Research Article

Machine Vision for Detecting Defects in Liquid Bottles: An Industrial Application for Food and Packaging Sector

Omid Farhangi[1], Ehsan Sheidaee[1*] , Asma kisalaei[2]

[1]Biosystems Engineering Department, Tarbiat Modares University, Tehran, Iran
[2]Biosystems Engineering Department, Ardebil Mohaghegh University, Ardabil, Iran
 E-mail: sheidaee.ehsan@ut.ac.ir

Abstract: The quality control of liquid packaging, such as cooking oils and beverages (bottled water, soft drinks, juices, etc.), is crucial due to the inherent risk of leakage. This process involves inspecting bottles for cap and seal ring defects and addressing issues arising from the gradual degradation of filling machines, leading to variations in the surface level of liquid bottles over time. Additionally, proper label placement significantly contributes to the customer-friendliness of a product. This research aims to introduce an automated vision-based rating system designed for the online inspection of defects in liquid bottles. The system is versatile, applicable to both academic and industrial settings, and can be easily adapted for use with various types of transparent liquid bottles. The defect detection metrics include three measures of distance determination and pattern matching. The equipment used in this study includes a Complementary Metal Oxide Semiconductor (CMOS) camera with a USB connection, a laptop, and a 14-speed conveyor belt, among other components. The system demonstrated an average accuracy of 95.6%, with specific accuracies for surface level, cap, and label placement at 100%, 95%, and 92%, respectively.

Keywords: liquid level, label detection, cap defaults, classification, quality control

1. Introduction

The scrutiny of products on a production line has become an important aspect of the quality control process. It's important to ensure quality criteria are met during product inspection because without these standards, the product will be rejected. Visual inspection, while essential in many contexts, poses several challenges compared to automated approaches used in mass production. This method is slower and more prone to errors, leading to high labor costs, worker fatigue, and reduced accuracy. Additionally, visual inspection is often inconsistent due to environmental factors such as lighting conditions. These limitations highlight the need for more reliable and efficient inspection methods in modern manufacturing processes. Furthermore, visual inspection faces significant shortcomings due to a lack of concentration, the absence of standardized procedures, and a shortage of skilled workers. These issues further compromise the effectiveness and reliability of this method in ensuring product quality. When processing speeds on narrow conveyor belts exceed 1 meter per second and multiple parameters must be inspected simultaneously, traditional inspection methods become inefficient [1]. However, recent advancements in image acquisition technologies, data processing, image processing techniques, blockchain, internet of things, cloud computing, and artificial intelligence

have paved the way for a more efficient alternative [2-3]. Machine vision inspection is now a viable choice for various industrial applications [4-6] and detects dynamic objects for monocular recording [7]. Machine vision serves as a tool for quality control in automated production lines, finding applications in sectors like the food industry for examining surface defects [8-9], surface inspection [10], bottles [5, 11], fruit [12-13], egg [14-15], nut [16-17], fabric [18], mechanical parts [19-20] and composite materials [21] as well as the pharmaceutical industry for inspecting medicine sheets. Notably, this method offers significant advantages, including continuous operation without the need for process interruptions or manual inspections [22].

In today's market, product packaging serves as a vital indicator of quality, directly affecting consumer appeal and sales. This importance extends to liquid bottles, which require thorough inspection after packaging. Before reaching the consumer, these packaged bottles must undergo comprehensive scrutiny from multiple perspectives to ensure their integrity and quality [23]. A well-executed and flawless package is crucial for ensuring the safety and quality of a product from the production line to the point of consumption. Machine vision, now integral to this process, is used not only in product quality control but also across various fields such as breweries, and product selection [24-25]. As technology advances, integrating machine vision into quality control processes has become essential for iconic brands [26]. This strategic embrace of innovation ensures that each consumer experience is more than just a transaction; it is an assurance of premium quality and unwavering reliability [27]. This approach solidifies these brands' standing in the competitive food industry, helping policymakers and food manufacturers guide consumers through the complex array of product alternatives and streamline their decision-making process [28-29].

Brosnan et al. [30] explained the essential components of a computer vision system and provided a comprehensive review of recent advancements in the food industry. In another study "Design of Automatic Vision-based Inspection System for Monitoring in an Olive Oil Bottling Line," Abdelhedi et al. [6] compared the development and performance of two machine vision inspection methods on a high-speed conveyor belt. The researchers utilized by Otsu threshold [31] and edge detection techniques to inspect the caps and liquid levels of the bottles in real time [6]. Younes et al. [11] applied machine vision to examine metal sheets for defects, employing a system comprising a camera for image capture, specialized lighting to reveal defects, data visualization, image processing methods for defect inspection, and an automatic ejection system. Campos et al. [22] conducted research titled "Inspection of bottle crates in the beer industry through computer vision," focusing on inspecting bottle crates for cracks in handles, identifying wrong bottles through cap differences, and detecting empty spots. Pithadiya et al. [32] investigated an optimal edge detection technique for inspecting liquid levels, while Duan et al. [12] utilized a machine vision inspection system to examine beer bottles for defects in walls, floor, and top openings. Li et al. [33] developed a machine vision system to inspect micro-cracks in eggshells, employing a pressure chamber with a vacuum pressure of 18 kPa to force open micro-cracks, and capturing images with the machine vision system. Baigvand et al. [34] employed a machine vision system to classify dried figs based on size, color, and split size. The grading algorithm, implemented using LabView, sorted figs into five qualitative grades based on the specified parameters, with results indicating a sorting accuracy of 95.2% for all classes. The mean processing and grading rate of the system was recorded at 90 kg/h [34]. This paper details the development of an automated machine vision system for the precise measurement and control of the dimensional characteristics of medical glass vials. It addresses challenges in visual inspection through innovative image capture techniques and proposes a heuristic segmentation method for border extraction. Additionally, it evaluates an integrated approach that combines machine learning and post-processing methods, tested on real samples [8, 35], saliency detection of the glass bottle bottom [36], empty or fills bottle [37-38], port defects [39], bottle wall and bottle bottom [12], edge computing for logistics packaging box [40], bottle surface [41-42] and plastic bottle inspection on the seated cap, vials on the body dimensional [35], label alignment and surface defects [43-44]. Packaging liquid products in plastic and glass bottles stands out as one of the globally favored methods, extensively employed in the food and pharmaceutical sectors [45-46]. To ensure quality, various sensors, and deep learning methods are employed to inspect these bottles for liquid level, cap defects, label placement, external objects, and other parameters, effectively classifying them as either good or defective [47-48]. These include an Ultrasonic sensor for liquid-level inspection, a photoelectric sensor for cap inspection, and an electromagnetic sensor (radio) for barcode verification [49-51]. According to these studies (Table 1), related research has identified specific flaws in various parts of the bottle using image processing and electronic sensor techniques.

Table 1. Related research work for bottle defection

Defect of bottle	Technique for identify	Reference
dimensional of glass vials	machine vision	[35]
empty or filled	automated visual inspection system (AVIS)	[37]
surface defect	visual attention model and wavelet transform	[42]
caps inspection	image processing, deep learning	[47]
structural defects or composite material properties	laser ultrasonic sources and guided wave sensing	[49]
foreign bodies in glass containers	ultrasound sensor	[51]

These limitations of visual inspection emphasize the necessity for more reliable, efficient, and automated inspection methods. Recent advancements in technology, including image acquisition, data processing, and machine learning, offer promising alternatives to overcome these challenges. Image process inspection, provides continuous, high-speed, and precise quality control, ensuring consistent and accurate inspection results without the drawbacks associated with manual inspection. By adopting machine vision and other advanced technologies, industries can significantly enhance their quality control processes, reduce labor costs, and improve overall production efficiency. This shift towards automation not only addresses the inherent shortcomings of visual inspection but also aligns with the evolving demands of modern manufacturing, ensuring superior product quality and reliability.

In the current investigation, a significant departure from conventional methods was made by exclusively utilizing a CMOS sensor (camera) to evaluate three critical parameters: cap defects, liquid level, and label placement. This strategic shift reflects a deliberate move towards leveraging advanced imaging technology as the primary means of quality assessment, highlighting the potential of machine vision in enhancing inspection processes. The central aim of this research extends beyond the immediate scope of the study. It seeks to introduce an innovative, efficient, and automated machine-vision-based grading system designed specifically for defect inspection in bottles along production lines. By focusing on critical aspects such as cap defects, liquid levels, and label placement, the system aims to offer a comprehensive and reliable solution to quality control challenges.

2. Materials and methods

2.1 Overview of the system's hardware

This study introduces a comprehensive overview of the system in Figure 1. The hardware comprises conveyor belts, a power system, a power transmission system, a light source, a digital camera, a mechanical ejector, and a laptop depicted on the labView code. The camera captures continuous images of bottles moving along the conveyor belt. Subsequently, these images are transmitted to computer software for processing and inspection, leading to the acceptance or rejection of the product. The entire operation is completed in just a few milliseconds, contingent on factors such as response time (delay), camera speed, and computer processing speed.

Figure 1. Comprehensive perspective of the system

This section is divided into two main parts:

Components: The system includes conveyor belts, a power system, light sources, a digital camera, a mechanical ejector, and a laptop running LabVIEW software.

Operation: The camera captures continuous images of bottles moving on the conveyor. These images are processed by the software to determine product quality and accept or reject products within milliseconds, depending on system speed and processing capabilities.

2.2 *Elements of the visual system*

The visual system incorporates a 5MP HD camera with a resolution of 1,280 × 720 pixels and a maximum frame rate of 30 FPS, featuring a fixed and unchangeable zoom. For this approach, the resolution was tailored to the region of interest, set at 752 × 416 dimension. Due to its digital design, the camera eliminates the need for a frame grabber (an analog-to-digital image converter) and connects directly to the computer via a USB port. In terms of signal-to-noise ratio (SNR) and dynamic range, CCDs surpass Complementary Metal Oxide Semiconductor (CMOS) image sensors [52]. Cameras with a higher dynamic range can concurrently capture details in both light and shadow. Nevertheless, innovative technologies have addressed this concern, such as Fluid Crystal, employed in this camera to generate clear and realistic images across diverse environments. The time cycle is defined as the duration between two consecutive image acquisitions, determined by the distance (d) between two successive bottles and the traveling speed (V). This results in a frame rate of 2 frames per second (fps). It is important to highlight that the camera has the capability of achieving a frame rate of 30 fps. The selection of lighting plays a crucial role in determining the quality and relevance of the captured image. Employing fixed and appropriate lighting not only simplifies image processing but also creates an optimal environment for real-time and continuous product monitoring. The complexity of subsequent processing relies on the contrast between objects and the background. In this study, backlighting was the chosen lighting technique, achieved by positioning an SMD light behind a sheet of Calc paper to provide a well-lit background for the object. This approach enhances the inspection of liquid levels and bottle caps in two parts:

Camera Specifications: A 5MP HD camera with a 1,280 × 720 pixel resolution and a 30 FPS frame rate, connected via USB.

Lighting: A backlighting technique is used, with SMD lights behind Calc paper to provide optimal illumination for inspecting liquid levels and bottle caps. The lighting box is made from white polystyrene with dimensions tailored to the fixed focus of the camera.

While many studies typically use indirect lighting to reduce shadows, this method was not employed in this research to avoid a decrease in contrast along the edges of objects. The lighting chamber, measuring 53 × 33 × 33 cm, is constructed from white polystyrene, and the roof is covered with black cardboard to diminish brightness within the chamber, thereby enhancing image contrast. This specific dimension was selected due to the camera's fixed focus distance of 40 cm in this setup. Uniform white light was utilized to illuminate both the roof and sides of the chamber, as shown in Figure 2a. The sequence of the bottle is illustrated in Figure 2b.
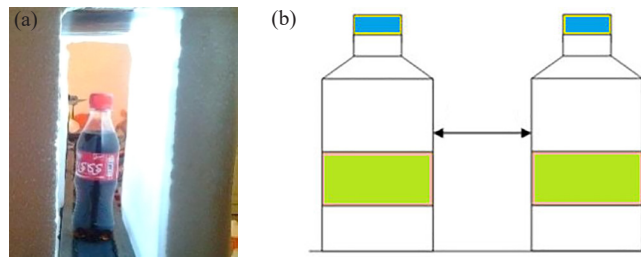
Figure 2. Indicating (a) Lighting box (b) The distance between two consecutive bottles

2.2.1 *Communication protocol*

In this study, a USB-to-RS232 interface was utilized to create a unidirectional connection from the computer to the actuator. Commands sent through the interface trigger the ejector's motion to remove defective products. The program's output is binary, where 1 signifies a standard product and 0 denotes a faulty product. When needed, a current is generated through the interface to facilitate the ejector's movement, allowing for the extraction of the defective product. This mechanism transforms the linear movement of the engine into an accurate model, effectively eliminating the faulty product from the production line. The mechanism converts the linear motion of the motor into semi-rotary motion, effectively removing samples from the production line. A 90-degree bracket is used to create an adjustable-height chassis that supports both the mechanism and the operator. The linear actuator, which operates on a 12-volt direct current, is easily installed on this chassis. It consumes 2 amps of current under minimum load and 4 amps under maximum load (Figure 3). This section operates in two steps: Interface: A USB-to-RS232 interface connects the computer to the actuator. Commands trigger the actuator to remove defective products.

Output: The system outputs binary signals (1 for standard products, 0 for defective products). A current generated through the interface activates the ejector to remove defective items.
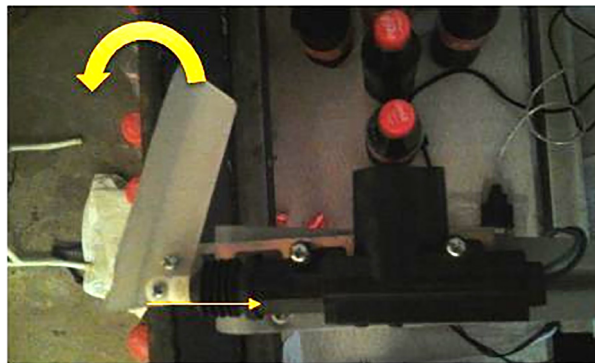

Figure 3. The mechanism of ejection system

2.3 *Features of system software*

In the course of this project, LabVIEW 2011 emerged as the software of choice. LabVIEW, distinguished for its graphical programming language rooted in the G programming language, played a pivotal role in handling tasks related to image acquisition and algorithm design. The diverse range of palettes employed, including Vision Acquisition, Visual Assistant, and Programming, underscored the flexibility and adaptability of LabVIEW for various aspects of the project. A crucial aspect of the project involved forging a seamless connection between the hardware and software components. This integration was expertly managed through the utilization of the Instrument I/O palette and the RS232 port. Notably, the baud rate was meticulously set to 9,600, ensuring efficient and reliable communication

between the hardware elements and the LabVIEW software. This strategic configuration not only facilitated the smooth execution of the project but also highlighted the nuanced control and precision offered by LabVIEW in interfacing with the underlying hardware systems. Depending on the specific inspection needs and the application context, the machine vision inspection system uses various image processing techniques, such as pattern recognition, matching, and thresholding methods. This study applies functions in a machine vision palette, including edge detection for inspecting liquid levels and label placements, and pattern matching for assessing cap defects. The images are received in MJPG format and RGB by the camera as the bottles move along the conveyor belt. The image is converted to grayscale and the areas outside the ROI are masked to improve processing efficiency in the three processing phases:

Software: LabVIEW 2011 handles image acquisition and algorithm design.

Inspection Techniques: Pattern recognition, matching, and thresholding methods are used. Specific functions include edge detection for liquid levels and label placements and pattern matching for cap defects.

Processing: Images are converted to grayscale and masked to improve processing efficiency.

2.3.1 Inspection methods

In the processing phase for liquid level inspection, the following steps are undertaken: The Region of Interest (ROI) is defined. The clamp (Rake) function is invoked to determine the maximum distance between the cap and liquid level. The result obtained from step (2) is then compared with the edge strength or threshold level (Figure 4a). As the function returns a pixel value, employing a case structure and comparing it with the desired value (90 pixels) allows us to determine the standardization of the liquid level. For label placement inspection, the following procedures are executed: Define the Region of Interest (ROI), Invoke the clamp (Rake) function initially with a threshold of 46 to assess the horizontal placement of the label, Compare the result from step (2) with the reference value using a case structure, Call the clamp (Rake) function again with a threshold of 23 to examine bottles without labels, Compare the result from step (4) with the reference value using a case structure, Combine the outcomes of steps (2) and (4) using a logical operator, resulting in a Boolean value; 1 signifies correct label placement, and 0 indicates incorrect placement or the absence of a label (Figure 4b). For the examination of cap defects, an efficient online object detection was conducted using a pattern-matching algorithm. The process involves the following steps: The Region of Interest (ROI) is provided as input to the pattern-matching function and a reference pattern (Standard cap, depicted in Figure 4c) is defined, chosen, and assigned the highest score of 1,000.
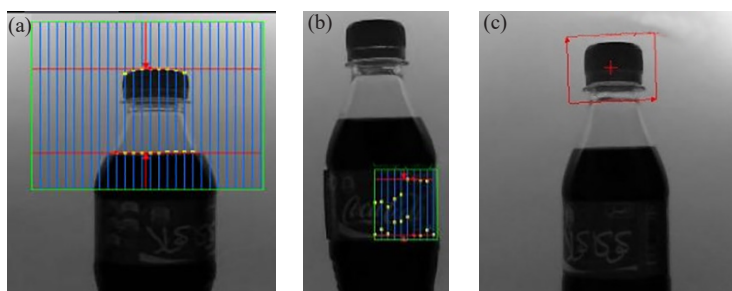

Figure 4. Introduce (a) Liquid level edge detection (b) Label detection (c) inspect cap defaults

In response to the rocking motion exhibited by bottles on the conveyor belt, the angle input was adjusted to [-45, +45], enhancing the system's ability to achieve a more robust match. Following this modification, caps were compared to a reference cap, and after iterative testing, the minimum score required to categorize a cap as standard was determined. Caps scoring below this threshold were marked as defective.

The inspection process remained effective even when multiple matching caps were identified. Moreover, parameters for configuring match counts were incorporated. The program skillfully detected, tracked, and followed the standard cap along the conveyor belt from right to left. The following flowchart shows the process and different parts of the algorithm concerning the inspection of cap, liquid level, and label placement (Figure 5).
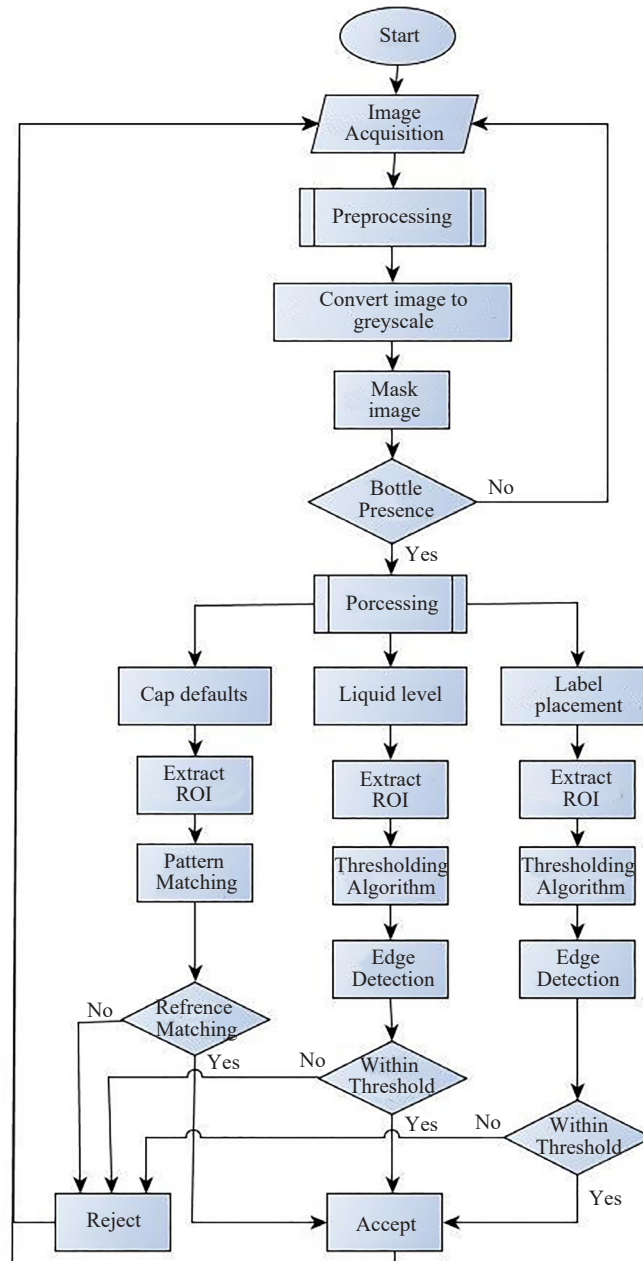
Figure 5. Flowchart for cap default, liquid level, label placement inspection

3. Results and discussion

The investigation into determining the suitable feeding distance and system capacity involved the transportation of bottles at varying speeds, namely 12, 15, and 20 cm/s, along the conveyor belt. This process allowed the bottles to traverse in front of the camera, capturing images with commendable quality, clarity, and sustained brightness. Through meticulous analysis of the acquired images, it was discerned that the ideal separation between bottles is 10 cm. This optimal spacing is crucial for efficient and smooth operation within the system. Furthermore, the study identified that the most effective feeding speed, ensuring a harmonious flow, is 20 cm/s. These findings contribute valuable insights to the enhancement of the overall performance and productivity of the feeding system. In the context of the conveyor system, where the conveyor is set to a speed of 20 cm/s and the feeding distance is precisely 10 cm, the investigation yielded a calculated cycle duration of 500 ms. This cycle duration encompasses the entire sequence from the initiation

of material movement to its subsequent processing.

Notably, the program's processing time, which is established within a well-defined window of 150-250 ms, stands as a critical component in this operational framework. This timeframe allows for the seamless execution of the necessary computations and operational tasks, ensuring that the system functions with efficiency and accuracy (Figure 6).
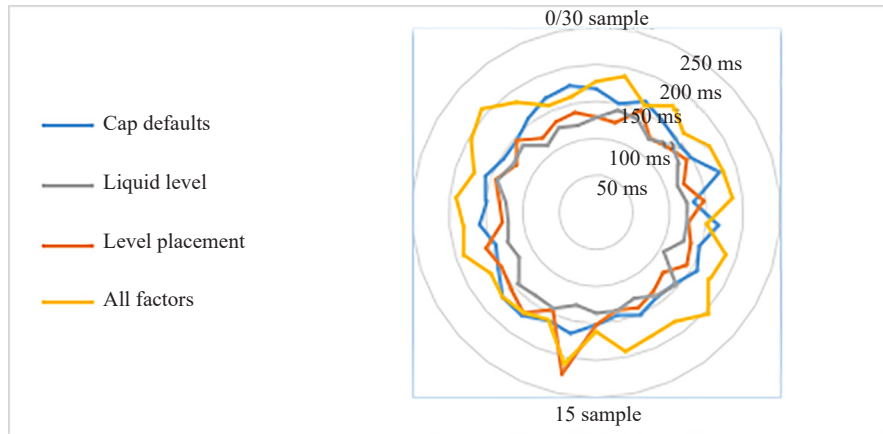

Figure 6. Program run time, while inspecting cap defaults, liquid level, label placement and all of them in same time

The liquid-level detection algorithm has the lowest processing time, while the highest processing time is associated with the main algorithm, encompassing the detection of all three parameters. The judicious allocation of time in the processing phase underscores the meticulous design and optimization of the system, guaranteeing that each cycle unfolds within the defined parameters to meet operational requirements. Consequently, this harmonious integration of conveyor speed, feeding distance, and processing time contributes to the overall effectiveness and reliability of the system.

The utilization of front lighting resulted in heightened brightness, a reduction in contrast, and consequently, a decline in inspection accuracy. In the assessment of liquid level and label placement, specific thresholds were established. The liquid level inspection involved the calculation of the distance between the cap and the liquid level, while the label placement inspection determined the minimum horizontal distance of label placement. For cap default inspection, a comparison was conducted by matching it against a reference cap pattern, and subsequent scoring was implemented to assess its conformity. This comprehensive approach to inspection parameters ensures a thorough evaluation of both liquid level and label placement, addressing key aspects of product quality and conformity within the inspection process (Table 2).

Table 2. Minimum limit threshold of classification

Grading type	Threshold	Score
Cap defaults	-	830
Liquid level	86	-
Label placement	23-46	-

In the realm of fluid packaging, encompassing products like oils and beverages where the risk of leakage and liquid residue is prevalent, there arises a crucial need to scrutinize the cap and sealing ring. The degradation of filling machines over time can lead to a decline in accuracy. With variations in the volume of liquid contained in bottles impacting the

liquid level, there arises a necessity for effective liquid level control. Additionally, the positioning of labels plays a pivotal role in influencing the consumer-friendliness of a product.

Therefore, the importance of thorough inspection and quality control for both packages and bottles cannot be overstated. This imperative task is facilitated through the utilization of machine vision systems. Dedicated efforts have been invested in replicating and scrutinizing prevalent defects associated with key parameters such as cap defaults, liquid level irregularities, and label placement issues. This meticulous approach ensures a comprehensive examination of potential flaws in the packaging process. Frequently encountered cap defects consist of the absence of a sealing ring, incomplete attachment of the sealing ring, missing caps, and partially closed caps (3mm or 1/4 rotation open, which may result in potential leakage), as presented in Figure 7a. In the case of a standard Coca-Cola bottle with a 300 cc capacity, there is an allowable variance of ± 3% or 9 cc. To address the impact of turbulence on liquid-level inspection, this variance is doubled to ± 6% or 18 cc. Bottles deemed defective are those found to be empty or containing less than 18 cc, 36 cc, and 55 cc, as outlined in Figure 7b. Common label defects encompass bottles without labels, labels that are worn-off, and instances of incorrect label placement, as demonstrated in Figure 7c.

Figure 7. Common defects, (a) Cap, (b) Liquid level, (c) Label defects

Upon scrutinizing Table 3, it is evident that the liquid level inspection component stands out with exceptional accuracy, and perfection at approximately 100%. In contrast, the accuracy of label placement appears to be comparatively lower, settling at around 92% within the system. These accuracy metrics shed light on the robust performance of the liquid level inspection process, indicating a highly reliable and precise evaluation of liquid levels. On the other hand, the slightly lower accuracy in label placement suggests potential areas for improvement or optimization of the system's ability to precisely position labels on the products. The remarkable accomplishments in automated inspection presented by various researchers highlight the evolving capabilities of machine vision systems in diverse applications. Duan et al. [12] demonstrated exceptional proficiency by achieving a high accuracy of 97% in meticulously examining the walls and bottom of glass beer bottles. This precision is indicative of the effectiveness of their inspection algorithm in detecting subtle details. These findings collectively underscore the potential for advancements in machine vision technologies to enhance quality control and inspection processes across various industries, ranging from manufacturing to agriculture. Another study introduces a machine-vision-based system utilizing controlled lighting conditions and image processing techniques. The proposed system achieves a 95% accuracy in identifying defects such as seated caps, body dents, and label misalignment, offering a practical and feasible solution for rapid inspection without the need for extensive computational resources or large training datasets [44]. As researchers continue to refine and expand upon these methodologies, the landscape of automated inspection is poised for continuous improvement, paving the way for more accurate and efficient quality assessments in diverse domains.

Table 3. Quantity of samples and predictions generated

Grading type	Expert		System		Accuracy
	Standard	Non-standard	Valid	Invalid	
Liquid level	20	80	100	0	100
Cap defaults	20	80	95	5	95
Label placement	20	60	74	6	92

Expand the defect detection system to recognize a wide range of defects beyond the current system. This can include more subtle surface imperfections, color inconsistencies, and micro-cracks. Develop adaptive algorithms capable of learning from new defect types over time, enhancing the system's ability to identify emerging quality issues. Investigate the system's adaptability to various bottle shapes and sizes, including different neck designs, cap types, and body shapes. This could involve redesigning the imaging setup and adjusting the detection algorithms to accommodate diverse bottle geometries. Collect and annotate a large dataset of bottle cap images with various defects to train and validate deep learning models. This could improve the system's performance and reduce false positives and negatives. Investigate methods to further optimize the image processing pipeline for faster analysis, such as parallel processing and hardware acceleration using GPUs. Provide comprehensive training materials and support to help users fully understand and utilize the system's capabilities, ensuring optimal performance.

5. Conclusion and future works

The system consistently identified standard bottles accurately, never flagging them as defective. Instances of incorrect inspections were linked to issues such as worn-off labels and poor sealing ring connections. In those cases where defects were present, the system effectively identified and removed defective bottles from the production line through the actuator, demonstrating flawless performance. The actuator's efficiency was noteworthy, aligning seamlessly with the conveyor belt's speed (20 cm/s) and the 10cm distance between bottles, resulting in a required inspection time of 500 ms per bottle. Considering the program's processing time of 150-250 ms, the system's performance was deemed acceptable. The operational capacity of the system was established at 7,200 bottles per hour. During testing and analysis, the system was evaluated with the assumption that flaws were limited to one side of the bottle. The results of this research indicate that the algorithm's performance is well-suited for integration into production lines. Its applicability extends to liquid packaging in various industries, including the food and chemical sectors, showcasing its potential for widespread use. In future research, two cameras will be strategically positioned on either side of the sample for detailed examination. High-resolution and hyperspectral cameras will be utilized to detect both external defects and internal content of the samples.

Authors contribution

Omid Farhangi: Conceptualization, Data curation, Validation, Writing-original draft Ehsan Sheidaee: Writing-original draft. Asma kisalaei: Visualization, review & editing.

Data availability

Supplementary data to this article can be found online at.

Conflict of interest

Authors declare there is no conflict of interest at any point with reference to research findings.

References

[1] Coito T, Martins MS, Firme B, Figueiredo J, Vieira SM, Sousa JM. Assessing the impact of automation in pharmaceutical quality control labs using a digital twin. *Journal of Manufacturing Systems*. 2022; 62: 270-285. Available from: doi:10.1016/j.jmsy.2021.11.014.
[2] Taherdoost H. An overview of trends in information systems: Emerging technologies that transform the

information technology industry. *Cloud Computing and Data Science*. 2023; 4(1): 1-16.

[3] Khamkar R, Das P, Namasudra S. SCEOMOO: A novel Subspace Clustering approach using Evolutionary algorithm, Off-spring generation and Multi-Objective Optimization. *Applied Soft Computing*. 2023; 139: 110185. Available from: doi:10.1016/j.asoc.2023.110185.

[4] Kumar DP, Kannan K. A roadmap for designing an automated visual inspection system. *International Journal of Computer Applications*. 2010; 1(19): 34-37.

[5] Možina M, Tomaževič D, Pernuš F, Likar B. Real-time image segmentation for visual inspection of pharmaceutical tablets. *Machine vision and Applications*. 2011; 22: 145-156. Available from: doi:10.1007/s00138-009-0218-7.

[6] Abdelhedi S, Taouil K, Hadjkacem B. Design of automatic vision-based inspection system for monitoring in an olive oil bottling line. *International Journal of Computer Applications*. 2012; 51(21): 39-46.

[7] Hasan MRM, Alani NH. A comparative analysis using silhouette extraction methods for dynamic objects in monocular vision. *Cloud Computing and Data Science*. 2022; 3(1): 1-12.

[8] Duan F, Wang Y, Liu H. A real-time machine vision system for bottle finish inspection. *ICARCV 2004 8th Control, Automation, Robotics and Vision Conference*. China: IEEE; 2004. p.842-846.

[9] Jin J, Li J, Liao G, Yu X, Viray LCC. Methodology for potatoes defects detection with computer vision. *Proceedings the 2009 International Symposium on Information Processing.* Oulu: Academy Publisher; 2009.p.346-351.

[10] Chu H-H, Wang Z-Y. A vision-based system for post-welding quality measurement and defect detection. *The International Journal of Advanced Manufacturing Technology*. 2016; 86: 3007-3014. Available from: doi:10.1007/s00170-015-8334-1.

[11] Younes MA, Darwish S, El-Sayed M. Online quality monitoring of perforated steel strips using an automated visual inspection (AVI) system. *2011 IEEE International Conference on Quality and Reliability*. Bangkok, Thailand: IEEE; 2011. p.575-579.

[12] Duan F, Wang Y-N, Liu H-J, Li Y-G. A machine vision inspector for beer bottle. *Engineering Applications of Artificial Intelligence*. 2007; 20(7): 1013-1021.

[13] Farzand Ahmadi V, Ziyaee P, Bazyar P, Cavallo E. Development and testing of a low-cost belt-and-roller machine for spheroid fruit sorting. *AgriEngineering*. 2020; 2(4): 596-606.

[14] Sheydaee E, Bazyar P. Design and fabrication of egg quality assessment system based on image processing. *Turkish Journal of Agricultural Engineering Research*. 2021; 2(1): 124-132.

[15] Mota-Grajales R, Torres-Peña J, Camas-Anzueto J, Pérez-Patricio M, Coutiño RG, López-Estrada F, et al. Defect detection in eggshell using a vision system to ensure the incubation in poultry production. *Measurement*. 2019; 135: 39-46. Available from: doi:10.1016/j.measurement.2018.09.059.

[16] Sheidaee E, Bazyar P. Hosseinpour-zarnaq M special system for classifying and sorting walnut base on image processing. *Green Reports*. 2022; 3(9), 1-5.

[17] Ziyaee P, Farzand Ahmadi V, Bazyar P, Cavallo E. Comparison of different image processing methods for segregation of peanut (Arachis hypogaea L.) seeds infected by aflatoxin-producing fungi. *Agronomy*. 2021; 11(5): 873.

[18] Wang T, Chen Y, Qiao M, Snoussi H. A fast and robust convolutional neural network-based defect detection model in product quality control. *The International Journal of Advanced Manufacturing Technology*. 2018; 94: 3465-3471. Available from: doi:10.1007/s00170-017-0882-0.

[19] Zhang L, Yang Q, Sun Q, Feng D, Zhao Y. Research on the size of mechanical parts based on image recognition. *Journal of Visual Communication and Image Representation*. 2019; 59: 425-432. Available from: doi:10.1016/j.jvcir.2019.01.035.

[20] Ngo N-V, Hsu Q-C, Hsiao W-L, Yang C-J. Development of a simple three-dimensional machine-vision measurement system for in-process mechanical parts. *Advances in Mechanical Engineering*. 2017; 9(10): 1-11.

[21] Chrysafi A, Athanasopoulos N, Siakavellas N. Damage detection on composite materials with active thermography and digital image processing. *International Journal of Thermal Sciences*. 2017; 116: 242-253. Available from: doi:10.1016/j.ijthermalsci.2017.02.017.

[22] Campos M, Ferreira M, Martins T, Santos C. Inspection of bottles crates in the beer industry through computer vision. *IECON 2010-36th Annual Conference on IEEE Industrial Electronics Society*. Glendale, AZ, USA: IEEE; 2010. p.1138-1143.

[23] Odinikuku WE. Quality assurance and quality control in a bottle manufacturing company using statistical quality control. *Journal of Materials Science Research and Reviews*. 2018; 1(2): 51-58.

[24] Islam M, Sahriar R, Hossain B. Enhanced automatic surface and structural flaw inspection and categorisation using

image processing both for flat and textured ceramic tiles. *International Journal of Computer Applications*. 2012; 48(3): 1-10.

[25] Dutta S, Jaipuria S. Reducing packaging material defects in beverage production line using Six Sigma methodology. *International Journal of Six Sigma and Competitive Advantage*. 2020; 12(1): 59-82.

[26] Azzahra S, Fachira I. The influence of bring back our bottle program on the body shop indonesia brand image, brand trust, brand love and brand loyalty. *Asian Journal of Research in Business and Management*. 2022; 4(3): 283-295.

[27] Roy A, Dutta H, Griffith H, Biswas S. An on-device learning system for estimating liquid consumption from consumer-grade water bottles and its evaluation. *Sensors*. 2022; 22(7): 2514.

[28] Folwarczny M, Sigurdsson V, Menon RV, Otterbring T. Consumer susceptibility to front-of-package (FOP) food labeling: Scale development and validation. *Appetite*. 2024; 192: 107097. Available from: doi:10.1016/j.appet.2023.107097.

[29] Kühne SJ, Reijnen E, Granja G, Hansen RS. Labels affect tood choices, but in what ways? *Nutrients*. 2022; 14(15): 3204.

[30] Brosnan T, Sun D-W. Improving quality inspection of food products by computer vision-a review. *Journal of Food Engineering*. 2004; 61(1): 3-16.

[31] Abdullah M, Nashat S, Anwar SA, Abdullah M. A framework for crack detection of fresh poultry eggs at visible radiation. *Computers and Electronics in Agriculture*. 2017; 141: 81-95. Available from: doi:10.1016/j.compag.2017.07.006.

[32] Pithadiya KJ, Modi CK, Chauhan JD. Selecting the most favourable edge detection technique for liquid level inspection in bottles. *International Journal of Computer Information Systems and Industrial Management Applications (IJCISIM)*. 2011; 3(1): 034-044.

[33] Li Y, Dhakal S, Peng Y. A machine vision system for identification of micro-crack in egg shell. *Journal of Food Engineering*. 2012; 109(1): 127-134.

[34] Baigvand M, Banakar A, Minaei S, Khodaei J, Behroozi-Khazaei N. Machine vision system for grading of dried figs. *Computers and Electronics in Agriculture*. 2015; 119: 158-165. Available from: doi:10.1016/j.compag.2015.10.019.

[35] Eshkevari M, Rezaee MJ, Zarinbal M, Izadbakhsh H. Automatic dimensional defect detection for glass vials based on machine vision: A heuristic segmentation method. *Journal of Manufacturing Processes*. 2021; 68: 973-989. Available from: doi:10.1016/j.jmapro.2021.06.018.

[36] Zhou X, Wang Y, Xiao C, Zhu Q, Lu X, Zhang H, et al. Automated visual inspection of glass bottle bottom with saliency detection and template matching. *IEEE Transactions on Instrumentation and Measurement*. 2019; 68(11): 4253-4267.

[37] Sharma S, Krupa KV, Gandhi R, Jain A, Shah N. Empty and filled bottle inspection system. *ICTACT Journal on Image and Video Processing*. 2015; 6(2): 1122-1126.

[38] Duan F, Wang Y-N, Liu H-J, Tan W. Empty bottle inspector based on machine vision. *Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat No 04EX826)*. Shanghai, China: IEEE; 2004. p.26-29.

[39] Fu L, Zhang S, Gong Y, Huang Q. Medicine glass bottle defect detection based on machine vision. *2019 Chinese Control And Decision Conference (CCDC)*. Nanchang, China: CCDS; 2019.

[40] Yang X, Han M, Tang H, Li Q, Luo X. Detecting defects with support vector machine in logistics packaging boxes for edge computing. *IEEE Access*. 2020; 8: 64002-64010. Available from: doi:10.1109/ACCESS.2020.2984539.

[41] Patel N, Mukherjee S, Ying L. Erel-net: A remedy for industrial bottle defect detection. *Smart Multimedia*. 2018; 11010: 448-456. Available from: doi:10.1007/978-3-030-04375-9_39.

[42] Zhou X, Wang Y, Zhu Q, Mao J, Xiao C, Lu X, et al. A surface defect detection framework for glass bottle bottom using visual attention model and wavelet transform. *IEEE Transactions on Industrial Informatics*. 2019; 16(4): 2189-2201.

[43] Kazmi M, Hafeez B, Khan HR, Qazi SA. Machine-vision-based plastic bottle inspection for quality assurance. *Engineering Proceedings*. 2022; 20(1): 9.

[44] Kazmi M, Hafeez B, Aftab F, Shahid J, Qazi SA. A deep learning-based framework for visual inspection of plastic bottles. *IEEE Access*. 2023; PP(99): 1-14.

[45] Huang B, Ma S, Wang P, Wang H, Yang J, Guo X, et al. Research and implementation of machine vision technologies for empty bottle inspection systems. *Engineering Science and Technology, an International Journal*. 2018; 21(1): 159-169.

[46] Tsai M-F, Liu B-C, Hsieh S-L. Body thickness and bottom defect detection methods for products made by bottle blowing machines to meet quality requirements. *The International Journal of Advanced Manufacturing Technology*. 2024; 130(1): 541-551.

[47] Horputra P, Phrajonthong R, Kaewprapha P. Deep learning-based bottle caps inspection in beverage manufacturing and packaging process. *2021 9th International Electrical Engineering Congress (iEECON)*. Pattaya, Thailand: IEEE; 2021.

[48] Wang J, Fu P, Gao RX. Machine vision intelligence for product defect inspection based on deep learning and Hough transform. *Journal of Manufacturing Systems*. 2019; 51: 52-60. Available from: doi:10.1016/j.jmsy.2019.03.002.

[49] Djordjevic BB. Laser ultrasonic guided wave methods for defect detection and materials characterisation. *International Journal of Microstructure and Materials Properties*. 2014; 9(3-5): 338-347.

[50] Zhao B, Basir O, Mittal G. Conceptual design and evaluation of an ultrasonic system for bottled beverages' quality measurement and control. *Transactions of the Institute of Measurement and Control*. 2004; 26(1): 41-54.

[51] Zhao B, Basir O, Mittal G. A self-aligning ultrasound sensor for detecting foreign bodies in glass containers. *Ultrasonics*. 2003; 41(3): 217-222.

[52] Siricharoenchai R, Sinthupinyo W. Using efficient discriminative algorithm in automated visual inspection of feed. *2011 IEEE 3rd International Conference on Communication Software and Networks*. Xi'an, China: IEEE; 2011.