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Computer Vision in Reusable Container Management – Requirements, Conception, and Data Acquisition

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Abstract:

In container management, the reuse of small load carriers is a business alternative to disposal carriers. Reusable container management is furthermore a solution to improve the environmental impact of the logistic industry. The sorting and stock management of small load carriers are today primarily manual work and have consequently a low level of automation.

In order to increase the automation of returnable containers, it is crucial to establish a computer vision system that (i) classifies the containers and (ii) detects potential defects or stains. This paper provides an overview and a discussion of the applications that are already in use. Object detection is necessary for many actions in the container management business processes, such as inventory and stock management. Detection of defects on the small load carrier is required for scrapping the carriers to ensure a smooth process in any business process involving the carrier and to decide whether additional process steps, e.g., cleaning, are required.

The literature review in this paper establishes the demand for computer vision detection and shows the project setup necessary to conduct research in this area. The comparison with other applications of defect and anomaly detection supports the applicability and shows the need for further research in this specific academic field. This leads to a project outline and the research provides the technical implementation of the detections in container management. Accordingly, the research provides a workflow guide from data acquisition to a high-quality dataset of labeled anomalies of small load carriers.

JEL Classification: M11, M15

Keywords: Container Management, Computer Vision, Anomaly Detection, Object Detection.

1 Introduction

In every economy, the increase in economic development is coupled with an increase in material usage. A solution toward a new sustainable balance can be achieved with the reuse of products (Worrell et al., 2016, p. 592). The implementation of a closed loop in the supply chain of packages has seen great use in the consumer market. The reusable bottle is an example that society accepts the implemented logistic loop (Coelho et al., 2020, p. 2). 40% of the worldwide, produced plastic is used for packaging and this is destructive when estimating that packaging has a short product lifetime which is an indicator of great waste generation (Geyer et al., 2017, p. 1). In production logistics, the reusable small load carrier (SLC) is the package solution that reduces the waste of plastic and closes the logistic loop. The implementation of using plastic containers in a closed-looped transport system reduces CO2 emissions in the transport industry (Hekkert et al., 2000, p. 22). The logistics industry faces pressure to use reusable containers and understands their advantages. The research from Glock (2017, p. 563) has shown that the number of published papers about reusable containers or similar keywords has increased significantly since the year 2006. This indicates that this topic is scientifically relevant and meets the spirit of the time.

Companies use the SLC to ship safely items to the next company in the production process or to move items internally in the firm. The reusable container can have tailored inlays for the object dimensions and properties of the product. The SLC is stackable on pallets and does not need any other packaging, making it easier for humans and machines to handle. By protecting the shipped item from damage (Bertagnolli, 2022, p. 280), the SLC decreases the number of rejections. SLCs are therefore a fundamental part of the logistics industry. Consequently, the majority of companies see their SLC processes as critical or highly critical (Hofmann and Bachmann, 2013, p. 25). The change from disposal packaging to reusable containers is linked with a complex implementation in every step of the operation process. The amount and variation of SLCs are due to the complexity to protect the various components. The SLC can vary in shape, size, and color. Therefore, the stock management of those SLCs is complex. The container tracking over the closed loop is not yet optimized which leads to production disruption at the customer of the SLCs (Maleki and Reimche, 2011, p. 1). Accordingly, the majority of production companies have one to five employees dedicated to the management of containers. Other costs for the operation of container management include storage costs, handling costs, maintenance costs, depreciation costs, shortage costs, and administration costs. To reduce costs from storing the carriers near the factory and other cost expensive processes it is beneficial to outsource the container management to a logistic partner (Hofmann and Bachmann, 2013, p. 21 ff.).

A whole industry is dedicated to container management by shipping, sorting, washing, and storing the SLCs for their customers. The container will get dirty over time by handling the SLC in the production environment. This dirt can be oil sedimentations, sawdust from production, or other environmental influences such as rain or pollution. This contamination occurs mainly due to storing empty containers outside. In the logistic loop, the SLC must be clean to not damage the shipped item or disturb the production line. Therefore, the used SLCs need to go through a washing process (Hekkert et al., 2000, p. 11; Sobottka et al., 2014a, p. 103). All business processes linked to container management need the detection of the object and detection of any defects on the SLC. Otherwise, the scrapping of damaged containers or the whole stock management is inaccurate. The practice of applying machine learning to digital images of any business process in container management offers the potential to automate both object detection and defect detection. However, it is not yet fully implemented (Poss et al., 2018, p. 231). Computer vision can be used to analyze the environment and support business decisions.

This paper explores the use of computer vision for the detection of SLC and the detection of defects in container management. The goal of this research is to review applications of computer vision and define the outline of the project of implementing computer vision for SLCs. Furthermore, the goal is to introduce a workflow for a time-reducing and convenient process of image and label acquisition. Additionally, the paper describes and recommends a solution for the hardware design of image acquisition. The purpose of this paper is not to evaluate the accuracy or reliability of this architecture in detection. Rather, the goal is to evaluate the functionality of the architecture. The research of this paper is based on the data provided by a project partner, a container management firm, where a developed machine learning detection model will be implemented.

2 State-of-the-art

Computer vision provides a machine learning method to detect objects and detect anomalies in all kinds of industries and even in container management. Object detection is used by many applications from the industry and day-to-day life like autonomous driving (Ranft and Stiller, 2016, p. 9) and face recognition (Ranjan et al., 2018, p. 67). This demonstrates that learning-based object detection is already established in many different industries.

Because of this general knowledge of object detection, this paper provides further information regarding the object detection of SLCs in container management. Poss et al. (2018, p. 231 ff.) trained multiple computer vision models with 2,000 images of SLC placed combined on pallets with the goal to achieve reliable object detection. They were able to achieve the highest performance by using the Single-Shot-Multibox-Detector (SSD). However, this model was still not powerful enough for use in container management because the trained models are not able to generalize. They suggest increasing the image training samples and to train different models. In a separate study by Bohm et al. (2020, p. 513 ff.), the RetinaNet model was applied to 360 images of three different SLCs arranged on pallets. By including precise sizes and ratios of the SLCs in the machine learning algorithm, the model was able to successfully identify the SLCs according to their respective dimensions. This is because each SLC can only occupy a specific location on the pallet and therefore has fixed positions on the image. As a result, object detection accuracy improves to 99.9%. They suggest expanding the variety of SLCs in the study and do not claim effectiveness of their model when handling a larger number of objects, particularly for SLCs of similar sizes. They conclude that computer vision object detection for SLCs is of interest to researchers and the industry. Further research should investigate individual SLC object detection and increase the varying size of SLCs. It is also shown that different convolutional neural network (CNN) models should be tested to achieve higher performance.

Anomaly detection based on computer vision has seen a great improvement in various applications in the last few years. Different CNN-models are tuned for their specific problem. Anomaly detection provides a robust solution for industries such as quality control and predictive maintenance. This is proven by many publications in different industries. Li et al. (2018, p. 80) used a You-Only-Look-Once (YOLO) network to detect six types of defects on the surfaces of cold-rolled steel stripes. With a 99% recall rate, they can provide the location and size of defects, improving the quality of steel strip production. Research in the field of aircraft quality control shows that accurate detection of cracks can be achieved within 0.1s. The trained network YOLOv3-light has an average precision of 38.7% for detecting and classifying the size of cracks at different locations on the aircraft (Li et al., 2019, p. 9). The fast recognition makes it possible to detect cracks on live video, making it useful for quality control operators. Microstructural defects can also be detected using computer vision. Badmos et al. (2020, p. 892) trained multiple CNN-models to detect anomalies such as external particles or deformed electrodes in Li-ion battery cells. By comparing traditional CNN-models, completely re-trained CNN-models on a battery dataset, and fine-tunable models, they showed that fine-tuned CNN-models are preferable. They identified the small size of the dataset as one reason for the result. With a fine-tuned VGG19 model, they achieved defect detection with an F1 score of 99%. Further microstructural defects on printed circuit boards get detected by the Tiny-YOLO-v2 network trained by Adibhatla et al. (2020, p. 6). They achieved 98.82% accuracy in detecting eleven defects on such boards by training the model on 11,000 images. Computer vision is also used to notice defects in infrastructure. Tao et al. (2020, p. 1496) proposed a new CNN-model for detecting missing insulators on power lines. They achieved 96% recall by combining two architectures, one for locating power line insulators on the image and one for defect detection on the localized region of the image. The introduction of data augmentation techniques resulted in improved accuracy of the trained model. The images were subjected to various modifications, including adjustments to brightness and blur, as well as changes to the background of selected images. Other infrastructure research is conducted on surfaces such as roads and bridges. Feng et al. (2017, p. 305) trained a ResNet CNN-model with 603 images of road and bridge surfaces with four different types of defects. They achieved an accuracy of 87.5% by deep-active learning the model. To detect defects in catenary support components in the electrified railway industry, Chen et al. (2018, p. 259) combined three CNN-models. Catenaries in China have three different joints, which are detected by one SSD model. The second model uses the YOLO architecture to locate the fastener at the former joints. The last model classifies the fastener into three different states, i.e., normal, missing, and latent missing. The dataset has about 40,000 images of the fasteners. The final CNN-model is fully trained with data augmentation on only 560 images of fasteners due to the limitation of images of defects. The research showed that the combination of CNN-models results in promising accuracy for this application, although further advances are needed to successfully detect additional defects, such as cracks. Overall, this review of applications highlights the significant progress that has been made in anomaly detection in recent years, with many industries using computer vision techniques for quality control purposes.

Like the developments in computer vision in general, computer vision for container management has seen some development over the past few years. The different types of defects that can occur with an SLC are summarized in Chapter 3. Liang et al. (2019, p. 8) described a ShuffelNet V2 network that is capable of detecting label defects on plastic containers with an accuracy of 99.88%. The detected defects can fall into one of four different states. To expand their dataset, the researchers used data augmentation techniques to create a collection of 100,000 images from 22,000 original images. This knowledge is transferred to inspect two other types of containers. By fine-tuning the model with an additional 2,084 images, the defect detection accuracy on the new containers was 99.59%. The study faced challenges due to the varying backgrounds of the containers and the infrequency of defects, which were overcome through the use of data augmentation. Zoghlami et al. (2019, p. 3766) used a Convolutional Autoencoder to classify color images of SLCs, both individually and on pallets. The model is able to detect removable stickers on SLCs, which may prevent a vacuum gripper from securely holding the object. In addition, it analyzes the stability of stacked SLCs on pallets. The researchers used 1,100 sticker-free images of three different SLCs and 100 anomalous data to train the sticker defect model. This autoencoder model has ten convolutional layers as encoders and decoders and achieves an accuracy of 93.46%. For the second trained model, they used 1,600 images of normal stacks and 100 images of unstable stacks on a pallet, including a fourth depth channel in the input image, and used the same architecture as the first model. The stack model resulted in an accuracy of 84.31%. The authors concluded that their models are efficient and fast enough to be used in industrial environments. Sobottka et al. (2014b, p. 306) explored various measurement techniques for detecting the level of contamination of SLCs, ranging from optical to mechanical, acoustic, magnetic, and chemical methods. They found that visual detection is the most comprehensive approach to identifying defects and has proven effective in industrial applications. They developed a concept for detecting common defects and contaminants using multiple cameras and lighting. Because their research is a concept for future testing, they did not specify the number of defects, containers, or detection results. Their concept involved capturing one image per side of the SLC by rotating the SLC 90°. However, visual shadows that are not visible in the images and defects hidden under contamination, such as dust, are the limitations of this strategy. In an article, based on the previously mentioned research, Sobottka et al. (2014a, p. 106) conducted a case study to investigate the detection of dirt as a defect on the SLC. They concluded that the use of multiple cameras and stable lighting is critical for accurate detection. In addition, they recommended the use of a conveyor belt to ensure consistent image capture, resulting in uninterrupted material flow. By placing SLCs one at a time on the conveyor and implementing automated sorting, the operator's workload can be significantly reduced. This approach has the potential to increase efficiency and productivity in the process.

Object detection and anomaly detection have been used in container management to detect SLCs on pallets or to identify specific defects such as dirt or unremoved stickers. However, to our knowledge, object detection in container management has not yet succeeded in identifying all types of SLCs in an entire customer catalog. Similarly, anomaly detection in container management has not used a model to detect multiple defects simultaneously or to identify individual SLCs that need to be scrapped due to some type of defect. The next chapter will demonstrate the importance of such detections.

3 Problem Definition

The DIBCO project, a collaboration between the Technical University of Applied Sciences Würzburg-Schweinfurt (THWS) and several logistics companies, aims to improve the efficiency of returnable container management by combining the knowledge of each project partner. The detection of SLCs and their various defects using computer vision is a crucial aspect of the project. There are more than 100 different types of SLCs and more than 300 different inlays in the respective depot that need to be accurately identified. This research proposes computer vision object detection to achieve reliable stock and storage management of all SLC variants. In container management, different types of defects need to be detected. To ensure that each SLC is accurately labeled in the production, it's necessary to detect any labels or stickers from previous production or customers. In addition, identifying and removing removable defects, such as dirt, is critical to meeting customer quality expectations. If non-repairable defects such as cracks or deformations are present, the SLC must be scrapped. Several other defects can also occur, including oil, grease, paint or adhesive residue, deformation, chipping, cracking, brittleness, fading, foreign objects, or rust (see Fig. 1). The logistics partner's quality control department has a customer-specific catalog of 14 different defects that, if severe enough, will result in a SLC being scrapped. This shows that it is not only necessary to identify the defect but also to analyze whether this defect has an impact on future production steps and therefore needs to be removed. For example, a small deformation is not necessarily a reason to scrap if the SLC still provides safety and all necessary operational functionality. This paper proposes computer vision anomaly detection to detect anomalous parts on the SLC and decide if the SLC needs to be scrapped.

Fig. 1. Examples of defects at a SLC: rust (left) and deformation (right)

4 Project Outline

This paper presents a comprehensive approach to computer vision-based detection of SLCs, as illustrated in Fig. 2. Each step of the project requires additional activities. This project outline for computer vision in container management could serve as a reference for other computer vision projects looking to establish a detailed project outline. The first task is to define the research problem, which has been done in previous research and is summarized in this paper. The literature review establishes the need for computer-based detection and outlines the project setup required to conduct research in this area. In addition, a comparison of other defect and anomaly detection applications highlights the applicability of the proposed approach and emphasizes the need for further research in this academic area. The technical implementation of the detection application in the container management industry is also discussed, along with the necessary hardware design. In addition, this paper provides a data acquisition workflow guide to produce a high-quality dataset of labeled anomalies in small load carriers in collaboration with industry partners.

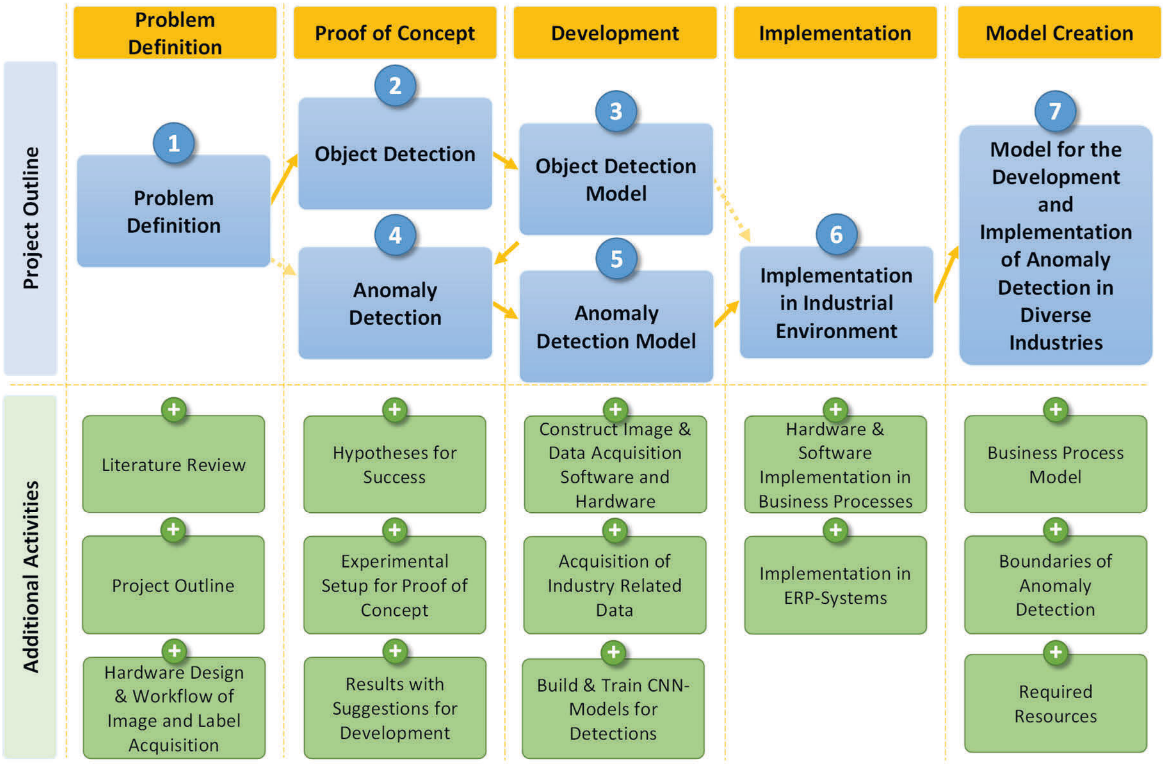

Fig. 2. Project outline

Following the problem definition, the project requires a proof of concept and the development of a computer vision model for both object detection and anomaly detection of SLCs. Therefore, in steps two and four the functionality of the computer vision setup will be tested for object detection and anomaly detection with a proof of concept. The third and fifth steps of the project include the detection model development. To be successful, the proof of concept must contain the hypotheses, including the desired outcome, the resources required, and the technical and business characteristics. In addition, the proof of concept demonstrates the experimental setup on a small scale and provides evidence that the model can be implemented for industrial use. The results of the proof of concept also suggest an organized approach to the development process.

Once the proof of concept is established, the two detection models are developed in the laboratory. First, a sufficient image acquisition software and hardware are constructed. Following, several industrially relevant images with specific labels are acquired at the depot of the project partner. Next, the model architecture is defined and the model is developed using the training data. Test results are generated by applying industry-related data to measure the accuracy of the model. Finally, the research team discusses the results. As shown in Fig. 2, the proof of concept and development of the object detection and anomaly detection models are separated and sequenced. This is because each model requires different architectures and has different goals to achieve. Both detection models must be coordinated to use the same image, which is more efficient and reduces costs. Therefore, the data collection should be similar. The dotted arrow in Fig. 2 from step one to step four represents the simultaneous application of both detection models.

Once the detection models are developed, the project partner intends to integrate the models into its container management system. However, this is only feasible if the results of the development are aligned with the project partner's existing business processes. In addition, the digital data generated by the developed models must be incorporated into the existing ERP system, which will initiate postings based on this data. If the project progresses according to steps one through six, the DIBCO project will achieve its goals.

The seventh step of the project is to transfer the knowledge gained to other industries facing anomaly detection challenges. A model will be created to help companies and project teams design and implement anomaly detection for their industrial problems. It provides a business process model plan and a project plan for implementing anomaly detection, as well as the resources required and the capabilities of this technology.

5 Design and Implementation of a Data Acquisition Setup

The following chapter discusses the implementation of a reliable image and label acquisition system. After the hardware design of an industry-oriented portal, this paper provides a time-reducing and efficient workflow for data acquisition.

5.1 Hardware Design

Fig. 3 shows the setup for capturing the images needed to train and apply classification and anomaly detection models in industrial applications. The setup consists of a portal with attached cameras and lighting, and a roller conveyor that transports SLCs. The setup ensures that standardized data sets are captured. To generate a new image, a container management company employee places an SLC on the roller conveyor in front of the portal and aligns it with the guide rail attached to one side of the roller conveyor. The SLC is transported to a defined location by automatically driven rollers so that similar images are captured. A light barrier ensures that only one SLC is in the camera's field of view and that all external surfaces are captured, preventing defects from being obscured by other SLCs. After passing through the portal, the SLC is automatically sorted. This setup integrates the image acquisition process into the existing business process and is an industrial solution. It ensures a stable, error-free, and time-efficient process by automating the positioning of SLCs and capturing all necessary images.

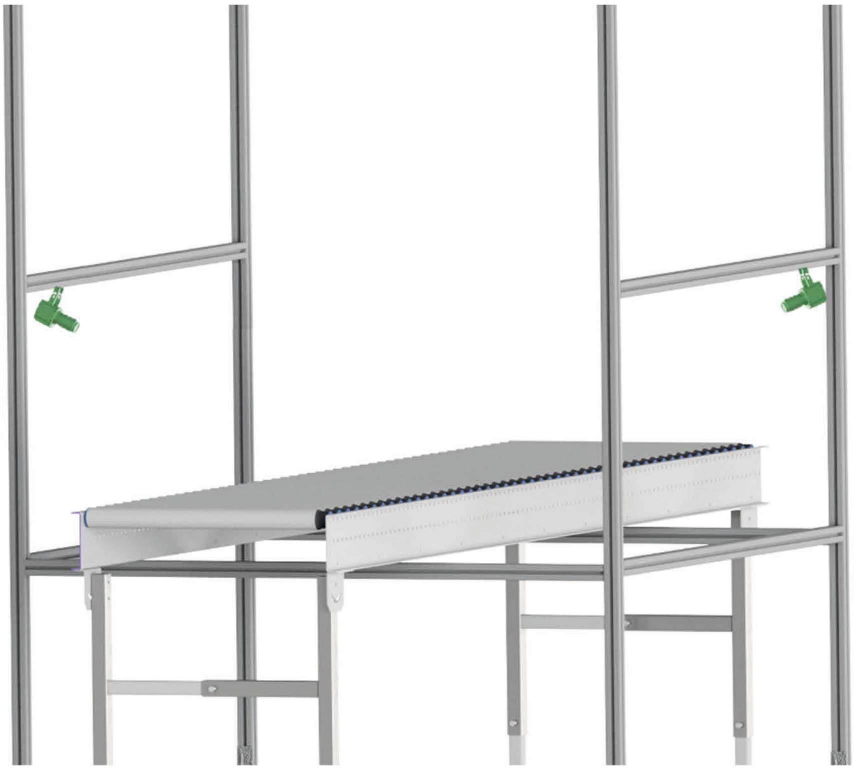

Fig. 3. Roller conveyor and portal [image courtesy of TAF INDUSTRIESYSTEME GmbH]

The structure of the portal, as shown in Fig. 3, is made of aluminum construction profile bars that can be easily adjusted. It is positioned to surround the roller conveyor with the single SLC. To ensure that the center of the largest SLC is aligned with the center of the transverse and longitudinal bars, the base area of the portal is a square, making it suitable for all types of containers serviced at the project partners' depot. Two cameras are mounted diagonally above the SLCs to ensure that the cameras are always facing the center axis of the SLCs. The cameras are adjusted to center the largest SLCs in the image. The height of the camera position is chosen to capture the inner surface of even the tallest SLCs with the highest walls. The diagonal positioning of the cameras allows all four sides of the SLCs to be captured, which is necessary for both object detection and anomaly detection. A crucial design consideration involves choosing between color cameras and high-resolution monochrome cameras. In this context, RGB cameras are decidedly more advantageous than monochrome cameras, as certain defects, such as rust and color residues, exhibit distinctive colors.

The design of the portal allows a variety of camera positions to be tested during the research process. The height of the bars, and thus the cameras, can be adjusted to study the effect of camera height on the models. Additional cameras can also be added, such as an overhead camera to capture the entire interior of the SLC for defect detection. A central lighting panel is used to provide uniform lighting across all SLC sizes, while ambient lighting is dimmed throughout to maintain external lighting uniformity. To eliminate the effect of ambient lighting, the portal is darkened. The flexible design of the portal allows the number, placement, and selection of cameras and lighting to be changed, allowing researchers to find the optimal setup. To prevent vibrations from affecting the camera, the portal is kept separate from the roller conveyor.

5.2 Workflow for Acquisition of Training Data

To detect defects using a computer vision model, a large number of images with various defects must be acquired. To achieve this in a short amount of time while also ensuring similarity to real-world scenarios, this research proposes a workflow for generating these training images. Two teams with different areas of expertise are needed for this: Team-Labeling-Tool and Team-Defect-Recognition. The Team-Labeling-Tool is skilled in using labeling software to label images, while the Team-Defect-Recognition works in container management and is trained to detect and evaluate defects and classify SLCs. This team has already sorted and recognized defects based on customer specifications.

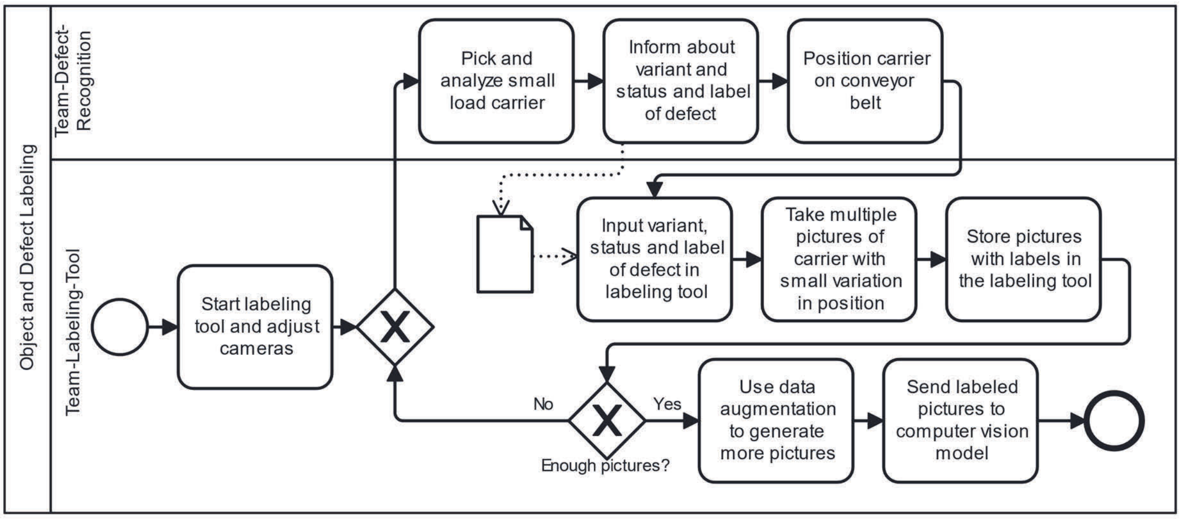

Fig. 4. Workflow for generating a high-quality dataset of labeld SLCs

The workflow shown in Fig. 4 starts with the Team-Labeling initiating the labeling tool and setting up the necessary equipment. Team-Defect-Recognition then takes an SLC and inspects it as they would in their normal day-to-day work. They provide the Team-Labeling with information about the variant, status, and label of the defect of the SLC. The variant is needed for object detection to classify the SLC, while the status indicates whether the SLC should be scrapped or included in the production cycle. The defect labels serve as the basis for the SLC scrap decision, and these three pieces of information are used as training data for anomaly detection. The acquired information is then processed by the labeling tool to convert it into a standardized format.

After the SLC is positioned on the conveyor by Team-Defect-Recognition, Team-Labeling takes multiple images of the SLC from different angles and positions, rotating the SLC by small angles and/or translating it by small distances. Fixed positions are defined for each new SLC on the roller conveyor to increase the number of training images and to train the models to recognize the SLC in different positions. This is necessary because the SLCs will not stop in the same position in the future automated process. These steps are performed manually to ensure control over the different positions.

The next step is to rotate the SLC 180° and repeat the process of capturing images from different angles and positions. This is necessary because the direction in which the SLC is placed on the roller conveyor is not defined in the automated process. The image files and defect labels obtained from these images are then stored in the labeling tool. Team-Labeling decides whether enough images have been captured for the anomaly detection model. If not, Team-Defect-Recognition selects a new SLC and the process starts over.

Training the model requires more images than can be taken from the actual SLCs. Therefore, data augmentation is used to generate additional images with slight variations from the original images, representing slightly different environmental conditions, such as changes in brightness. This action is performed if the Team-Labeling has acquired enough images of SLCs. Finally, all the acquired data is transferred to the machine learning model in a practical format.

6 Conclusion

This paper serves as a guideline for a project focused on object detection and anomaly detection of SLC. It is important to note that this paper does not provide experimental results or findings. Rather, it serves as a project outline, emphasizing the key objectives, proposed methods, and potential challenges associated with the project. It is intended to serve as a starting point for further research and experimentation in this area. The proposed project outlines a potential approach for developing effective object detection and anomaly detection models for SLC and provides a framework for further experimentation and refinement of these computer vision models.

In conclusion, the use of reusable containers in the logistics industry is becoming increasingly important to reduce waste and CO2 emissions. However, implementing a closed-loop system for these containers requires complex processes, including container management, cleaning, and detection. This paper highlights the potential use of computer vision to detect SLCs and defects, which can significantly improve the efficiency and accuracy of container management and it presents a project outline for a computer vision project for SLCs. Also, it presents a hardware design for image acquisition and outlines a workflow. While this paper does not evaluate the accuracy or reliability of the proposed architecture in detection, it serves as a guide for implementing a machine learning detection model for container management. To move this project forward, it is recommended to follow the project outline and prioritize conducting a proof of concept for object and anomaly detection of SLC. This next step will lay the groundwork for further research and ensure that the project is on the right track from the start. It is important to note that any subsequent research should be aligned with the overall goals and objectives of the project to maximize its potential impact. By following the project outlines, researchers can ensure that their work is effective and ultimately contributes to the advancement of knowledge in this important field. Overall, the use of computer vision for SLC type and defect detection is a promising approach that can help optimize container management processes and reduce costs for organizations.

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