Design and Development of a Digital Twin for Monitoring Railway Infrastructure

Javier Fuentes[1], Franck Fierro[1], Rafael Barea[1], Elena López-Guillén[1] and Luis M. Bergasa[1]

***Abstract*— The aim of this work is to develop a digital twin application to ensure an optimal level of reliability when launching a larger project based on the identification of trains and detection of defects that allow for safe freight transport on spanish trains. The digital twin framework consists of three parts: the "physical product" which consists of a scanning camera placed on a track gantry, the "virtual product" which includes a model based on real-time data representing the freight car detected by the perception system, and the data flow connections. The camera images will be post-processed through an artificial intelligence detection model (YOLOv8), trained to detect all the elements necessary for the safety of the vehicle and the cargo. Field studies have demonstrated the effectiveness of the proposed digital twin framework and its potential to identify railcars and detect defects in freight wagons.**

I. INTRODUCTION

In recent years, the railway industry has embraced increasing levels of digitalization aimed at enhancing safety and resource optimization through technological innovation. Among these advancements, digital twins have gained significant attention within infrastructure engineering, enabling real-time monitoring and more efficient predictive maintenance [1]. On the other hand, there is a great interest in the whole world for climate-friendly transportation and in Europe in particular. The Europe's Rail joint undertaking [2] is investing in the modernisation of Railways to fulfill sustainability goals and reduce pollution. Some studies shows that the EU logistics sector is pushed to make a drastic modal shift from truck transport to the more efficient rail transport in order to achieve the EU's climate goal of net zero greenhouse gas emissions by 2050 [3]. In addition, the public demand for the improvement of life quality results in the revolution in railway constructions [4].

On the other hand, maintenance is one of the most important activities in the operational stage over the life cycle of railway systems since detrimental accidents may occur if the track condition is deficient. For this reason, accurate defect detection is crucial for ensuring the trustworthiness of intelligent railway systems [5]]. Aware of this fact, many countries have developed regulations and recommendations regarding the identification of defects and failures in rolling stock and subsequent actions [6] [7]. The main incidents that must be detected include derailments of vehicles and containers, collisions, brake-related incidents, wagon overloads, and wheel overheating/deformations. For this reason, defect detection in the railway system has become a priority objective. To address these issues, recent studies have developed several approaches using Convolutional Neural Network (CNN) models to detect railway defects with high accuracy [5]. Despite progress in Computer Vision (CV) techniques, railway defect detection remains challenging due to multiple factors [8], such as the complexity of railway infrastructure, variations in lighting and weather conditions, and the presence of noise in image data [9].

A digital twin, a precise virtual replica of a physical object or system, allows for remote monitoring, analysis, and improvement of performance in a safe and controlled manner. This technology has proven valuable in critical industrial sectors, where it aids in reducing risks and maximizing operational precision [10]. With the recent development of AI models, the integration of Deep Learning (DL) models into the Digital Twin (DT) framework has shown promising results in railway defect detection [11]. Nevertheless, the shape of defects on containers is highly variable and training samples are limited. To address this problem, in [12] a high-performance pretrained vision-language model (VLM) for defect detection is proposed, and the results show an improvement in the performance of the defect detector.

A. Related Works

Automated railway infrastructure inspection is an area of significant importance in civil and railway engineering. It involves the use of advanced technologies such as sensors, drones, computer vision systems, and artificial intelligence algorithms to efficiently and accurately assess the condition of railway infrastructures, such as tracks, bridges, signals, tunnels, and stations. The goal of this automation is to improve safety, reduce operational costs, and minimize downtime, which can significantly affect the efficiency of the railway system.

One of the primary methods employed is the use of aerial vehicles (drones) equipped with cameras that can fly over the tracks and capture high-resolution images, which are then processed using computer vision algorithms to detect faults such as cracks, deformations, corrosion, and other structural damages [13].

Other methods involve using sensors placed along the infrastructure to collect real-time data and generate detailed reports on the condition of the assets [14]. One of the most prominent approaches is the use of Convolutional Neural

*This work has been supported by the Spanish PLEC2023-010343 project (INARTRANS 4.0) from MCIN/AEI/10.13039/501100011033, PID2021-126623OB-I00 project, funded by MICIN/AEI and FEDER, TED2021-130131A-I00, PDC2022-133470-I00 projects from MICIN/AEI and the European Union NextGenerationEU/PRTR, and ELLIS Unit Madrid funded by Autonomous Community of Madrid.

[1]J. Fuentes, F. Fierro, R. Barea, E. López-Guillén and L.M. Bergasa are with the Electronics Departament, University of Alcalá (UAH), Spain.{rafael.barea, elena.lopezg, luism.bergasa}@uah.es

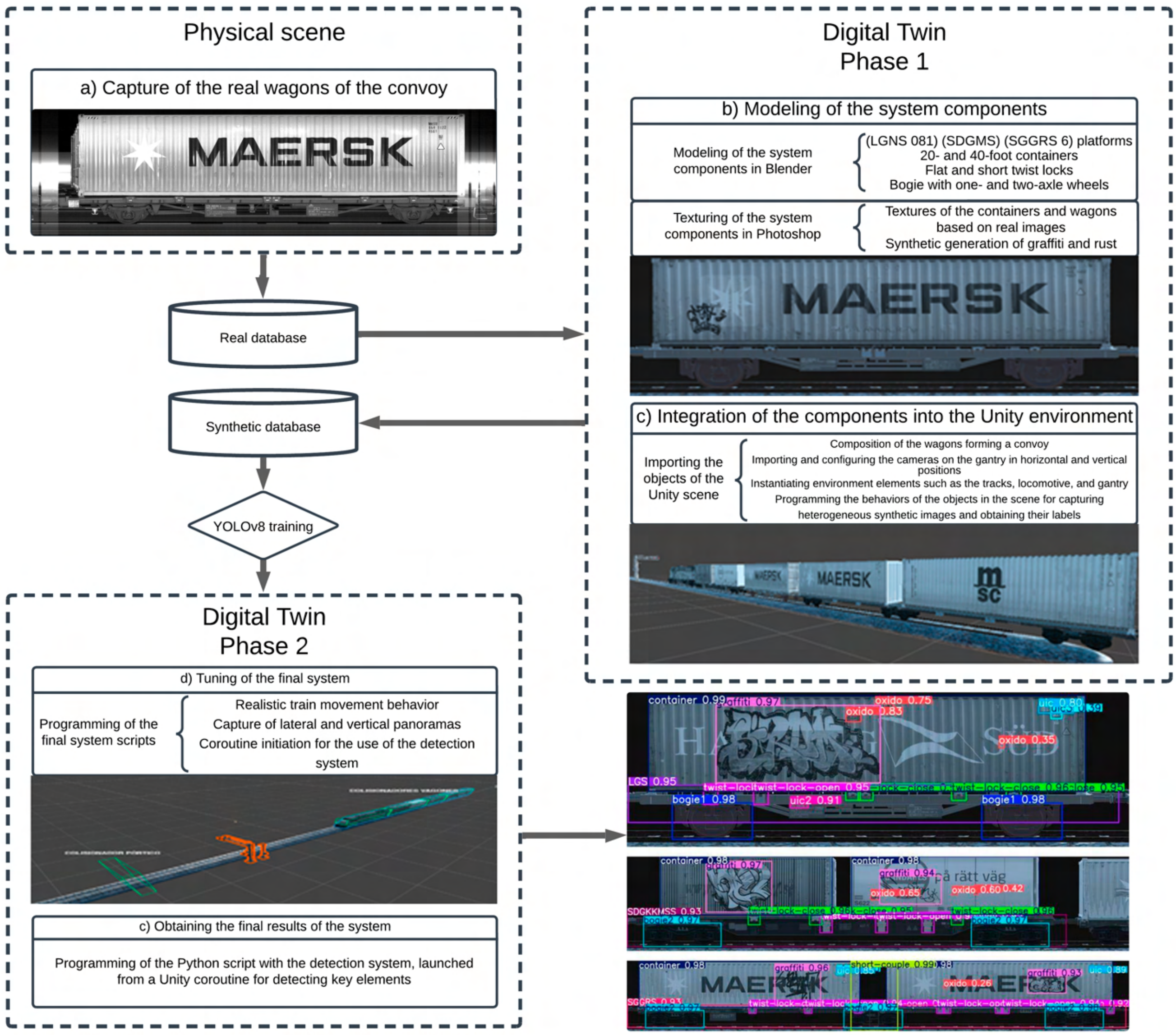

Fig. 1. DT-based framework for monitoring railway infrastructure.

Networks (CNNs). These AI techniques are used to analyze images captured by high-resolution cameras installed on railway infrastructure and detect structural and wear defects in critical parts of the trains, as well as perform predictive diagnostics, anticipating failures before they occur [15]. Finally, Allread [16], using deep learning and computer vision techniques, has created a system capable of recognising container BIC codes, wagon UIC codes , dangerous goods signs and rotating anchor bollards. These systems help plan preventive maintenance, minimizing the risk of unexpected failures and optimizing the lifespan of the wagons [17].

Nowadays, the use of Digital twin (DT) offers a new paradigm to promote the development of defect detection in railway infrastructures. Digital Twin (DT) consists of creating the virtual model of a physical entity digitally, by means of bidirectional mapping and real-time interaction between physical entities and virtual models. Digital twins have become quite popular in recent years in rail. In [18] they use a DT for anomaly detection for real-time tool condition monitoring in machining. [19] shows that DT-based applications in both rail and road can potentially be extensive in addressing operation, energy, safety and maintenance objectives. [20] develops railway applications of Augmented DT for derailment rate prediction in train operations by studying wheel and rail damage.

B. Contribution

This paper focuses on the design and development of a digital twin for monitoring Spanish railway infrastructure. Using an augmented reality environment, a monitoring system is implemented that leverages an artificial intelligence (AI)-based object detection model to capture, analyze, and identify critical elements that may jeopardize the safety of freight trains [20]. The YOLOv8 detection AI [21] was selected for its high accuracy and efficiency in identifying patterns and objects within images, enabling the detection of components such as container locks, whose integrity is crucial to cargo safety and general railway operations. Finally, a VLM is proposed to improve the performance of the object detector.

This digital twin contributes substantially to reliability and resource optimization, simulating in real-time the behavior of railway infrastructure and its interaction with monitoring elements. This paper examines the architecture of the developed system, the process of database creation, and the results obtained from detection tests conducted under various environmental conditions. This study holds potential as a replicable solution for the railway industry, advancing safety protocols and efficiency through cutting-edge technology.

II. Metodology

A. System framework

A TD-based framework for monitoring railway infrastructure and detecting defects in wagons is proposed. As shown in Fig. 1, the framework consists of a physical scene and a DT scene. Firstly, using digital twin technology, the perception system (cameras) obtains a sequence of real images of the convoy (wagons and platforms). Secondly, the wagon configuration scheme is adjusted based on the digital twin's knowledge of wagon and platform types. After that, the mapping and data interaction between the physical and twin scenes is performed and the anomalies in the wagons are detected. Finally, a report is generated with the composition of the convoy and the defects found.

The DT-based defect detection and convoy composition flow is commented below: (1) Image acquisition system. A high resolution ToF camera acquires the images of the wagons composing the convoy. (2) Detection system. This section is implemented using a Yolov8 detection algorithm that is deployed on a server. The detection of the convoy composition and wagon defects is performed on the images collected in real time. The yolov8 detection module has been previously trained using synthetic images realistically modeled in the digital twin. (3) Report generation. The system generates a report indicating the composition of the convoy, identification codes of containers and platforms, defects in wagons and failures in safety elements.

B. Database

For the present work, a initial database of 6,000 images of freight trains was used. All the images were taken using a scanning camera, with the objective of photographing the entire visible surface of the wagon. The actual database initially had basic labels in COCO format for some elements: BIC and UIC codes of the platforms and containers, dimensions of the containers, etc. Figure 2 shows an example of freiht wagon and labels (green rectangles are used to locate codes and defects).

The database has been completed by manual labeling of other elements of interest (using the LabelStudio tool):

- Wagon and container license plates: ILU/UIC codes.

TABLE I. Wagon models

Model	Shaft	Wheels	Twist Locks	Articulated	Containers
LGNS 081	2	1	16	No	1
SDGMS	2	2	16	No	2
SGGRS 6	3	2	24	Yes	2

- Container dimensions.
- Boggies of the wagon: Number of wheels per boggie.
- Type of wagon platform.
- Detection of safety elements: Twist locks (open/close).
- Surface defects such as graffiti and rust (surfaces in poor condition).

With all this, a real image database of 6,000 fully labeled freight wagon images is finally available.

C. Virtual Modeling

The modeling process consisted of digitizing each type of wagon using the real metrics of the wagons using the Blender tool [22]. Once the structure of the wagons has been modeled, the textures have been incorporated based on the real database using the Photoshop tool [23].

The three most repeated platform models have been implemented in the real database (table I).

For the pieces that compose the wagons, several types of containers and safety elements such as short and long twist locks (open/close) have been modeled as shown in the figure 3.

The containers and the bogies of the wagons have been imported from some 3D model libraries and have been modified to have 4 different models. In the same way as with the rest of the 3D objects, different textures of the containers have been designed, based on the real database, to obtain a more heterogeneous synthetic database. The container models with their textures can be seen in the figure 4.

1) Convoy implementation: Once the individually developed elements are available, the wagons and the complete convoy are modeled. Figure 5 shows the result of the virtual modeling of a freight train.

2) Virtual dataset: For the generation of hyper-realistic synthetic images of freight wagons a single script has been realized that randomizes some elements of the wagon as:

- Textures of the container and wagons. Different types of wagons with different platforms and containers are generated.
- Status and location of twist locks. Security elements are placed in their real location and in open/close state.
- Graffiti and rust: examples of graffiti and rust with a random shape and size are painted on the texture of the containers.

Using the Unity engine [24], we simulate the operation of the convoy circulating along a track and when it passes through the gantry we obtain virtual images of the convoy based on the cameras placed in the gantry. The figure 6 shows the convoy circulating under the implemented gantry.

Fig. 2. Freight wagon image with initial labels

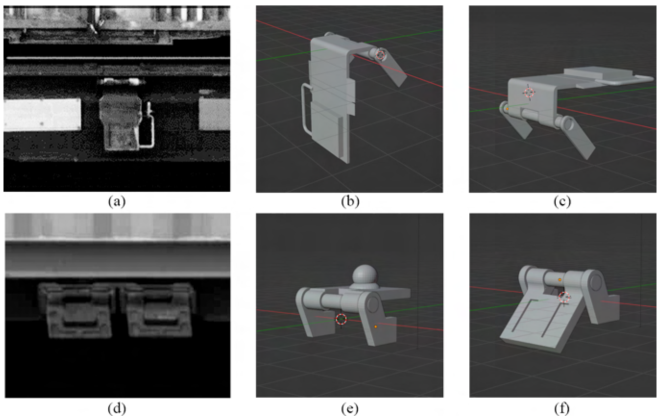

Fig. 3. Twist locks.

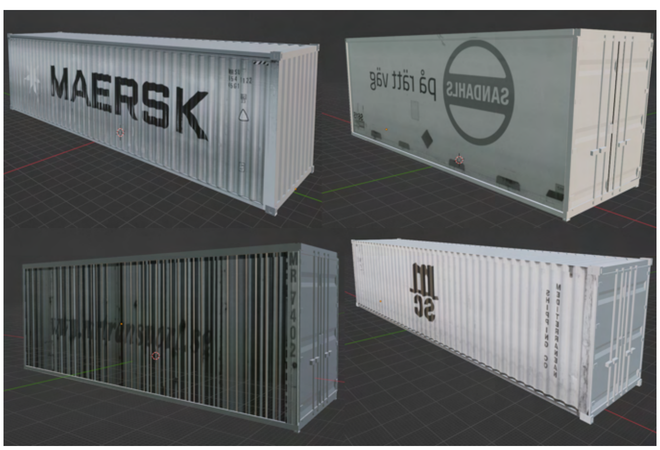

Fig. 4. Containers.

Fig. 5. Convoy.

Fig. 6. Gantry.

In this way, a system has been developed that allows the parameters of the elements that make up the convoy to be configured and virtual images to be generated automatically. A database of 6,000 virtual images has been generated, including all types of platforms, containers, codes and number plates, position and condition of safety elements, etc. Defects such as graffiti and rust stains are also randomly painted. At the same time and in an automated way, files with the labels corresponding to each image are generated in YOLO format for subsequent detection using Deep Learning techniques.

3) Virtual dataset training: The core of the defect detection is an application based on the YOLOv8 model. The YOLOv8 model is one of the most advanced detection model for real-time detection. YOLOv8 introduced new features and optimizations that make it an ideal choice for various object detection tasks in a wide range of applications. We train the model using the previously created virtual dataset. We train our models to convergence using a single NVIDIA RTX 3090. The table II shows the training performance achieving 93.27 % accuracy in defect identification and detection. Figure 8 shows the normalized confusion matrix

Fig. 7. Detections on virtual image.

where it can be seen that the system is able to identify the platform type, identify ILU codes, detect containers, detect boggie type, identify the state of safety elements (twist lock) and detect defects.

TABLE II. Validation set perfomance

Metric	Yolov8x
Success Rate [%]	93.27

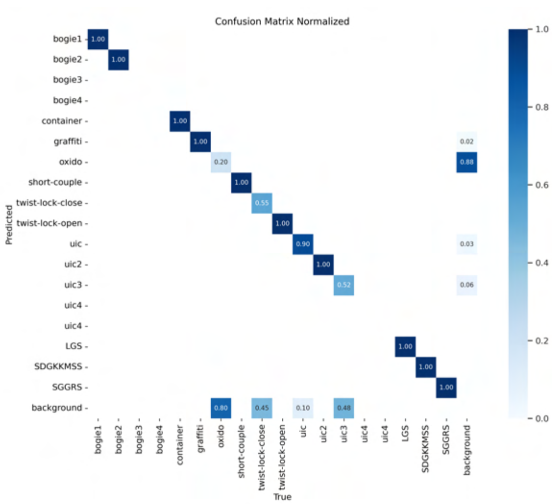

Fig. 8. Confusion matrix.

D. Results. Digital Twin data flow

Once the virtual model has been trained, the system must be validated in real conditions by processing the images obtained by the perception system placed on the gantry.

For this purpose, when the perception system detects a convoy on the track, it generates a sequence of images comprising the different wagons. These images are processed and analyzed by the detection system. This results in the identification of the wagons, the type of platform and container being transported, the safety elements and possible defects.

As shown in the figure 9, the model makes detections similar to those of the synthetic images, which means that the model behaves correctly in the physical process.

Subsequently, a report (JSON format) containing all the information collected from the convoy is generated with the detected data. If any anomaly or safety defect is detected, the corresponding alarm signals are reported.

III. Conclusions and Future works

A framework based on a digital twin can make a substantial contribution to rail maintenance management and railway infrastructure inspection. This study focuses on the design and development of a digital twin for the monitoring of the Spanish railway infrastructure and presents the effectiveness of the proposed DT framework in the identification of platforms and containers, as well as in the detection of defects in wagons. This digital twin contributes substantially to reliability and optimization of resources, simulating in real-time the behavior of railway infrastructure and its interaction with monitoring elements. The framework consist of an augmented reality system that leverages an artificial intelligence (AI)-based object detection model to capture, analyze, and identify critical elements that may jeopardize the safety of trains and freight wagons. The YOLOv8 detection AI is used for its high accuracy and efficiency in identifying patterns and objects within images, enabling the detection of components such as container locks, whose integrity is crucial to cargo safety and general railway operations. This paper examines the architecture of the developed system, the process of database creation, and the results obtained from detection tests conducted under various environmental conditions. The results obtained in defects detection are satisfactory and prove that this proposal has potential as a replicable solution for the railway industry, advancing safety and efficiency protocols through state-of-the-art technology.

One of the main problems encountered during the realization of this work has been the way to enter the defect information in the model. To date, most of the work related to the identification and detection of defects in railcars has been based on manual annotation by an expert. This often requires a large manual annotation effort, considerable computing power and large amounts of data for training. Visual language models (VLMs) offer a promising alternative due to their exceptional performance in visual reasoning in a variety of domains [25] . Therefore, our next goal is to investigate the use of VLM in automatic detection systems in order to improve the interpretation and reasoning about the relationships and coherence of the visual content of an image.

Fig. 9. Detections on real image.

REFERENCES

[1] A. Pool, “Digital twins in rail freight - the foundations of a future innovation,” October 2021.

[2] E. Union, “Europe’s rail joint undertaking,” December 2024.

[3] L. Brüll, “The role of digital twins on rail operations at eu container terminals : Crucial or negligible?,” July 2024.

[4] S. Kaewunruen, J. Sresakoolchai, and Y. Lin, “Digital twins for managing railway maintenance and resilience [version 2; peer review: 2 approved],” *Open Research Europe*, vol. 1, no. 91, 2021.

[5] L. F. Y. C. e. a. Ferdousi, R., “A reusable ai-enabled defect detection system for railway using ensembled cnn,” *Applied Intelligence*, vol. 54, no. 20, 2024.

[6] M. de transporte y movilidad sostenible, “informe comisión técnico-científica sector ferroviario,” 2024.

[7] U. Gov, “Rail accident investigation branch,” 2015.

[8] M. A. Rahman, H. Taheri, F. Dababneh, S. S. Karganroudi, and S. Arhamnamazi, “A review of distributed acoustic sensing applications for railroad condition monitoring,” *Mechanical Systems and Signal Processing*, vol. 208, p. 110983, 2024.

[9] F. Guo, J. Liu, Y. Qian, and Q. Xie, “Rail surface defect detection using a transformer-based network,” *Journal of Industrial Information Integration*, vol. 38, p. 100584, 2024.

[10] L. Xin, L. Xiu, and X. Wan, “Overview of digital twins application and safe development,” *Journal of system simulation*, vol. 31, no. 3, pp. 385–392, 2019.

[11] S. Ghaboura, R. Ferdousi, F. Laamarti, C. Yang, and A. E. Saddik, “Digital twin for railway: A comprehensive survey,” *IEEE Access*, vol. 11, pp. 120237–120257, 2023.

[12] Y. Tan, J. Shan, and J. Wang, “Multi-level supervised vision language model based steel surface defect detection,” in *Third International Conference on High Performance Computing and Communication Engineering (HPCCE 2023)*, vol. 13073, pp. 67–72, SPIE, 2024.

[13] P. Aela, H.-L. Chi, A. Fares, T. Zayed, and M. Kim, “Uav-based studies in railway infrastructure monitoring,” *Automation in Construction*, vol. 167, p. 105714, 2024.

[14] C. Dinesh, A. Kingson, K. Suresh, *et al.*, “Smart rail track diagnostics and surveillance system for enhanced railway in frastructure maintenance and safety using iot,” in *2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, pp. 225–230, IEEE, 2024.

[15] K. Oh, M. Yoo, N. Jin, J. Ko, J. Seo, H. Joo, and M. Ko, “A review of deep learning applications for railway safety,” *Applied Sciences*, vol. 12, no. 20, 2022.

[16] A. AI, “Renfe mercancías enhances wagon inspection with artificial vision,” 2025.

[17] W. Gong, M. F. Akbar, G. N. Jawad, M. F. P. Mohamed, and M. N. A. Wahab, “Nondestructive testing technologies for rail inspection: A review,” *Coatings*, vol. 12, no. 11, 2022.

[18] Z. Liu, Z.-Q. Lang, Y. Gui, Y.-P. Zhu, and H. Laalej, “Digital twin-based anomaly detection for real-time tool condition monitoring in machining,” *Journal of Manufacturing Systems*, vol. 75, pp. 163–173, 2024.

[19] M. Spiryagin, J. Edelmann, F. Klinger, and C. Cole, “Vehicle system dynamics in digital twin studies in rail and road domains,” *Vehicle system dynamics*, vol. 61, no. 7, pp. 1737–1786, 2023.

[20] E. Bernal, Q. Wu, M. Spiryagin, and C. Cole, “Augmented digital twin for railway systems,” *Vehicle System Dynamics*, vol. 62, 2024.

[21] G. Jocher, A. Chaurasia, and J. Qiu, “Ultralytics yolov8,” 2023.

[22] B. O. Community, “Blender - a 3d modelling and rendering package,” 2018.

[23] Adobe Inc., “Adobe photoshop.”

[24] Unity Technologies, “Unity,” 2023. Game development platform.

[25] E. Jin, Q. Feng, Y. Mou, S. Decker, G. Lakemeyer, O. Simons, and J. Stegmaier, “Logicad: Explainable anomaly detection via vlm-based text feature extraction,” 2025.