CollectByCycle: Towards an Automatized Condition Assessment for Bicycles

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***Abstract*—The detection of defective parts of complex products is a great challenge for the untrained eye and impedes the assessment of different conditions. Therefore, the necessity for smart solutions that bridge the gap between user awareness of a product state and the restoration service of an operator is at an all-time high. The goal of this paper is to outline the preliminary results regarding the generation of a data set in order to improve bicycle repair and reduce the verification time of the component condition assessment. To enable such a service, a total of 115 bicycles were collected and classified.**

***Index Terms*—Repairing, Data set, Labeling, Product breakdown Structure, Circular Economy**

I. Introduction

The earths' resources are scarce, and therefore the overall depletion capacity is restricted. This is demonstrated by the Earth Overshoot Day. This day represents the date from which on humanity has exceeded the resource depletion in comparison to the natural budget of the year. This date was in 2023 the 2nd of August [1]. For the reduction of resource consumption, it is important to avoid the production of new products. This would help to save resources. Repairing offers an opportunity to avoid the production of new products and extend the life span of products that are already in use. However, at the beginning of the repair process, the question arises of which components are exactly in need of repair in order to restore the products' functioning condition. Therefore, the aim of this work is to investigate, if it is possible to identify certain conditions of product components and enhance the process of defect detection by reducing the amount of time necessary. For this purpose, condition data and images of the retrieved bicycles were taken and labeled and an evaluation concept, for the later used Artificial Intelligence (AI)-based solution was developed. The first section of this work contains the Introduction. Section 2 includes the Domain Background and the Technological State of the Art. The following section describes the initial Project Setup and section 4 deals with Preliminary Results. In section 5, the overall Conclusion and Discussion is drawn with an outlook of the subsequent steps of the project.

II. Background

The development of support tools in the sustainability domain for various tasks is a highly anticipated field in nowadays computer science and the IT-Industry [2]. Sustainability demands and necessities accelerate the development of these tools and lead to scientific challenges to enhance the information significance of the designed solution. In order to design solutions for domains like repair, not only the technological foundation must be assessed and evaluated but the domain-wise governing factors as well. Therefore, the *Background* section is divided into the *Domain Background* and the *Technological State of the Art*.

A. Domain Background

Product lifecycle-prolonging actions are one of the core mechanisms enabling the transformation of our linear economy. Short product usage cycles lead to higher amounts of waste that need to be processed, as well as a higher amount of energy consumption due to the production of new goods to replace the old or defective ones [3]. Therefore, the need for tools to support lifecycle prolonging measures becomes more and more important. Especially in the field of repairing, the hurdles limiting repairers are often, besides the economic barriers, the information gap regarding the specific defect, which causes the malfunction of the product [8]. Digitized tools can hereby help overcome these hurdles by enhancing the information density of a specific product, which reduces repairing time and supply chain planning for the repairer [9].

B. Technological State of the Art

The usage of Artificial Intelligence for support in analysing data is nowadays widely state of the art [4]. In the field of optical defect detection the usage of machine learning, especially Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), is already used and showed promising results in many applications. Papageorgiou et al. line up in a short overview of the application of Computer Vision for defect detection in manufacturing, which technologies are the most common, and discuss the impact of the different machine learning technologies for certain applications. Hereby, they describe 2D as well as 3D based detection technologies

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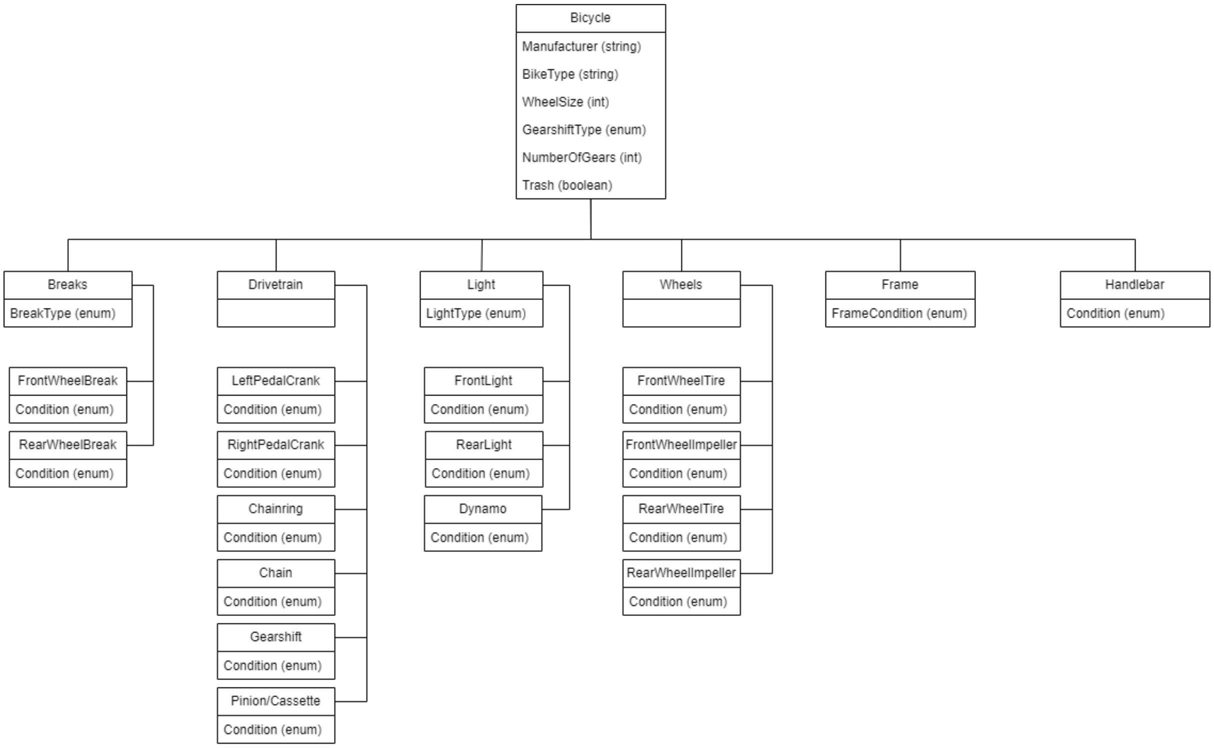

Fig. 1. PBS for the Bike data acquisition

[6]. Especially in the area of detecting product production issues on the external surface, the usage of CNNs is already an accepted technology. Hereby, the usage of pattern recognition showed how surface failures can be detected to enhance quality control [5]. A broader application-driven view is shown by Saberironaghi et al., where the scope includes also different types of defects products can show based on their product lifecycle. Therefore, the application of deep learning for different kinds of data was shown in order to classify defects in products based on their specific fault pattern [7]. The mentioned references showed hereby three things: deep learning is a possible solution for defect identification, the necessity of a strategy to tackle small sample data sets, and the need to label those data in a structured way in order to gain accurate data out of the machine learning model. As a result, our experiment is dissected into different phases, which are described in the following section.

III. Project Setup

The conducted experiment aims to provide the data foundation for later targeted an AI-based defect identification demonstrator that is not only able to classify bicycles but further to detect missing or damaged parts, which affect the overall functionality of the bicycle in mechanical as well as legal terms. Therefore, the technical relevant parts of the bicycle have been classified in the form of a *Product Breakdown Structure (PBS)*, which sets the scope for the different product phases and is used for structuring our product labeling Figure 1. [10]. The PBS therefore defines the layout for the collection phase as well as the adjunct phases of the data recording described in the next subsection.

A. Project phases

The project is divided into four different phases. The first phase consisted of the collection of the bicycles. This was maintained with the help of a designed collection app, where users could register their old and/or superfluous bicycles. The bicycles were subsequently collected and stored, which led to the next phase. The bicycles were then inspected with the help of the designed questionnaire, which also set the foundation for our PBS. Afterward, images were taken from different perspectives of the bicycles and their components to generate a sufficient data set for each of the bicycles. This data set will be used as foundation in the following phase to train an AI-demonstrator, which detects missing components of bicycles.

B. Appraisal

The appraisal phase of the project contained the recording of the images to capture the features of the bicycle. Additionally, the bicycles were classified with the checklist containing the PBS shown in (Fig. 1.). Therefore, the image-capturing process consists of a total of six different images taken for each of the bicycles. The bicycles were photographed from both sides, as well as the front and rear, in order to capture the relevant components. The different views capture the components of the bicycle as well as the bicycle itself to later provide a sufficient sample data set to train the aspired model. In addition, two images were taken which show a

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more detailed view of the front tire as well as the back tire. This enables a more detailed view of critical components, like the brake system and the drive train.

For further information about the bicycles, which may not be visible, we developed the before-mentioned checklist, which will additionally be used to label the images taken above. In the first step, the checklist was developed with the goal of getting all the necessary information about the bicycle. This development was based on literature research and feedback from repairers. In the end, a useful checklist for scientific research purposes and for repair was created. This checklist yields to the already mentioned PBS, which is shown in (Fig. 1.). At first, general information about the bicycle was stored in different data types in accordance with the possible states of the components. The components were in advance classified. For example, the *condition* state can have three different states {**functional, defective, missing**} to determine the necessary repairs to reinstate the functional condition.

With the images and the results of the checklist, we can build the data set by linking specific conditions and bicycle types to the images in order to train the AI. We have therefore planned to use the PBS as the foundation for the labeling of the images.

IV. Preliminary results

The current state of the experiment already allows to draw of a few conclusions. The preliminary results can therefore be divided into a section concerning the overall derivation of certain parameters already visible in the collected data, and a section concerning the contextualized view regarding the later-developed machine learning system and the potential significance of the former. In the case of the images and their classification, we were able to link different states directly to the proposed PBS in order to determine the conditions of the bicycles' different components. Because of this, it was possible to separate the collected bicycles already in their responsive categories, which enables the operators to further process the bicycles.

A. Data set Overview

In order to design efficient assessment support for the operator, a sufficient data set is needed that fulfills the requirements regarding the categorization of the repairer. For this reason, a total of 115 bicycles were recorded and, as mentioned before, classified according to their type. Additionally, the data set was further enriched with the detailed data of the PBS, namely the condition of the different components the bicycle is composed of. For the recording process, the use of a twelve megapixel camera proved to be sufficient in terms of the overall resolution. The images provide ample resolution to identify the different components and potential damages. However, it needs to be seen if this is sufficient in order to receive an accurate assessment of the product state in terms of part damages and missing components. An example of an image taken from one side is visible in Figure 2. where we can see the labeling of both the tires of one of the bicycles. In this case, the front and rear tires are labeled and marked as a colored polygon. Also, the front and light, as well as the left pedal crank are edged and can be seen in the image. The bicycles that were collected are already mapping a great variance of the potential conditions and are therefore suitable to provide the variety needed for the proper training of the Artificial Intelligence. Additionally, a few special types were collected as well, for example, e-bikes, which require particular treatment based on their more complex product composition.

As already mentioned, the decision if a bicycle can be reused depends on different influencing factors. There are, however, some critical components regarding the mechanical functionality and critical components linked to legal requirements, like the German road traffic regulations (StVGO), that highly affects this decision. One example of such a part is the frame because it is not exchangeable. The frame of some bicycles is in very bad condition and could possibly be detected and classified with the according label with the help of a trained AI.

If we say ”bad condition”, we mean the frame may have corrosive spots, bulges, or superficial issues like numerous stickers that do not affect the functionality of the bicycle. However, this will be further divided since one affects the overall functionality deeply whereas the other solely is a cosmetics issue.

As in comparison, there are other components where the condition may or may not be visually apparent. As an example, it is fairly easy to tell if a tire is flat and therefore defective. However, a defect light caused by a damaged portion of the component is not always visible.

Fig. 2. Recorded bicycle with highlighted (human conducted) labeling for both tires.

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B. Domain context

The collected bicycles showed a huge variety in terms of the collected models and types, as well as their condition state. The total of 115 bicycles we received over the course of the collection period over one month was more than the authors initially anticipated over the given time frame. The project therefore already showed, that there is a certain willingness in the public to support sustainable causes. However, the authors did not conduct any economical or social science related research to investigate this further. For the broader application of such systems, additional influencing factors, especially economical ones like spare part prices, labor cost and transportation costs must be evaluated in depth in order to provide a substantial assessment of the disability of such models. This project therefore serves as a pilot for small sample product collection to examine the potential of this kind of experiment, where citizens can give their old and superfluous products away. After that, the products will be repaired and then returned to the usage cycle. Therefore, resources can be spared and production capacities can be optimized further. Still, the question remains, if such processes are feasible and can provide a suitable business model for product restoration companies.

V. Conclusion and Discussion

The paper described the collection of an image data set of bicycles in order to use them later on to train deep learning models. Therefore, an emphasis was put on the recording of data and the structure of the component labels. With the help of the PBS, the data can be labeled according to the suggested data model, which allows a component-wise classification of the parts which will therefore allow to assign the labels in a harmonized way. The project data set can therefore be used as well for a variety of classification or identification tasks and can bolster computer vision systems in the domain of repairing, refurbishing, and remanufacturing. The task the authors of the paper will try to investigate in the next step of the paper is the detection of missing components of a bicycle based on the bicycle's type, as well as a condition assessment of the quality of the different parts. If this step proves successful, the authors aim to design a system that already generates concrete repair instructions based on the current status of the bicycle, which could help the repairer further by already managing the supply chain necessary for repair. However, the overall mechanisms of the aspired system must be investigated further to clarify the applicability of the trained model, as well as the overlaying business model. For the Artificial Intelligence, the question remains, how additional data input could be used to bolster the accuracy of the model. A possible approach could be the use of a multimodal deep learning model, which benefits from multiple data inputs, for example, pre-assessments generated by the bicycle owners. Therefore, potential non visual factors could be accounted in a more detailed manner, which could led to other results in the overall assessment of the condition of the products. The success of the overall system is however depending as well on the accuracy of the AI component as on the proper conduction of the repairing task. To tackle both personal and economic shortcomings for the actual repair operation, a possible solution would be the attachment of a expert consulting system, which generates repair instructions based on the condition of the product. This could enable on the one hand enable repairing for laypeople, which do not possess the knowledge for bike repairing. On the other, it could benefit the repairers with additional knowledge and information to enable a faster repair conduction by providing services like the pre-selection spare parts. The data set therefore provides an interesting opportunity to investigate, how different types of data can improve services for Circular Economy applications.

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