Repairing is Caring - An Approach to an AI-Supported Product-Service-System for Bicycle Lifecycle Prolonging

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***Abstract*—Bicycles play an essential role in today's mobility ecosystems and are an important part of future mobility concepts. Bicycles develop defects as a result of frequent use both during and after the operational phase. In some cases, repairing can be a solution to prolong the duration of a bicycle's usage by restoring its condition while simultaneously preventing the generation of new waste. To plan the repair process, it is critical for both the bicycle's owner, referred to as the client, and the repair service provider to determine the defects and whether fixing the problem is worthwhile in this particular situation. Therefore, there is currently a gap in potential solutions for accelerating this process. The paper aims to investigate how Artificial Intelligence (AI) can support repair business models to increase the attractiveness of sustainable, prolonged solutions. Consequently, AI-based experiments were conducted to design two specific classifiers to examine the state of different kinds of bicycles. The AI-based models were trained, validated, and tested in these experiments to develop a product-service-system based on the images of the bicycles and the repair information collected from the repair service provider.**

***Keywords*—Bicycles; Repairing; Product-Service-System; Artificial Intelligence; Circular Economy.**

I. INTRODUCTION

The usage of bicycles is already part of current mobility solutions and is a key factor in sustainable mobility concepts of the future. The advantages of using bicycles are, for example, a reduction in the rate of emissions and the requirement for less space compared to other mobility solutions, which is a huge benefit in crowded urban spaces.

During the operational usage of bicycles over their lifetime, the occurrence of defects and damages is natural. For instance, the chain and tires of the bicycle normally have a shorter lifetime than other components due to the stresses afflicted upon them. As an option for prolonging the lifetime of a bicycle as a whole, these components can be exchanged or repaired fairly easily [1].

However, to repair the defects and assess if it is a feasible option for all the stakeholders, this information needs to be apparent. In addition, to decide for both the repair service provider and the client, the key is to identify and analyze the feasibility of a given bicycle properly. Nowadays, this process is still largely performed manually, which is time-consuming and requires an expensive workforce. Therefore, digital AI-based tools paired with the ecosystem could prevent stakeholders from undertaking time or cost-extensive processes to assess bicycles, shorten delays for the spare part delivery, and enable new business models in the field of repairing.

This work aims to address this issue and propose a possible solution for accelerating the respective process. The paper presents AI-based models for two specific use cases, capable of addressing different questions regarding the condition assessment of bicycles. This paper continues the scientific research work already presented by Geger et al. [2]. Additionally, the aspired repair ecosystem is presented, which allows the identified stakeholder to flesh out based on sustainable business models.

The following Sections of the presented paper are structured as follows: Section II describes the Related Work, and Section III presents the suitable Bicycle Repair Ecosystem. Subsequently, Section IV deals with the Scope of the AI support and the Data Recording, followed by the AI-based Methodology presented in Section V. Finally, the paper summarizes the Results and Analysis shown in Section VI, followed by the Challenges and Future Work in Section VII and the Conclusion in Section VIII.

II. RELATED WORK

One way to reduce waste and increase the lifespan of products is to transform from a linear economy to a circular economy. Most approaches to modeling the circular economy define reuse and repairing as the first actions to increase the lifespan of a product, as described in [3]. Therefore, the circular economy not only plays a major role in reducing waste but is also an effective way to create a sustainable ecosystem on a large scale.

When it comes to bicycles, one must decide whether a bicycle can be repaired, whether it is possible to reuse the components, or whether recycling is the best option. Consequently, a service platform is needed to determine which decision is the best for a repair service provider and which for the client. In addition, the platform must consist of the interests of clients and the repairer service providers concerning the circular economy. Blomsma et al. [4] illustrates one such example as they assess different lifecycle options in one system.

Moreover, the application of AI is increasingly crucial in today's world for making various lifecycle-based decisions, which is also a crucial component of the circular economy with the aim of achieving sustainability. One of the popular areas in the field of AI is deep learning. Deep learning utilizes multi-layered neural networks to learn from input data and make decisions. In the field of deep learning, a commonly utilized feedforward neural network is Convolutional Neural Networks (CNNs). CNNs are distinguished from other types of neural networks due to their ability to identify visual features for different tasks in vast amounts of data, as also pointed out by Yamashita et al. [5]. A CNN mainly comprises three types of layers. The Convolutional, Pooling, and Fully Connected Layers (FCLs). These layers can be ordered and utilized in multiple variations. The convolutional and pooling layers are utilized for feature extraction, and the FCL is for classifying the output.

Furthermore, one of the popular CNN-based architectures is InceptionV3 presented by Szegedy et al. [6], which proposed a new standard for classification tasks. In addition, another important strategy in the field of AI is transfer learning, which utilizes the AI-based models already trained on extensive datasets and adapts the output layers to meet the requirements of the new tasks, as described in [7].

In the context of bicycles, the different components of a bicycle are influenced by daily use to varying degrees. For example, a component of a bicycle could contain some rust, and this can be a reason for replacing the respective component. But this is not always true, as it depends on the amount of rust. For instance, Petricca et al. [8] utilized CNNs for rust detection of different products. However, besides the detection of a component condition, it is also interesting to find out about missing components. On the other hand, Zou et al. [9] utilized CNNs to detect missing components of historical buildings. In addition to the detection of components, the assessment of the product as a whole is another interesting area for the use of AI.

Most notably, the key question for the lifecycle assessment is whether a product is repairable or not. Liao et al. [10] investigated the questions by two approaches. One of the approaches was utilizing a supervised learning framework, which uses transfer learning with common machine learning architecture, including ResNet50, ConvNeXt, and VGG16. The other approach builds an unsupervised learning framework, which includes feature extraction and cluster learning with the goal of getting inside of the product design. A smartphone was used as an exemplary product.

However, a product lifecycle decision is necessary for making such a decision. Moreover, Liao et al. [10] emphasize several limitations in their study. The insufficiency of data affects product repairability since it is a multifaceted, intricate issue. Therefore, the author suggests incorporating various datasets in subsequent research. In addition, potential future directions proposed by the authors include evaluating results with expert opinion and considering other business and sustainability factors.

The presented work in this paper utilizes a bicycle dataset that was already created with the definition of the labels by Geger et al. [2]. The existing work presents four different project phases. The collected dataset consists of 115 distinct bicycles with several images taken from different angles and frames for each bicycle. Moreover, the images are labeled according to the Product Breakdown Structure (PBS) [2], defined together with the repair service provider. In addition to the information about each component of the bicycle, where the condition of every component was labeled, it was also labeled if the bicycle in general is repairable or not, based on the assessment of the repairer. Thus, the first phases till the creation of the dataset have been completed, and subsequent steps concerning the training of the AI-based models are presented in this paper.

III. Bicycle Repair Ecosystem

The offer for repair services for in-use goods is already showing an increase in the overall service demand [11]. To enable businesses to participate in this new kind of service environment, service blueprints are an essential enabler in implementing the necessary infrastructure and the corresponding processes. This is especially the case for Small and Medium Enterprises (SMEs) [12], which are in need of adaptable business models and structures.

Regarding a sustainable product-service-system for bicycles, all the participating stakeholders need to be taken into account to offer interfaces for the different service providers. These include, besides the *Client*, the *Repair Service Operator*, the *Digital System Service Operator*, as well as the *Logistics Service Provider*. As shown in Figure 1, the aspired ecosystem for the designed repairing service is depicted with the corresponding interactions between the stakeholders of the system. The different stages of the process are illustrated in Figure 1, marked with green along with the corresponding number of the steps.

To set up the necessary foundation for the repairing process, the *Digital System Service Provider* is responsible for providing the necessary infrastructure in terms of user interface (*App on Client Device*) as well as the pipeline to the backbone of the system, the *AI Server Infrastructure* with its models. Likewise, the Repair Service Provider should distribute his *Repair Assessment Criteria*, the information regarding his criteria on repairability, to the *AI Server Infrastructure*.

Starting with the recording of the defective bicycle, the process is initiated by the client, who is using the *App on Client Device* on his cell phone to capture photos of the damaged bicycle in order to enable the assessment of the damage (Step 1).

After the images are taken, they are sent (Step 2) via the application to the *AI Server Infrastructure*, where the models are hosted by the *Digital System Service Provider*.

The images are then processed in the next stage (Step 3) by the *General CNN Model: Defect Detection* as well as the *Individual CNN Model: Repair Assessment*, which is trained based on the *Repair Service Provider's Repair Assessment*

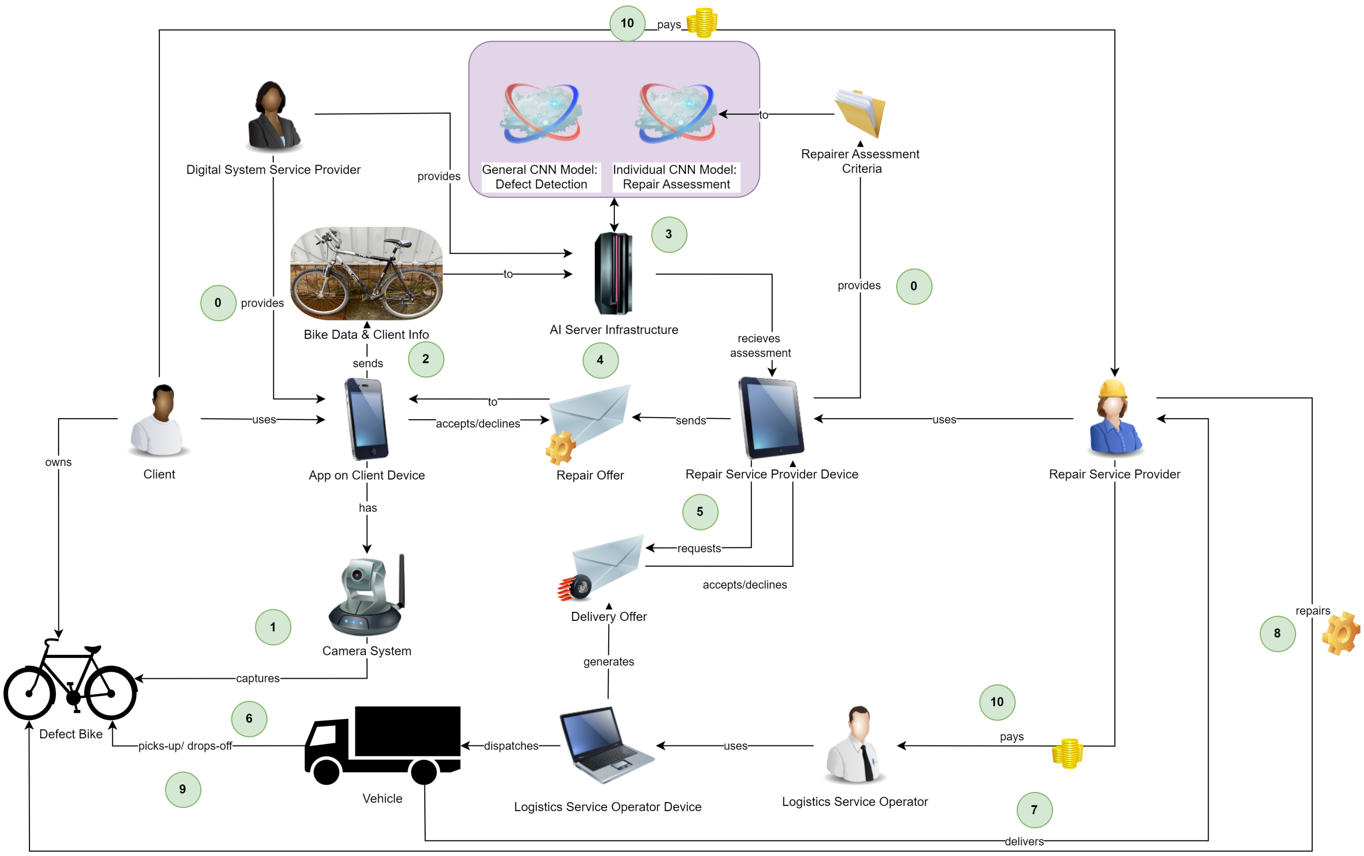

Figure 1. Product-Service-System for in-use bicycle repairing.

Criteria. The models are, therefore, analyzing the visible defect and missing parts on the bicycle and classifying the bicycle either as *reparable* or *not feasible for repair*, as described in Section IV.

The analysis of both the AI-based models is then transferred to the *Repair Service Provider*, who reviews the results and, if fitting for them, submits an offer to the *Client* (Step 4). If the client accepts the offer, the *Repair Service Provider* will contact the *Logistics Service Provider* to receive an offer for the transportation of the bicycle in the next step (Step 5).

By accepting the offer, the *Logistics Service Provider* will pick up the bicycle from the *Client* (Steps 6 and 7) to deliver it to the *Repair Service Provider*, who will fix and return it upon completion of the task (Step 8 and 9).

After the bicycle is delivered back to the *Client*, he pays the *Repair Service Provider*, who is paying on his terms the *Logistics Service Provider* for his logistics services.

IV. Scope of the AI-support

In order to address the requirements raised by the stakeholders, two distinct AI models are necessary to answer both the question about the repair worthiness of an item and the overall condition of its components. Those two models, although both based on CNNs, are different in their nature and how they are conceptualized in terms of data usage.

As described in Section I, the repairer needs essential information to determine if he is capable of repairing the bicycle and assessing the cost for repair on his side: *What is damaged?* and *Is it feasible for me to repair it?* We, therefore, handled those two information requirements as distinctive tasks, where we needed a specialized model for each of them. Hence, we designed two different labeling structures to enable the model to adapt to the two initial questions. For both models, a total number of 672 images were used for the training process, distributed in different labeling constellations.

The **General CNN Model: Defect Detection** is, therefore, responsible for identifying the different parts of a bicycle and their status in terms of damage or obsolescence of a given part. Its labeling structure is based on the PBS, as already introduced by the authors [2], in order to describe the composition setup of a bicycle and the functionalities of the different components. For this model, all the collected images of the different bicycles were classified and labeled according to the directly visible criteria. For example, in Figure 2, it is clearly visible that the chain that drives the shaft is broken. Also, the same applies to parts that are missing since they are for a given type of bicycle (e.g., mountain bicycle, trekking bicycle, etc.), not apparent. The model identifies, as a result, the type of component the bicycle is composed of as well as the general state of the same.

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Figure 2. Bicycle from the data set without a functioning chain.

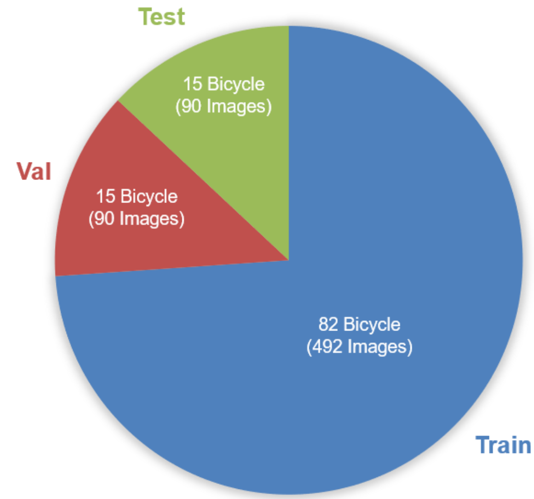

Figure 3. Bicycle-level stratified split of the dataset.

The **Individual CNN Model: Repairability Assessment** is in contrast to the further mentioned Model, much more relying on the context of the labeling since it evaluates the feasibility of the repairing process for a given repairer. The division in *reparable* and *not feasible for repair* is, therefore, subject to a multitude of different factors, including economic assessments and business model considerations, logistics management, and technical specialization and knowledge, as well as business-to-business contracts between repairers and certain manufacturers. The labeling process was conducted for this model in close collaboration with the repairer to reflect the decision a human repair operator would make by assessing the bicycle in front of them.

V. AI-BASED METHODOLOGY

This section elaborates on the AI-based methodology, including the experimental setup, preparation of training, validation, and test sets, and the AI-based architecture utilized with selected hyperparameters.

A. Preparation of training, validation, and test sets

The bicycle dataset consists of 115 distinct bicycles. However, a total of 112 bicycles, corresponding to 672 images, are considered for the experiments, excluding the children's bicycles. As outlined in Section II, each bicycle is captured from different angles and frames, resulting in multiple images belonging to each bicycle. The method makes the dataset more comprehensive, allowing for a more in-depth analysis of the bicycles' features and designs.

However, dividing the dataset at the image level could cause different frames of the same bicycles to appear in both the training and test sets. Consequently, when the model is tested on the unseen data, it may have already encountered the same bicycle from a different frame during the training phase, potentially compromising its ability to generalize effectively. Therefore, a bicycle-level stratified split is carried out as described in Figure 3.

As illustrated in Figure 3, 82 bicycles are utilized for training, with 15 bicycles allocated for optimizing the hyperparameters and another 15 for testing the final model performance. This structured approach enhances reliability and ensures robust evaluation.

B. AI-based Architecture and modeling process

The Constructed AI-based architecture utilizes the InceptionV3 network pre-trained on the ImageNet dataset [13]. The accessibility of pre-trained networks significantly facilitates the adaptation of CNNs in classification tasks, thereby diminishing the necessity for substantial computational resources and allowing for build-upon models trained on extensive datasets [7].

In addition, custom layers, including **GlobalAveragePooling (GAP), FCL, dropout**, followed by the **final FCL** for the target output classes, are added on the top of the pre-trained network as illustrated in Figure 4. Integrating custom layers on top of the pre-trained network can efficiently adapt the feature extraction capabilities to meet the requirements of the new tasks.

Subsequently, the model training is carried out utilizing the prepared training set and fine-tuned on the prepared validation set. The model is fine-tuned by freezing some of the pre-trained layers and allowing the remaining ones to train along with the custom layers. In addition, the process involves tuning several hyperparameters, including the selection of optimizer, learning rate, learning rate schedule, dropout rate, regularization rate, and batch size. Given that AI-based models are highly configurable through their hyperparameters, the fine-tuning of hyperparameters varies depending on the prediction task. Section IV already outlines the two distinct objectives this study addresses. Therefore, the considered hyperparameters, along with their fine-tuned values, are explicitly presented for the two prediction tasks in Subsection VI-A and VI-B.

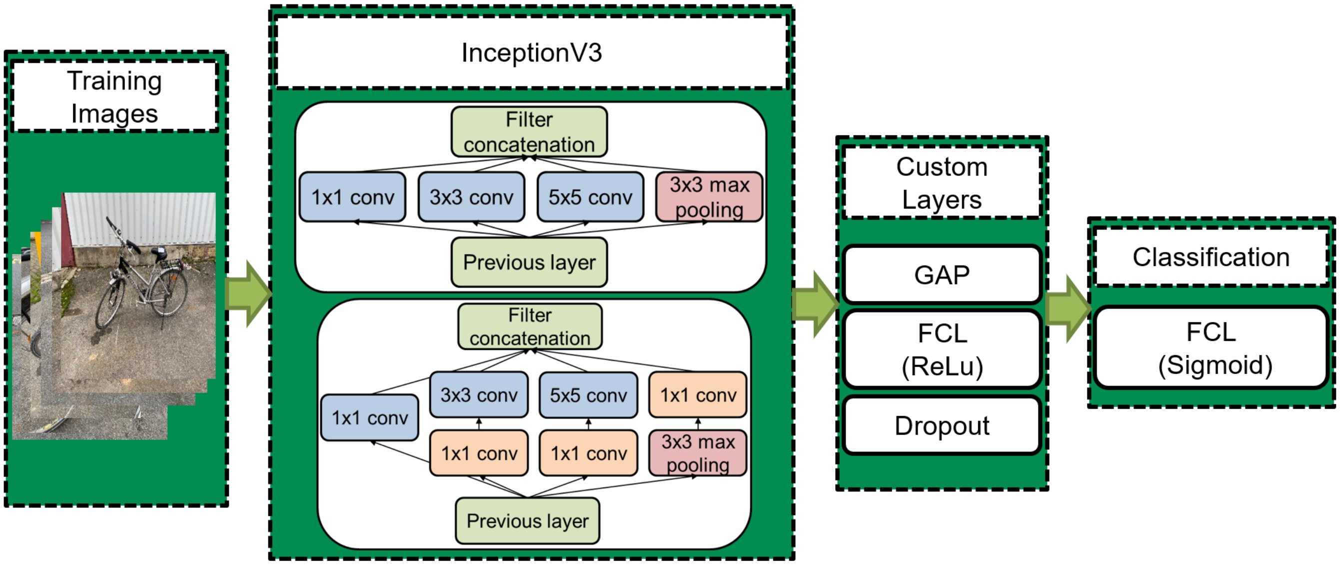

Figure 4. InceptionV3 architecture: Pre-trained on ImageNet dataset and fine-tuned with custom layers.

Moreover, early stopping is deployed to avoid overfitting and improve model generalization. Consequently, the training process is halted if the model performance does not improve on the validation set for 10 consecutive epochs. The early stopping technique is applied based on the monitoring of loss computed on the validation set. This technique allows the model to learn essential patterns without fitting the noise in the training data.

Most notably, the final classification for the bicycle for each use case is determined by counting the frequency of each predicted label across all images. As mentioned, each bicycle has multiple images captured from different angles and frames. The final classifier generates a prediction for each image after processing them independently.

Subsequently, these predictions are aggregated by deploying a majority voting mechanism. Consequently, the final class for the examined bicycle is determined by the prediction that receives the highest number of votes.

VI. Results and analysis

This section demonstrates the final effectiveness of the constructed models for two distinct prediction tasks. The task of detecting defects and assessing the overall repairability of the bicycles on unseen test data.

The information about each bicycle component, as well as the overall assessment of the bicycle's repairability, is derived from the PBS developed in collaboration with the repair service provider, as outlined in Section II. Moreover, this section includes the performance metrics of the constructed classification models, as assessed through the classification report and the confusion matrix for each of the presented prediction tasks.

A. Defect Detection

In the context of the defect detection task, the bicycle chain is selected as the component to be examined. After deriving the respective information from the PBS, the model is trained and tested using the prepared sets outlined in Subsection V-A and the architecture presented in Subsection V-B. In addition, Table I describes the selected hyperparameters with the fine-tuned values for the respective task.

TABLE I. HYPERPARAMETERS WITH THE CORRESPONDING FINE-TUNED VALUE FOR THE DEFECT DETECTION TASK

Hyperparameters	Fine-tuned value
Optimizer	Adam
Learning rate	0.0002
Learning rate scheduler	0.1953
Dropout rate	0.5918
Regularization rate	0.0767
Batch size	8
Number of layers to freeze	127

The detailed evaluation of the model's predictive capabilities to examine the bicycle chain is described in Table II. Table II highlights the key performance metrics, including the precision, recall, F1-score, and accuracy.

TABLE II. CLASSIFICATION REPORT SUMMARIZING FINAL MODEL PERFORMANCE FOR DEFECT DETECTION

	Precision	Recall	F1-score	Support
Functional	0.62	1.00	0.77	5
Defect	1.00	0.70	0.82	10
accuracy			0.80	15
macro avg	0.81	0.85	0.80	15
weighted avg	0.88	0.80	0.81	15

Finally, the confusion matrix focuses on the instances of misclassification. The confusion matrix for the defect detection task on the test set is visualized in Figure 5.

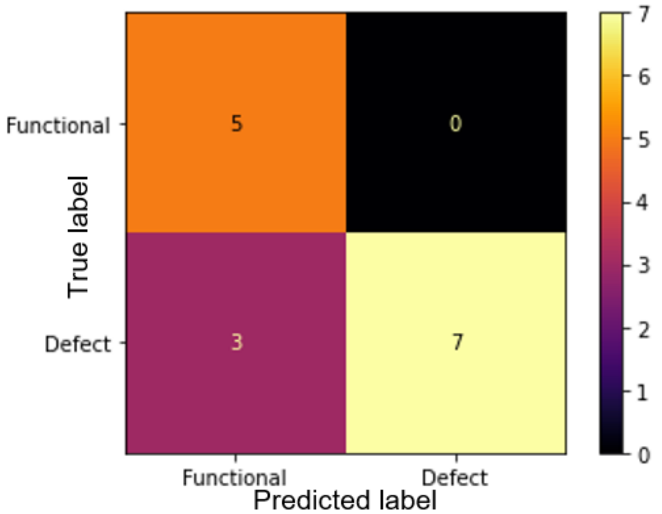

Figure 5. Confusion matrix representing the defect detection in the bicycle chain.

The results demonstrate a commendable performance, achieving a weighted average F1-score of 0.81 for 15 unseen bicycles. The model misclassified 3 of these bicycles, as indicated by the confusion matrix in Figure 5. Overall, the results suggest effective classification, considering the relatively small training set.

B. Repairability Assessment

The decision to assess repairability is subject to a multitude of different factors, including technical and economic assessments as well as business model considerations. The overall repairability assessment of the bicycle is carried out utilizing the same dataset split described in the Subsection V-A. In addition, the deployed model architecture is already presented in Subsection V-B but with different hyperparameters. Table III describes the considered hyperparameters and their corresponding fine-tuned values for the respective task.

TABLE III. HYPERPARAMETERS WITH THE CORRESPONDING FINE-TUNED VALUE FOR THE REPAIRABILITY ASSESSMENT TASK

Hyperparameters	**Fine-tuned value**
Optimizer	Adam
Learning rate	0.0005
Learning rate scheduler	0.2441
Dropout rate	0.4681
Regularization rate	0.0670
Batch size	8
Number of layers to freeze	84

Subsequently, the comprehensive performance analysis, including the precision, recall, which results in the F1-score, and accuracy of the repairability assessment classification model is presented in Table IV. The analysis indicates that the model attains a weighted average F1-score of 0.94 for 15 unseen bicycles, highlighting its capability to generalize effectively beyond the training set.

TABLE IV. CLASSIFICATION REPORT SUMMARIZING FINAL MODEL PERFORMANCE FOR REPAIRABILITY ASSESSMENT

	Precision	**Recall**	**F1-score**	**Support**
Repairable	0.86	1.00	0.92	6
Not Repairable	1.00	0.89	0.94	9
accuracy			0.93	15
macro avg	0.93	0.94	0.93	15
weighted avg	0.94	0.93	0.94	15

Finally, the confusion matrix provides a comprehensive assessment of the model's predictive performance, identifying specific instances of misclassification. The confusion matrix for the repairability assessment classification task is illustrated in Figure 6.

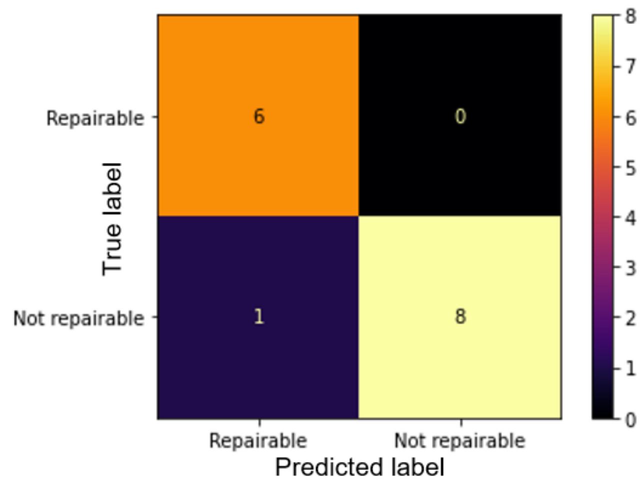

Figure 6. Confusion matrix representing the overall repairability assessment of the bicycle.

The confusion matrix demonstrates effective performance by the constructed model in distinguishing bicycles as repairable or not feasible to repair, with only one misclassification occurring among the 15 unseen bicycles in the test set.

VII. Challenges and Future Work

Although the application domain is outlined by the Product-service-system itself, there is still the necessity to deal with several challenges in that context. On the one hand, the proposed service system is, generally, still in its conception phase, and although it has been discussed with service partners in this domain, the overall applicability for maintaining repair services has still to be proven successful. The trained AI-based models, on the other hand, showed how AI-supported digital systems could leverage sustainable systems and enable a higher degree of knowledge generation at an earlier stage of the decision process.

Moreover, the presented classification results utilize the majority voting mechanism that efficiently considers the information provided from multiple viewpoints. In addition, the approach leverages the predictive outputs of a single classifier, based on the idea that variations in viewpoint can influence recognition performance. However, to better assess the robustness of the suggested approach, there are possible potential future directions. In addition to considering the information from multiple viewpoints, the proposed majority voting mechanism can be extended by taking the confidence scores assigned by the classifier to each image into account. Moreover, introducing a minimal confidence threshold may also contribute to reducing the influence of uncertain labels by ensuring that only predictions with a higher degree of confidence are included in the final vote.

Another possible future direction can be the extension of the proposed model functionality. So far, the defect detection model has only been trained to examine one specific component to prove the capabilities of the tuned hyperparameters. Therefore, it is necessary to examine in future research how the model would perform in the case of detecting multiple components. However, while it is possible to build a multi-output model to evaluate damages and thus guide repairability decisions, it encounters significant challenges. In general, finding the right balance between generalizability and specificity is essential as the models that are too specialized for one set of situations could not function effectively in a wider variety of situations. Therefore, it is essential to determine which particular output of the model will be examined on the validation set. This determination will help optimize the number of layers to freeze while utilizing a pre-trained model, as well as the selection of the optimizer with learning rate and the other hyperparameters.

Most notably, the model for repairability assessment, however, is, for now, trained on the requirements and specifications of one repair service provider. This means that for another repair service provider, a separate model needs to be trained if the specifications deviate from one another. Future research should, therefore, focus on how this system could be improved to reduce the expenditures for training and provide the framework to accommodate the diverse specifications of different repair service providers. Specifically, we propose a reconfigurable pipeline framework that facilitates the customization of training processes according to the specific requirements of each repair service provider. This flexibility would enable stakeholders of the system to select tailored training criteria, thereby ensuring that the resulting models are aligned with their unique operational contexts and respective needs. In addition, it is essential that the system incorporates functionality to dynamically switch between different models based on insights obtained from the training analysis and performance metrics. This dynamic adaptability would empower repair service providers to deploy the most suitable model in response to evolving conditions and particular challenges, thereby improving operational efficiency and advancing service quality across a spectrum of repair environments.

VIII. CONCLUSION

The paper presented a possible approach for an AI-supported repair ecosystem for bicycles, as well as two AI-based models optimized by hyperparameter tuning to detect damage and assess the overall feasibility of a given bicycle and its repair. The conceptualized ecosystem can be used in further research as a foundation to flesh out sustainable business models for repairing, remanufacturing, and refurbishing, and thus as a starting point for a demonstration of such systems in the scope of follow-up experiments. In addition, the reconfigurable pipeline framework that has been suggested for future development would make the system adaptable and customize the training process in alignment with the requirement of the repair service provider. As stated before, the system itself, as well as the AI-based components, still needed to be evaluated in their overall applicability for the Circular Economy Service domain to contribute to a broader application of smart and sustainable product services.

ACKNOWLEDGEMENT

This work was conducted in the scope of the project ”Life_TWIN” and funded by the Federal Ministry for Economic Affairs and Climate Action (Research Grant: 03EI5014A).

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