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Transforming System Test

STAN Cătălin[1], TOGHE Răzvan[2], VĂIDIAN Iulia[3]

[1]Marquardt Schaltsysteme SCS, Research and Development Department, Software Engineer

[2]Marquardt Schaltsysteme SCS, Research and Development Department, Software Test Engineer

[3]OMiLAB NPO, Berlin, Germany, Community of Practice Manager

Abstract

During the product System Test phase, it is necessary to determine the passed/failed status of tests by analyzing network signals. A second layer of verification is introduced by using a camera to take pictures triggered by these signals. An image recognition model is used to identify the successful operation of the product (tests passed), by processing the captured images. The main goal of the proposed method is the improvement of quality assurance techniques. The possibility of automated defect detection in the manufacturing process will lead to improved productivity, higher product quality, and transparency in reporting.

Keywords: System Test, image recognition, verification, conceptual modelling, resilience, sustainability, human-centric, industrial processes, automotive

1. Introduction

In today's rapidly evolving industrial landscape, resilience has become a critical characteristic for companies to ensure the continuity, reliability, efficiency, and quality of their industrial processes. Moreover, sustainability in the context of industrial processes is typically associated with reducing waste, conserving resources, and minimizing the environmental impact of production activities. By optimizing internal processes, a company can ensure its long-term operational efficiency. People are at the center of these processes. Therefore, a human-centered approach to process re-design is a must. It places the needs and experience of the people – engineers, operators, and stakeholders – at the forefront of process design and/or optimization and acknowledges that while automation and advanced technologies are crucial, the ultimate goal is to empower human workers.

In this paper we will present the optimization of a system testing process within Marquardt Company, following a conceptual modeling workshop facilitated by OMiLAB NPO and with participation of professors from the "Lucian Blaga" University of Sibiu. Marquardt Company is a German automotive supplier which considers the three pillars of resilience, sustainability, and human-centricity for its processes in order to keep up with the rapidly evolving industrial landscape.

1 Transformation of the industrial processes

1.1 Resilience of industrial processes

For the proposed use case, within the product verification activities at System Test, the introduction of a second layer of verification supports the resilience of Marquardt Company. The System Test phase plays a crucial role in verifying the functionality and quality of products before they are released to the market. Traditionally, this verification phase relies heavily on network signal analysis to determine the pass/fail status of tests. Nevertheless, relying on a single verification method introduces vulnerabilities, such as undetected defects that could compromise the quality of the product. Therefore, the introduction of a second layer of verification also acts as a means of increasing the trust level for test results and business trust between supplier and customer, with Marquardt being a supplier that focuses on pro-active testing. Automation of the prototyping process and industrial production series process also supports resilience.

1.2 Sustainability of industrial processes

As stated above, by optimizing internal processes, a company can ensure its long-term operational efficiency. The presented use case has no direct influence/impact on the changing market conditions, but it maintains Marquardt's internal operational efficiency and flexibility. As the image recognition approach matures and becomes a stable mechanism to validate tests, the network signal analysis approach could be phased out, at least in some cases. This will reduce waste and preserve resources. Further, it will also free up valuable test time (by removing the physical wiring, there is no need to solder additional wires or execute additional test-box preparation activities), resulting in much faster testing cycles.

1.3 Human-Centered approach for the industrial processes

This case study introduced engineers to Design Thinking and Conceptual Modelling techniques and tools as a proven approach towards finding an optimal solution. Using paper figures as actual anchors for discussion, engineers from Marquardt, professors at ULBS ("Lucian Blaga" University of Sibiu) in partnership with OMiLAB NPO conducted a joint workshop within this scope. The workshop had the following objectives:

- to encourage engineers to understand the operator's needs when designing processes,
- to foster creativity by encouraging engineers to explore possible solutions together before actually implementing them; the exploration proved to be iterative starting with the physical paper figures, digitalizing the co-created scenes and continuing to refine them .
- to collaborate across company departments, but also outside company, having invited engineers with different backgrounds and professors alike to work together to solve the given problem.

The workshop started with a presentation of the problem in focus, a setup for the tool environment by OMiLAB , followed by the actual debate/collaboration around a central table capturing the attention of all participants. The scenes created with the help of paper figures were captured and digitalized using the Scene2Model tool. The result of this workshop will be detailed in the next chapter.
Further, the implementation of this case study at Marquardt Company will help engineers to improve their programming skills and knowledge within image processing and computer vision domain. This is a win-win situation as there is an ever-growing need for engineers to expand their expertise in these emerging fields.
Another significant benefit derived from the automation introduced in System Test is the ability to free up engineers from repetitive and time-consuming tasks. They could be re-allocated to other higher-value work (e.g. optimizing current processes, innovating) resulting in greater employee job satisfaction.

2 The second layer of verification

As stated before the integration of a human-centered design approach was facilitated by a joint workshop between Marquardt, ULBS, and OMiLAB. In this section, we present the solution using screenshots of the digital scenes captured during the actual workshop. The human interaction and discussions, which were happening around physical paper figures, were digitally documented using the Scene2Model tool from OMiLAB. This tool captures the transition from the actual state (the “as-is” problem) to the future state (the desired solution), presented as a visual story consisting of four scenes (see Fig. 1).
There are many similar products under discussion, grouped by their features into what is referred to as the Switch Panel Product Family, which contains hundreds of variants. These products include, but are not limited to, dashboard panel controls, side door panels, or steering wheel panels. Each of these variants has specific testing requirements, therefore, the solution must be flexible enough to accommodate them.

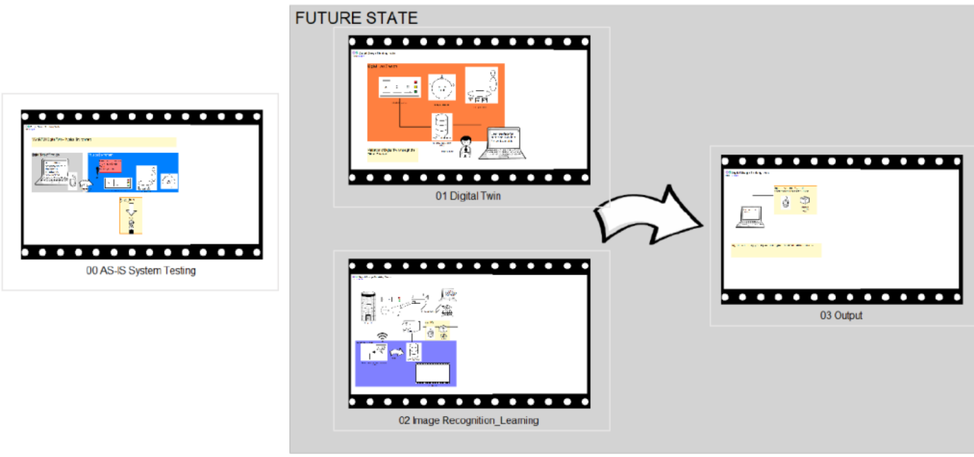

Figure. 1. STORYBOARD: Image Recognition for System Test

The concepts of Digital Twin and Digital Shadow are rather new to the engineers at Marquardt, but daily System Test activities show that the proprietary CANoe Network Simulator, together with the product’s signals descriptions and values, is a good

candidate for creating a Digital Shadow of these products. By adding the visual aspects of the product's various operating states, synchronized with signal values, this Digital Shadow can evolve into a Digital Twin.
The current System Test process involves testing the complete product using a Hardware-In-the-Loop (HIL) test bench connected to the network simulator via Fast Data eXchange (FDX) protocol. By using HIL, the solution fully integrates real-world hardware and simulated environments. Based on the signal values recorded during these tests, the test engineer validates the product's expected behavior. In addition, a human visual inspection is performed and a Test Report is generated as the final output (see Fig.2). Automating this process with image recognition further reduces the need for human visual inspections, thereby reducing the human error. As a result, the consistency and reliability of the test results is improved, enhancing business trust and overall product quality.
A first step towards the future state is the creation of a database containing images of the product's operating modes. Building this database will be time consuming at first, but we expect the effort to be paid-off after 3-4 test cycles. For example, the seat temperature button, which has three levels - low, medium, and high – would correspond to three distinct images showing one, two, or three LEDs illuminated respectively. Similarly, for a rotary knob, the different positions of the knob,

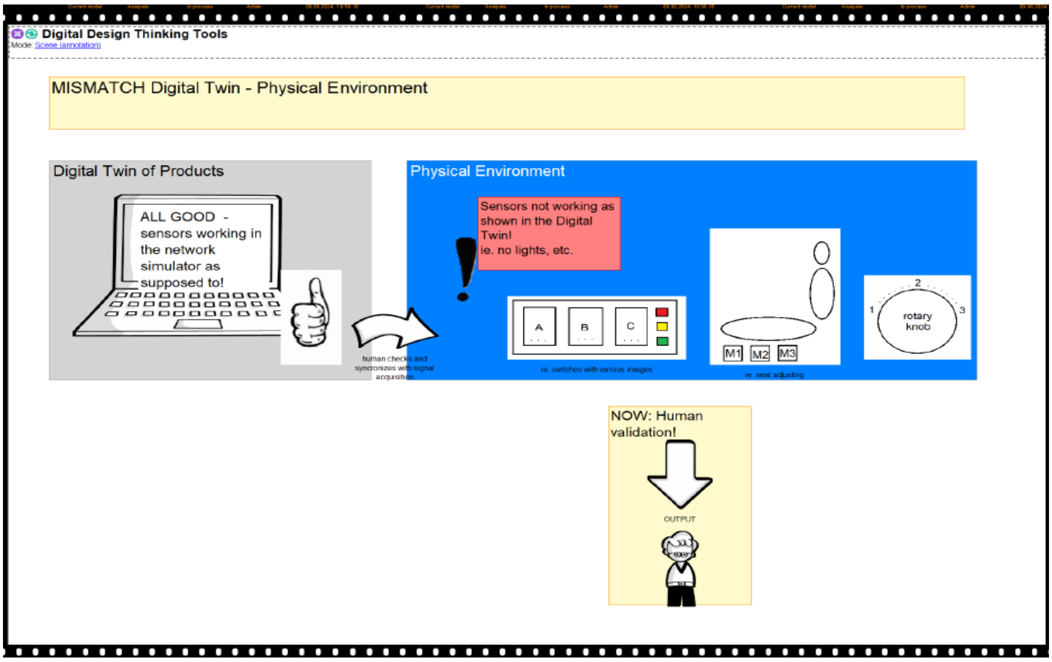

Figure. 2. AS-IS: System Testing

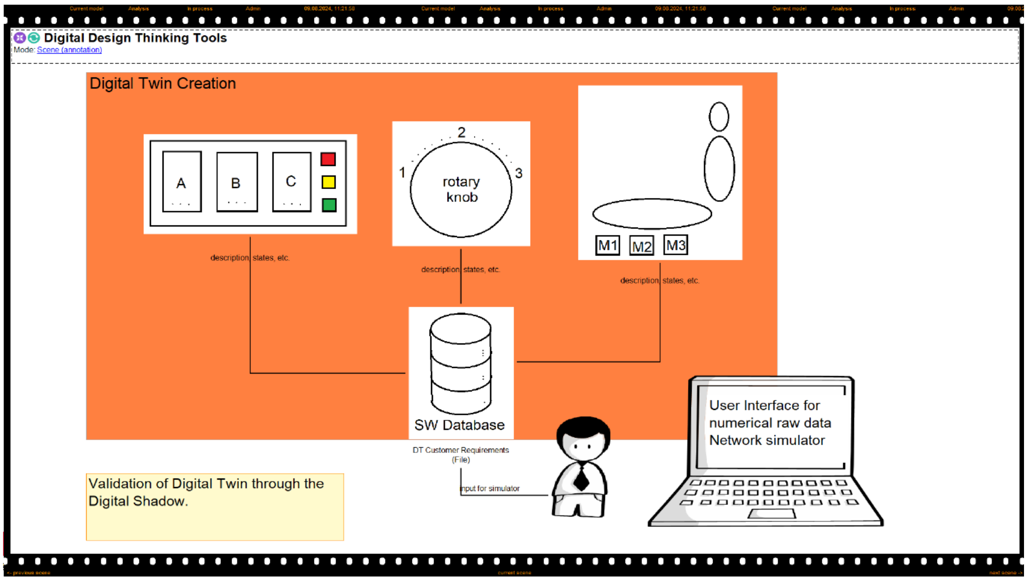

Figure. 3. FUTURE STATE: Digital Twin

indicate different functions, or different intensities. They would also be associated with distinct images.

Next, the solution then requires a mapping of these pictures to the product's signal values within the same database (see Fig.3). This will ensure that each signal state is accurately reflected by its corresponding visual representation.

These images form the basis for later training of a Machine Learning (ML) algorithm. The ML model will be used to analyze and correctly identify the images captured during real-world tests (see Fig.4). It will be trained on a diverse set of images, allowing it to generalize well across different product variants. This ensures that the solution remains effective, even for updated versions of the existing products. We should remember that one of the goals is to automate the verification of the product's response based on the simulation inputs.

In the future System Test setup, most of the existing equipment will remain in place, such as the product storage space, the mounting fixture, the data acquisition equipment, the HIL test-bench and the PC running network simulator. However, a camera will be added to capture images of the product (in JPG format) as it responds to the simulation inputs.

For the image recognition process, YOLOv5 will be used. YOLOv5 is well regarded in the open-source community and its use is well documented, making it an ideal choice. It has advanced object detection capabilities allowing it to quickly and accurately identify key features of the product. Its open-source nature also means it can be customized for Marquardt's specific internal use cases, offering flexibility as testing requirements evolve.

The image recognition will be handled by a separate PC, distinct from the one controlling the HIL test-bench. This dedicated machine, equipped with a powerful graphics processing unit (GPU), will handle the computational load, preventing the HIL system from being overburdened. . In this way it is ensured that the entire system remains stable enough and responsive, even when handling large image datasets. It also allows the HIL to focus solely on controlling the physical hardware. We can also appreciate the modularity of this solution as it provides flexibility for future expansions (e.g. adding hardware for more complex tests). The detection results will

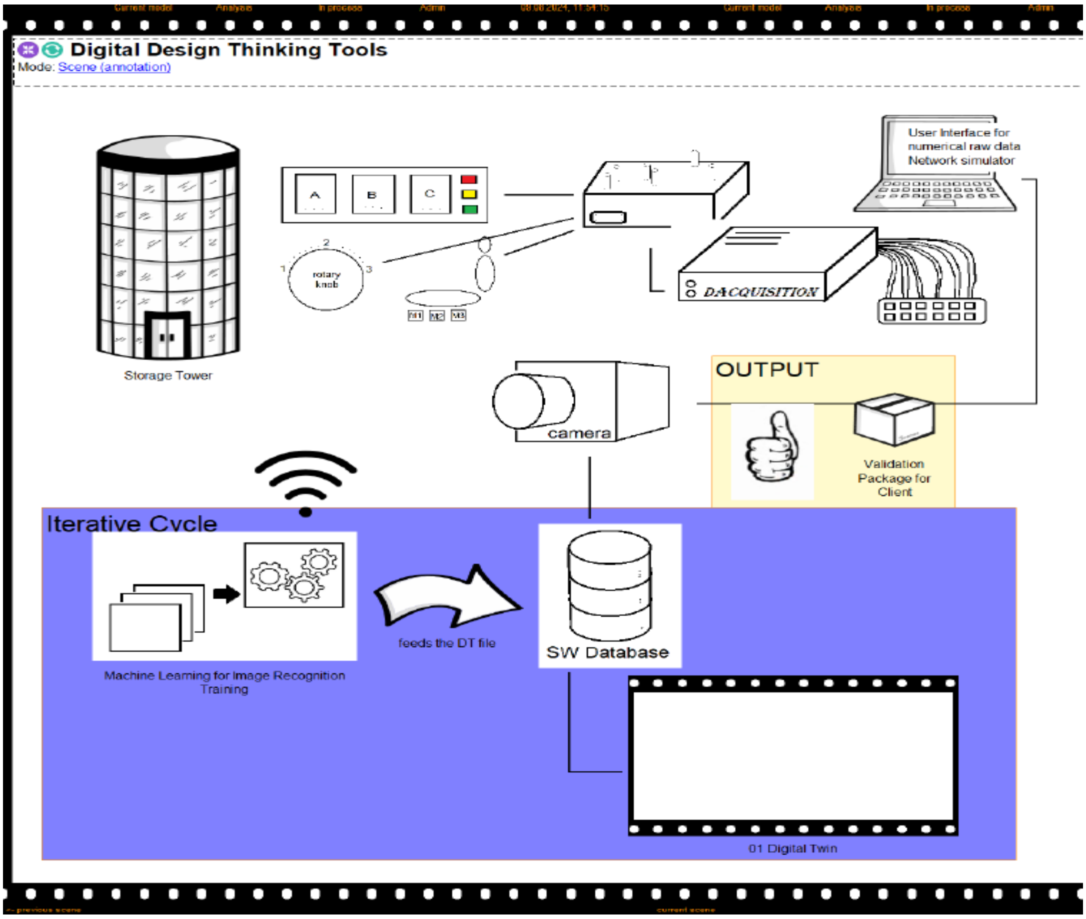

Figure 4. FUTURE STATE: Image Recognition Learning

be sent back to the main PC running the network simulator as JSON strings, including information about the test pass/fail criteria, the final image, and any other relevant information (see Fig. 6).

The final output of the solution is an automatically generated comprehensive test report, which includes test pass/fail criteria, visual evidence from the image recognition system, detailed signal data, and traceability between requirements and tests executed. This report is delivered to the customer as a Validation Package, providing transparency and confidence in the testing process at Marquardt (see Fig.5).

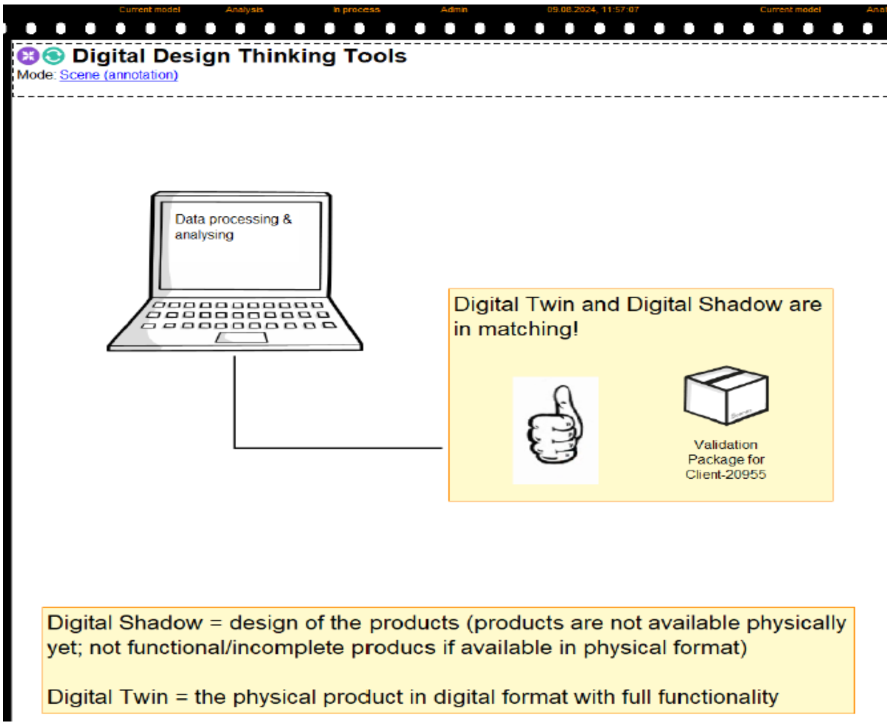

Figure 5. FUTURE STATE: Output

3 Key skills and necessary competences

The skills required to complete the tasks derived from this use case are the ability to analyze temporal events and signals, the ability to operate and deploy complex systems (hardware and software), and the capability to work effectively in a team environment.

The knowledge prerequisites are basic programming skills in Python, C#, or Java, and the use of computer vision libraries like OpenCV and deep learning frameworks such as TensorFlow or PyTorch. These tools are essential for training machine-learning models and deploying the image recognition components of the solution. Additionally, basic knowledge of common network protocols such as HTTP is required, as well as specific expertise in the automotive network simulators used at Marquardt (e.g. CANoe) and their protocols like FDX to ensure accurate communication between hardware and test environment.

Proficiency in mathematical concepts, mainly linear algebra, calculus, and probability is indispensable for Computer Vision Engineers. Data analysis skills are equally important to interpret the test results and tuning algorithms.

Soft skills like problem-solving and critical thinking are essential to troubleshoot complex system interactions and to identify potential issues early in the testing phase. Engineers should demonstrate attention to detail, especially when it is about test accuracy or the integration of various system components.

Furthermore, strong communication skills are vital for collaborating across teams and for documenting processes, and producing clear, concise reports (such as the final customer test report).

4 Results

The case study is in its early stages of development. While the transformation is not yet fully deployed, key components of the system have been prototyped and integrated. For example, the camera-based image recognition system and Machine Learning algorithm training have been implemented (see Figure 6), and early tests showed promising results (e.g. 90% average recognition accuracy). The Hardware-In-the-Loop (HIL) test bench and CANoe network simulator are already an integral part of the testing process with the second layer of verification (image recognition) being gradually introduced.

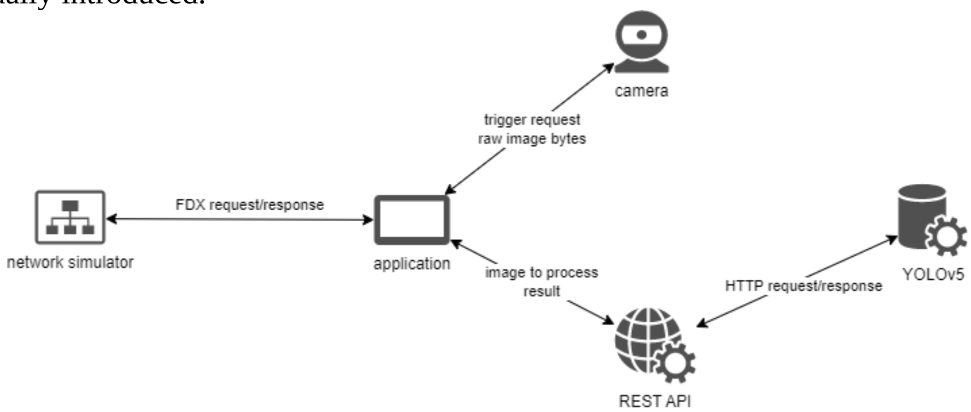

Figure 6. Implementation of main components of the solution

As the system matures we expect greater benefits in terms of productivity (e.g. an engineer would spend less time on visual inspection, therefore we estimate a 10% increase in his work efficiency), cost savings (e.g. related also to man-hours per task, a time reduction in System Test expected to be 15%-20%), reporting transparency (e.g. will include the real captures from the camera and have traceability to the executed tests) and customer satisfaction leveraging further business economic benefits.

5 Conclusions

The integration of advanced automation technologies, such as image recognition and machine learning, alongside more traditional Hardware-In-the-Loop (HIL) testing, represents an important shift for Marquardt in its journey towards Industry 5.0. The proposed solution supported by both human-centered design and Digital Twin concepts, demonstrates the potential to improve product development processes (e.g. System Test phase) and business processes alike, reducing manual errors and enhancing both accuracy and transparency.

By automating repetitive tasks, engineers are freed up to focus on more creative and high-value activities, this aspect being an important step in the Industry 5.0 vision: technology empowers people, not replaces them.

Marquardt's experience shows the value of collaborative innovation between teams, jointly working on solutions with external partners like ULBS, OMiLAB and also integrating the latest machine learning algorithms with existing network simulation and testing infrastructure. Based on these experiences we outline below some key recommendations for transitioning to Industry 5.0:

- Adopt a human-centered approach: engaging employees in the design and implementation process – through workshops, training, and collaboration – ensures that technologies empower people not replace them. The introduction of Design Thinking into Marquardt's process is a good example of how collaborative problem solving can lead to innovative solutions.
- Invest in skill development and lifelong learning: as companies introduce new technologies like computer vision and machine learning, employees will need to upgrade their skills, knowledge, and competencies for new roles. Companies should invest in training programs, not only in technical areas like Python, and machine learning, but also in soft skills like teamwork and Design Thinking.
- Be data-driven: the success of Industry 5.0 lies in the ability to collect real-time data from physical and digital systems. A data-driven approach is no longer optional, as continuous monitoring and feedback loops will improve product quality faster than ever and maximize operational efficiency.

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References

[1] Gonzalez Rafael C., Woods Richard E., *Digital Image Processing*, London; Sydney, Pearson Prentice Hall, 2018.
[2] https://www.pyimagesearch.com/2015/12/07/local-binary-patterns-with-python-opencv/
[3] Forsyth, D. A., & Ponce, J. (2002). *Computer vision: a modern approach*. Prentice Hall professional technical reference.
[4] Karagiannis, D. (2024). Digital Twins for Design Thinking Support Innovative Business Models, The Kyoto Economic Review, 2024, Volume 198, Issue S, Pages S123-S146, Released on J-STAGE. DOI: https://doi.org/10.57475/keizaironso.198.S9
[5] Karagiannis D. et al. (2020). OMiLAB: A Smart Innovation Environment for Digital Engineers. In: Camarinha-Matos L.M., Afsarmanesh H., Ortiz A. (eds) Boosting Collaborative Networks 4.0. PRO-VE 2020. IFIP Advances in Information and Communication Technology, vol 598. Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-62412-5_23
[6] OMILAB Team. (2020). A Digital Innovation Environment powered by Open Models Laboratory. DOI: http://doi.org/10.5281/zenodo.3899990
[7] Vaidian, I., Jurczuk, A., Misiak, Z., Neidow, M., Petry, M., Nemetz, M. (2022). Challenging Digital Innovation Through the OMiLAB Community of Practice. In: Karagiannis, D., Lee, M., Hinkelmann, K., Utz, W. (eds) Domain-Specific Conceptual Modeling. Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-93547-4_3
[8] Muck, C., Palkovits-Rauter, S. (2022). Conceptualizing Design Thinking Artefacts: The Scene2Model Storyboard Approach. In: Karagiannis, D., Lee, M., Hinkelmann, K., Utz, W.

(eds) Domain-Specific Conceptual Modeling. Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-93547-4_25

[9] Toncian, V., Florea, A., David, A., Morariu, D., Cretulescu, R. (2024). Leveraging Collaboration for Industry 5.0: Needs, Strategies and Future Directions. In: Camarinha-Matos, L.M., Ortiz, A., Boucher, X., Barthe-Delanoë, AM. (eds) Navigating Unpredictability: Collaborative Networks in Non-linear Worlds. PRO-VE 2024. IFIP Advances in Information and Communication Technology, vol 726. Springer, Cham. https://doi.org/10.1007/978-3-031-71739-0_21