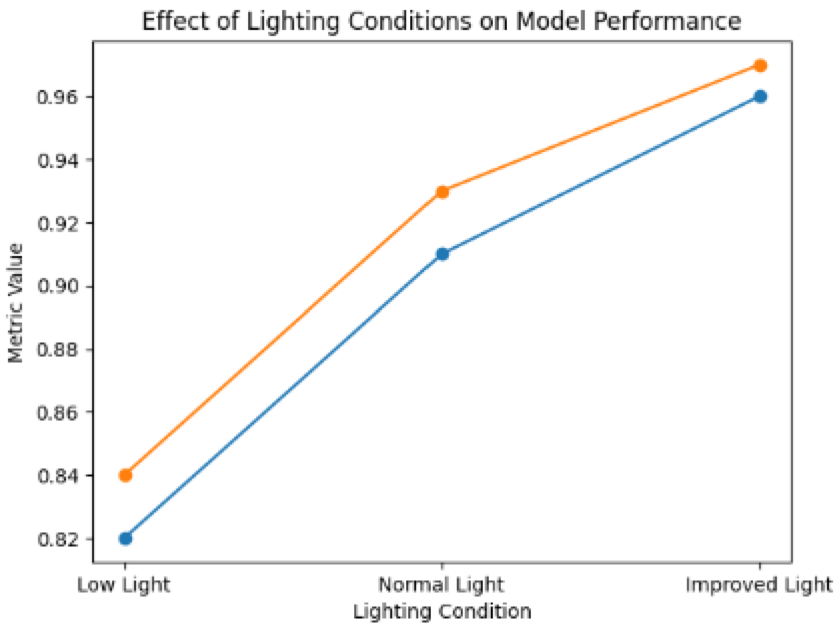

Figure 3. Comparison Under Varying Lighting Conditions

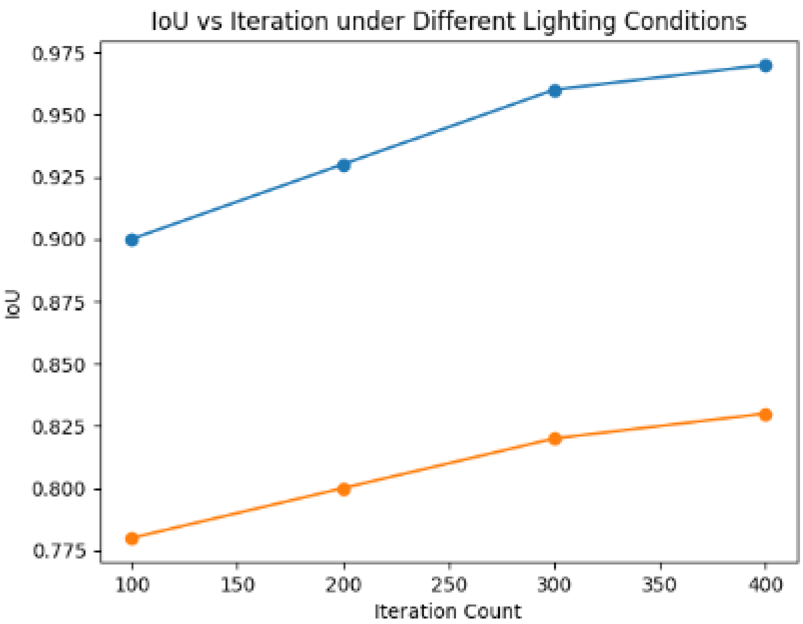

Figure 4. Comparison Under Varying Lighting Conditions

During the comparative tests, no significant delay or inconsistency was observed between the sensor lamp and the image processing–based outputs. Thanks to the real-time operation capability of the image processing–based system, reliable position information was obtained within the mechanical movement time of the piston. This indicates that the system can be used in the production line without causing additional delays.

Especially in welding production environments, situations were observed where the sensor lamp was active, but the sensor cable was at risk of damage due to welding spatter. In contrast, since the image processing–based system does not require physical contact, it was not affected by such environmental factors. In these tests, where the sensor lamp was used only as a reference, the image processing–based approach was evaluated as a reliable alternative against sensor failures.

This comparative evaluation shows that the developed system can perform the same function as physical piston sensors not only in theoretical or laboratory environments but also under real production line conditions. The simultaneous detection of the piston's forward movement with the sensor lamp is considered an important finding supporting the accuracy of the image processing–based approach.

As a result, the image processing–based sensorless clamp position detection system stands out as a reliable alternative for industrial production lines due to its ability to produce consistent results simultaneously with physical piston sensors, operate synchronously with the sensor lamp, and be less affected by environmental conditions. This approach directly contributes to preventing unplanned downtimes caused by sensor failures, reducing maintenance and spare part costs, and increasing production continuity.

Results Obtained from Image Processing–Based Clamp Position Detection

In this study, a deep learning–based object detection model was trained using a cropped image dataset created to detect the open and closed positions of pneumatic clamps. The images used in the training process were obtained from a real production line and included challenges representing industrial environments, such as welding spatter, variable lighting conditions, and background complexity.

To evaluate the model performance, multiple experiments were conducted using different training parameters. During training, an early stopping mechanism was applied, and the training process was automatically terminated when the minimum loss value was reached. In preliminary experiments, although the maximum epoch number was set to a high value, it was observed that the model reached a stable point in most trainings between 80 and 100 epochs. Therefore, in order to perform a comparable and objective evaluation, the epoch value was kept constant, and the experiments were repeated by increasing the number of iterations.

The accuracy, loss, and reliability metrics obtained from the experiments are presented in Figures 5.1–5.3. When the IoU and loss graphs are examined, fluctuations are observed in the model outputs at low iteration numbers. As the number of iterations increases, these fluctuations decrease, and the model achieves more stable learning. This indicates that with more iterations, the model becomes more robust against environmental noise.

Evaluation of Performance Metrics

To quantitatively evaluate the model performance, F1 score, IoU, and loss metrics were used. The performance metrics obtained for different iteration values are presented in Table 5.1.

As seen in Table 5.1, with the increase in iteration number, the F1 score and IoU values generally increase, while the validation loss values decrease. It was observed that the model exhibited the best performance in terms of both accuracy and stability at medium iteration levels. At higher iteration values, limited fluctuations occurred in some metrics; however, the overall performance remained within acceptable limits.

This indicates that the model achieved balanced learning on images representing real production environments without overfitting. In addition, the limited performance gains with longer training durations suggest that terminating the training at this stage is appropriate.

Evaluation of Visual Results

In addition to numerical metrics, the prediction results of the model were also evaluated visually. For this purpose, prediction outputs and overlay results obtained at different iteration values were compared on randomly selected test images from the dataset. The relevant visual results are presented in Figure 5.4.

In visual evaluations, it was observed that at low iteration values, clamp boundaries were not clearly defined and misclassifications occurred in some regions. With an increase in iteration number, especially the clamp endpoints and moving regions were detected more accurately and showed a high level of overlap with the original images. This demonstrates that the model can produce reliable results despite challenges such as complex backgrounds and welding spatter.

Model Behavior under Industrial Environment Conditions

To evaluate the industrial applicability of the model, scenarios involving intense welding spatter and potential physical damage to cables and sensors were considered. It was observed that the image processing–based approach was not affected by such environmental factors compared to physical piston sensors and provided an alternative capable of eliminating production downtimes caused by sensor failures.

In addition, due to the contactless structure of the system, the need for piston sensors, cabling, and mounting hardware is eliminated, which contributes to reducing maintenance costs. The real-time operation capability of the model enables clamp position information to be obtained without causing additional delays in the production line.

Performance metrics according to lighting conditions

Lighting Condition	IoU	F1 Score
Low lighting	0.82	0.84
Normal lighting	0.91	0.93
Improved lighting	0.96	0.97

Figure 5. Performance metrics according to lighting conditions

IoU change according to the number of iterations

Iteration	IoU (Good Lighting)	IoU (Low Lighting)
100	0.90	0.78
200	0.93	0.80
300	0.96	0.82
400	0.97	0.83

Figure 6. IoU change according to the number of iterations

Discussion

The obtained results show that the image processing and deep learning–based sensorless clamp position detection approach provides a strong alternative to traditional sensor-based systems. While similar studies in the literature generally focus only on detection or monitoring, in this thesis, the detection results were evaluated in a form that can be directly integrated into the production process.

The accuracy and stability results achieved by the model are sufficient for applicability in real production environments. Moreover, the limited performance gains at higher iteration values indicate that the model architecture and dataset size were balanced appropriately for this study.

In this thesis, a solution is proposed to detect the open and closed positions of pneumatic clamps used in industrial production lines without the need for physical piston sensors by using camera-based image processing and deep learning methods. In traditional production lines, piston position information is mostly obtained through magnetic or inductive sensors. However, these sensors frequently fail due to environmental factors such as welding spatter, high temperature, and vibration, especially in welding production environments, negatively affecting production continuity.

Within the scope of this thesis, an image dataset containing the forward (open) and backward (closed) positions of pneumatic clamps was created using images obtained from a real production line. The images represent real industrial challenges such as variable lighting conditions, welding spatter, and background complexity. Necessary preprocessing steps were applied, and a deep learning–based object detection model was trained.

During the training process, an early stopping mechanism was used to prevent overfitting. Although high epoch values were defined in preliminary experiments, the model reached a stable point between 80 and 100 epochs in most trainings. Therefore, to ensure a comparable and objective evaluation, the epoch value was kept constant, and experiments were conducted by increasing the number of iterations.

As a result of the experiments, the F1 score, IoU, and loss metrics obtained for different iteration values were analyzed. The results showed that as the iteration number increased, the F1 score and IoU values generally increased, while the validation loss values decreased. The highest F1 score was achieved at medium iteration levels, and performance gains were limited at higher iteration values. This indicates that the model achieved balanced learning on images representing real production environments.

The model prediction results were evaluated not only through numerical metrics but also through visual outputs. On randomly selected test images, it was observed that as the iteration number increased, clamp boundaries became clearer and showed a high degree of overlap with the original images. While some incorrect detections were observed at low iteration values, these errors were significantly reduced at higher iteration values.

To evaluate the industrial applicability of the developed system, comparative tests were conducted with the piston sensors currently used in the production line. During these tests, the sensor lamp detecting the forward position of the piston and the outputs of the image processing–based system were monitored simultaneously. The results showed that when the sensor lamp was active, the image processing–based system also detected the clamp position as “forward/open,” and when the sensor lamp was inactive, the “backward/closed” state was detected. This synchronization demonstrates that the developed approach produces results consistent with physical sensors.

In addition, tests conducted under different lighting conditions showed a decrease in model performance at low light levels. However, after adding a fixed and controlled lighting source to the production line, the IoU and F1 score values increased significantly, and the performance became stable. This indicates that the performance decrease was caused by environmental lighting conditions rather than model inadequacy.

As a result, it has been demonstrated that the image processing–based sensorless clamp position detection system developed in this thesis can perform the same function as physical piston sensors, is resistant to sensor failures, and can operate reliably under real production line conditions. The system offers significant advantages in eliminating sensor and cabling costs, reducing maintenance requirements, and preventing production downtimes.

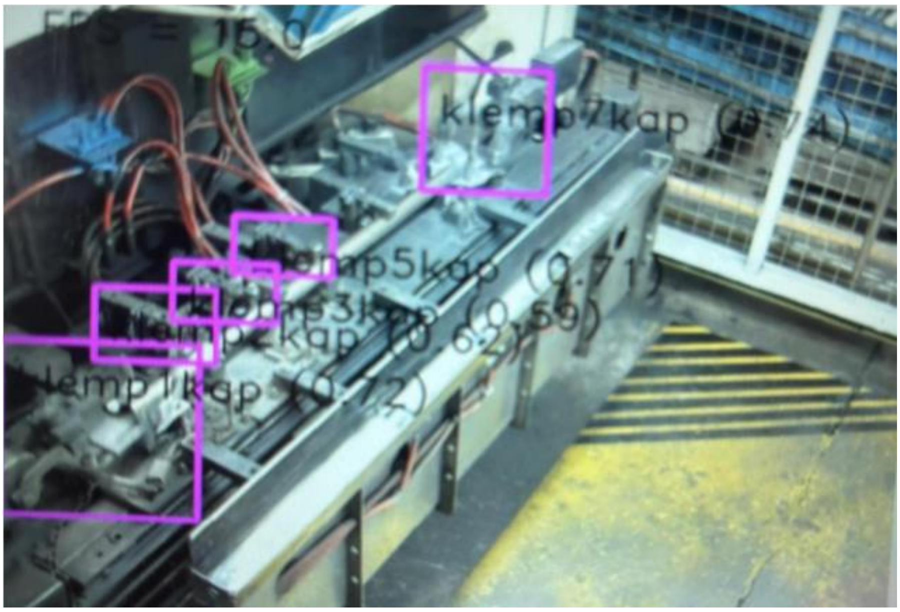

Figure 7. Application in Production Lines

Figure 8. Application in Production Lines

Conclusion

In this thesis study, a solution is proposed to detect the open and closed positions of pneumatic clamps used in industrial production lines without the need for physical piston sensors, by using camera-based image processing and deep learning methods. In traditional production lines, piston position information is generally obtained through magnetic or inductive sensors. However, these sensors frequently fail due to environmental factors such as welding spatter, high temperature, and vibration, especially in welding production environments, which negatively affects production continuity.

Within the scope of this thesis, an image dataset containing the forward (open) and backward (closed) positions of pneumatic clamps was created using images obtained from a real production line. The images represent real industrial challenges such as variable lighting conditions, welding spatter, and background complexity. Necessary preprocessing steps were applied to these images, and a deep learning–based object detection model was trained.

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As a result of the experiments, the F1 score, IoU, and loss metrics obtained for different iteration values were analyzed. According to the experimental results, as the number of iterations increased, the F1 score and IoU values generally increased, while the validation loss values decreased. It was observed that the highest F1 score was achieved at medium iteration levels, while performance gains were limited at higher iteration values. This indicates that the model achieved balanced learning on images representing real production environments.

The prediction results of the model were evaluated not only through numerical metrics but also through visual outputs. In randomly selected test images, it was observed that as the iteration number increased, the clamp boundaries became more clearly separated and showed a high degree of overlap with the original images. While incorrect detections were observed in some regions at low iteration values, these errors were significantly reduced at higher iteration values.

To evaluate the industrial applicability of the developed system, comparative tests were conducted with the piston sensors currently used in the production line. During these tests, the sensor lamp detecting the forward position of the piston and the outputs of the image processing–based system were monitored simultaneously. The results showed that when the sensor lamp was active, the image processing–based system simultaneously detected the clamp position as "forward/open," and when the sensor lamp was inactive, the "backward/closed" state was detected. This synchronization demonstrates that the developed image processing–based approach produces results consistent with physical sensors.

In addition, tests conducted under different lighting conditions showed a certain decrease in model performance at low light levels. However, after adding a fixed and controlled lighting source to the production line, the IoU and F1 score values increased significantly, and the performance became stable. This indicates that the performance degradation was caused by environmental lighting conditions rather than model inadequacy.

As a result, it has been demonstrated that the image processing–based sensorless clamp position detection system developed within the scope of this thesis can perform the same function as physical piston sensors, is resistant to sensor failures, and operates reliably under real production line conditions. The system offers significant advantages in eliminating sensor and cabling costs, reducing maintenance requirements, and preventing production downtimes.

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