STM JOURNALS

Journal of
Image Processing & Pattern Recognition Progress

ISSN: 2394-1995
Volume 11, Issue 1, 2024
January—April
DOI (Journal): 10.37591/JoIPPRP

https://journals.stmjournals.com/JoIPPRP

Review JoIPPRP

Detectiverse: Advancing Supply Chain Efficiency with AI-Enhanced Screw Counting

Aaron Sam A.S.[1], Shanmuga Pradeepan R.[1], Sobana R.S.[1], S. Rathnamala[2,*], A. Karthick Kumar[3]

Abstract

Accurate screw counting is essential in the manufacturing sector to ensure efficient inventory management and maintain quality control standards. The current manual counting method is prone to errors and lacks the ability to identify the source of missing screws. To address this challenge, we propose implementing an automated screw counting system at Indo Metal Tech in Ambattur, Chennai. This system would utilize advanced image processing and machine learning algorithms to detect and tally screws within trays captured by cameras. The algorithm incorporates user-triggered actions, real-time feedback, and user verification to ensure accuracy and adaptability to changing manufacturing conditions. This innovative solution not only improves efficiency and accuracy but also facilitates collaborative manufacturing practices. The system, equipped with a camera and sophisticated image processing algorithms, effectively and precisely handles these challenges. Additionally, the solution's versatility is enhanced by QR codes for collaborative counting and the option for continuous counting between trays. This reduces human error rates and establishes a framework for enhanced traceability and quality control in the manufacturing process. Overall, this proposed solution not only meets the immediate need for precise screw tallying but also lays the groundwork for an improved, simplified, and collaborative manufacturing process.

Keywords: Computer vision, image processing, object detection, pre-trained models, screw counting

INTRODUCTION

Counting closed figures such as screws in tray manufacturing for industry introduces additional complexities especially considering potential losses during shipping. During transportation, trays may experience vibrations, shocks, or movements that can alter the arrangement of screws. This introduces uncertainty in the initial count and makes it challenging to guarantee the exact number of screws upon arrival. The condition of the packaging can affect the count accuracy [1].

If packaging is damaged or compromised, screws may shift or be lost during transit, impacting the final count. Verifying the accuracy of the initial count after shipping, is challenging, as the state of the screws may have changed. Traditional counting methods may not be suitable, requiring innovative solutions like RFID tracking, computer vision, or weight-based systems. In manufacturing settings, recognizing closed figures ensures quality control by identifying anomalies, defects, or irregularities in the tray contents. The ability to automatically

***Author for Correspondence**
S. Rathnamala
E-mail: rathnamala@sethu.ac.in

[1]Student, Department of Computer Science and Engineering, Sethu Institute of Technology, Virudhunagar, Tamil Nadu, India
[2]Associate Professor, Department of Computer Science and Engineering, Sethu Institute of Technology, Virudhunagar, Tamil Nadu, India
[3]Assistant Professor, Department of Computer Science and Engineering, Sethu Institute of Technology, Virudhunagar, Tamil Nadu, India

Received Date: March 11, 2024
Accepted Date: March 20, 2024
Published Date: April 03, 2024

Citation: Aaron Sam A.S., Shanmuga Pradeepan R., Sobana R.S., S. Rathnamala, A. Karthick Kumar. Detectiverse: Advancing Supply Chain Efficiency with AI-Enhanced Screw Counting. Journal of Image Processing & Pattern Recognition Progress. 2024; 11(1): 21–26p.

detect and analyze closed figures contributes to the development of automated systems, reducing manual intervention and enhancing efficiency in processes involving trays of diverse contents [2].

Implementing real-time monitoring systems during shipping can help identify potential issues early on. Ensuring synchronization between the initial count, shipping records, and the received count is crucial. Any discrepancies need to be addressed promptly to avoid incorrect inventory information. Upon receiving trays, employing efficient counting mechanisms, such as computer vision systems integrated with cameras, can help verify the actual count of screws in real-time, allowing for quick identification of discrepancies. Establishing transparent communication channels between manufacturers and shipping partners can facilitate the exchange of information regarding any observed discrepancies, enabling collaborative efforts to resolve issues related to missing screws. Ensuring the accuracy of screw counts in trays, post-shipping, requires a combination of proactive measures during packaging, real-time monitoring, and innovative verification methods to adapt to the challenges introduced during transportation [3].

PROBLEM STATEMENT

Indo Metal Tech, situated in Ambattur, Chennai, faces a critical challenge in the manual counting of screws within their manufacturing processes. The current manual counting method is prone to errors and lacks the ability to pinpoint whether screws are missing from their end or the opposite side of the production line. This inefficiency in counting not only hampers the accuracy of inventory management but also poses a significant obstacle to quality control [4]. The company seeks a technological solution that can automate the screw counting process, providing a reliable and real-time mechanism to identify missing screws. The objective is to enhance efficiency, reduce human error, and establish traceability within the manufacturing workflow as shown in Figure 1. The ideal solution should seamlessly integrate into the existing operations of Indo Metal Tech, offering a systematic approach to screw counting and enabling quick identification of discrepancies in screw quantities between their side and the opposite end of the production line [5].

EXISTING SOLUTION

Counting of screws in company was performed manually by laborers on a shift basis. There was no new and unique technology involved in the counting process. The accuracy and efficiency of the task are primarily dependent on the skills, attention, and effort of human workers [6].

Figure 1. The tray containing the Screws.

The existing manual screw counting process is labor-intensive because it requires substantial manual effort from workers. There is no real-time feedback mechanism; the results of the screw count are not immediately available or accessible during the counting process. The manual counting process has limited traceability. This lack of traceability can pose challenges in quality control, as it becomes harder to ensure consistency and reliability in the counting process [7].

LITERATURE REVIEW

The literature review for implementing a machine learning model for screw counting in trays through cameras should cover relevant studies, methodologies, and advancements in computer vision, image processing, and object detection. Exploring on state of the art object detection techniques, such as Faster R-CNN, YOLO (You Only Look Once), these assess their applicability for detecting and counting screws in tray images. It focuses on applying machine learning in manufacturing settings and identifying successful implementations of computer vision for quality control, inventory management, and automation in similar industries [8].

We examined the literature related to image processing algorithms tailored for detecting objects in complex backgrounds; considered approaches for handling variations in lighting conditions and diverse screw shapes within trays; and investigated research on real-time monitoring systems in logistics and manufacturing for understanding how such systems leverage cameras, sensors, and machine learning for continuous monitoring, ensuring timely identification of discrepancies. We explored literature discussing adaptive learning models that can adjust to changes in manufacturing environments, and considered research on models that demonstrate resilience to variations in tray designs, screw types, and lighting conditions [9].

We reviewed studies focusing on techniques to reduce false positives and false negatives in object detection; identified methodologies that improve the accuracy of screw counting systems and mitigate potential errors; and examined literature on the integration of machine learning models into manufacturing workflows, to understand how successful implementations seamlessly incorporate automated counting systems into existing processes. We explored research addressing data security and traceability in machine learning applications to understand how sensitive information, such as screw counts, can be securely managed, and traceable records can be maintained. This literature review will provide a foundation for understanding existing knowledge, methodologies, and potential challenges in implementing a machine learning model for screw counting in tray manufacturing [10].

PROPOSED SOLUTION

To overcome this, we propose an automated solution using Python and computer vision. This system incorporates a camera connected to a computer for capturing trays and employs advanced image processing techniques to detect closed objects, specifically screws, within the trays. It connect a camera to the computer for capturing high-resolution images of trays containing screws. Then it utilizes Python to implement robust image processing algorithms for detecting closed objects (screws) within the captured images.

It employs state-of-the-art object detection techniques, possibly leveraging pre-trained models, to identify and localize screws in the images. Developing a counting algorithm in Python to accurately count the number of detected screws in each tray. It implements a real-time feedback mechanism to display the counted number of screws on the computer interface as soon as the image processing is complete. This creates a user-friendly interface that showcases the tray images and the corresponding screw count. This interface will facilitate easy monitoring and verification. This Python-based solution offers an automated and accurate approach to screw counting, significantly improving efficiency and reducing manual errors for Indo Metal Tech. The real-time feedback and integration capabilities ensure a seamless implementation within their manufacturing operations.

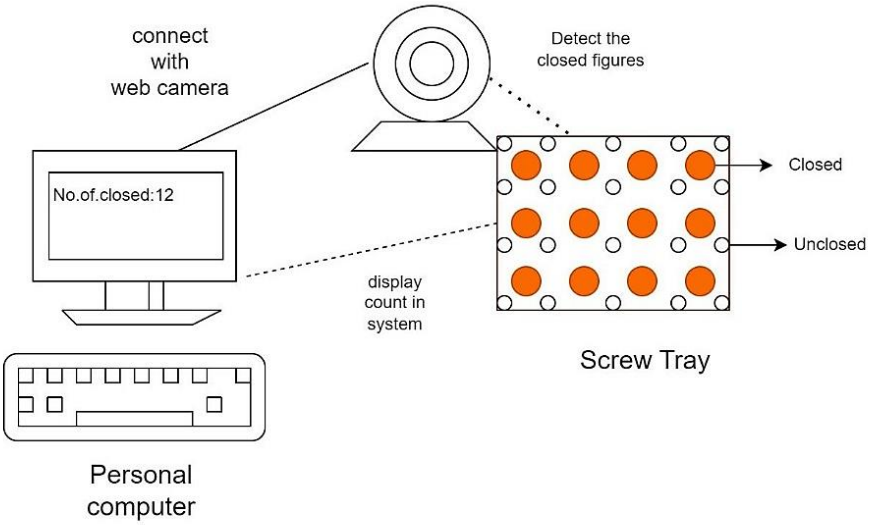

Figure 2. Block diagram of Detectiverse process .

BLOCK DIAGRAM

Figure 2 shows the block diagram of Detectiverse process. It contains materials like personal computer, camera, and screw in tray, as shown in Figure 2.

Setup: Connect a camera to a computer.

Computer Model (Python): Develop a Python model for screw counting using computer vision. This model is installed on the computer.

Tray Placement: Place a tray containing screws under the connected camera.

Capture and Count (Camera): Trigger the camera to capture the tray by pressing the F5 button on the computer keyboard. The Python model processes the captured image, counts the screws using computer vision algorithms, and displays the count on the computer screen in real-time.

Completion: After counting all trays, terminate the process by pressing the Escape button on the computer keyboard.

METHODOLOGY

Camera Integration: Connect a camera to the computer within the metal company's manufacturing facility. Ensure the camera is appropriately positioned to capture images of trays containing metal objects.

User Interaction: Develop a user-friendly interface on the computer. Upon placing a tray under the camera, the user initiates the detection process by pressing the F5 button on keyboard. This triggers the camera to capture images of the tray contents.

Image Capture and Processing: Implement image processing algorithms that analyze the captured images. Utilize computer vision techniques to detect closed objects (metal components) within the tray. This step involves the prediction of closed objects based on the features extracted from the images.

Real-Time Detection: Enable real-time detection to provide immediate feedback to the user as the camera processes the images. This ensures prompt identification of closed objects in the metal trays.

User Verification: Display the detected closed objects on the user interface. The user can visually verify the accuracy of the detection results. If needed, adjustments can be made before proceeding to the counting phase.

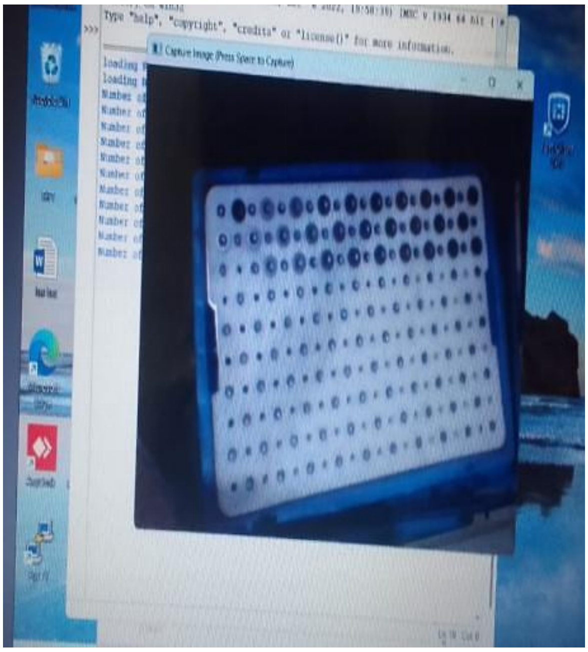

Figure 3. The tray is captured using the camera.

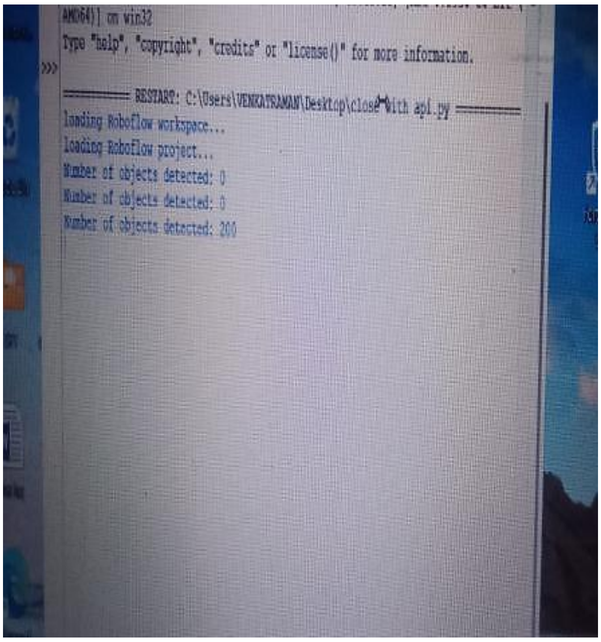

Figure 4. The output is displayed in the PC.

Counting Initialization: Once the user is satisfied with the detected objects, pressing the space bar triggers the counting phase. The system now focuses on accurately counting the closed metal objects within the tray.

Display Count Results: Display the final count of closed metal objects on the user interface. Ensure the results are easily accessible and comprehensible for the user.

Data Logging and Traceability: Log the counting results for traceability and future reference. This step contributes to maintaining records of metal components processed, aiding in quality control and inventory management.

Integration with Manufacturing Workflow: Seamlessly integrate the entire process into the metal company's manufacturing workflow. Ensure compatibility with existing systems and protocols to enhance operational efficiency.

RESULT

Installation of a camera-equipped device to take pictures of trays holding screws. Python-based computer vision techniques are used to process the taken pictures. In order to identify and count the number of screws in each tray, these algorithms examine the photos. On the computer screen, the counted number of screws is shown in real time. This makes it possible for prompt verification and response, making counting process monitoring simple. The screw counting process can be made more efficient by automating tasks that previously required manual labour. The use of computer vision technology minimizes the risk of errors associated with manual counting methods, ensuring greater accuracy in the screw counts as shown in Figures 3 and 4.

CONCLUSION

Finally, the automated screw counting solution that uses computer vision and Python offers Indo Metal Tech in Ambattur, Chennai, a revolutionary answer. Technology must be used to address the company's problems with manual counting, which cause mistakes and obstructions in quality control and inventory management. The system that has been put into place, which has a camera and sophisticated image processing algorithms, effectively and precisely handles these problems. Indo

Metal Tech is able to automate the counting process and easily incorporate this solution into their current manufacturing operations because to the real-time feedback system and user-friendly interface. The system precisely identifies and counts screws in trays by utilizing cutting-edge object identification techniques and Python- based algorithms.

It also provides instantaneous feedback for monitoring and verification. The solution's versatility is further enhanced by the addition of QR codes for collaborative counting and the possibility of continuous counting between trays. This lowers human error rates and lays the groundwork for enhanced traceability and quality control in the manufacturing process. Consequently, the suggested resolution not only fulfils the pressing requirement for precise screw tallying but also establishes the foundation for an enhanced, simplified, and cooperative manufacturing procedure at Indo Metal Tech. The effective deployment of this automated system is anticipated to yield substantial improvements in productivity, minimize errors, and establish traceability, hence augmenting Indo Metal Tech's manufacturing capabilities overall.

Future Work

Future work that is being proposed would incorporate QR codes into the screw counting procedure, giving screw count data on trays a visual representation. The detected screw count data will be encoded into QR codes, making it simple to scan and retrieve count details. Cross-verification by the other end of the manufacturing line is made possible by this solution, enabling both ends to independently confirm counts and spot inconsistencies. Collaborative counting procedures and standardized communication are promoted when the other side adopts a similar QR code approach. Furthermore, a method for continuous counting between trays will be put in place. To ensure a cumulative count, QR codes on following trays will carry aggregated counts from prior trays. This approach aims to enhance collaboration, transparency, and efficiency in the manufacturing environment by providing real-time verification and facilitating data-sharing between different sides of the production line.

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