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INTEGRATING DIGITAL TWINS AND COMPUTER VISION FOR REAL-TIME INDUSTRIAL MONITORING: AN EXPLORATORY STUDY WITH COLOR DETECTION

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This article investigates how Digital Twins (DT) and Computer Vision (CV) technologies can be integrated into industrial environments to enhance real-time monitoring, object detection, and process control. The research began with a comprehensive literature review to establish the fundamental concepts and potential synergies between DT and CV. Following that, a functional prototype was developed using Python, color-based object recognition, and webcam-based image feeds to simulate real-world industrial scenarios. This study contributes to the ongoing development of Digital Twin and computer vision integration by demonstrating a proof-of-concept prototype capable of real-time object color detection in an industrial-like learning environment. The system was successful in identifying the physical objects utilized in the proof-of-concept. Evaluation tests under varying conditions confirmed the detection effectiveness and accuracy, indicating significant potential for industrial applications such as quality control, automation, and operational efficiency.

Palavras-chave: Digital Twin, Computer Vision, Prototype Development, Industry 4.0, Real-Time Monitoring, Object Detection, Smart Manufacturing

1. Introduction

The introduction of Industry 4.0 technologies has transformed manufacturing processes by promoting the integration of physical and digital systems. Among these, Digital Twin (DT) and Computer Vision (CV) stand out for their transformative potential. DT, which serves as a virtual replica of physical assets, allows for dynamic, real-time synchronization between the physical and digital domains (BARRICELLI; CASIRAGHI; FOGLI, 2019). Computer vision, a subfield of artificial intelligence, allows machines to interpret and act on visual data by utilizing advanced imaging and machine learning algorithms (GILL et al., 2024). When DT and CV are combined, they enable real-time industrial monitoring, simulation, and control, creating an important framework for automation.

This integration is especially important in today's complex industrial environments that require flexibility. CV eliminates the need for manual input in pick-and-place operations by detecting object coordinates in real-time, whereas DT simulations validate and optimize robot actions, reducing human error and improving adaptability (CHIDDARWAR; JAKHOTIYA; RAHUL, 2024). Such implementations demonstrate the practical benefits of combining DT and CV for streamlined automation.

The practical application of DT-CV systems is based on cyber-physical production systems (CPPS), which enable real-time operational control via interconnected physical and cyber layers. DING et al. (2019) proposed a DT-CPPS architecture to improve smart manufacturing by enabling real-time data flows and system interoperability. Furthermore, the use of Digital Twins in IIoT systems has improved the synchronization and adaptability of physical devices to virtual models (JIANG; GUO; WANG, 2021).

In this context, Learning Factories—also referred to as Learning Labs—play a crucial role as experimental environments for testing and validating emerging technologies before they are applied in full-scale production. Learning Factories have emerged as important educational and experimental environments for implementing such advanced technologies. These factories act as controlled testbeds to reduce uncertainties and evaluate new technology integration (ABELE; METTERNICH; TISCH, 2019; DURÃO et al., 2019). They are especially important in training workers and validating DT-CV systems before implementing them in real-world production environments.

In order to fulfill increasingly complex customer needs and a greater product variety (ELMARAGHY et al., 2013), flexible production lines have also been implemented, as well as testbed facilities where new technologies can be experimented with and assessed prior to entering the production stage. Using learning factories (ABELE; METTERNICH; TISCH,

2019) is one alternative to manage uncertainties (DURÃO et al., 2019; MARZOLLA et al., 2024), and to explore technology demonstrators in a relatively controlled, but still reality-grounded industrial environment, also with a strong teaching-learning context. As such, they can be ideal to implement proof-of-concept Digital Twin prototypes, which can be studied and developed for later adoption in manufacturing companies.

Despite the promise of DT and CV integration, practical implementations and validations remain limited, especially in educational testbeds like learning factories. Synchronization delays, complex system modeling, and limited standardization impede the full implementation of DT-CV solutions. Furthermore, as stated by Grieves and Vickers (2017), human factors and emergent behaviors frequently introduce uncertainties that could threaten system reliability. To overcome these barriers, effective integration strategies and validation frameworks are required.

Drawing on relevant literature and validated frameworks, this study aims to develop and validate a proof-of-concept integration of Digital Twin and computer vision technologies within a learning factory environment, focusing on real-time object detection and synchronization between physical and digital layers. Our application includes the color identification of the object picked by a pneumatic setup, which uses a scaled-down version of a transfer line controlled by an industrial CLP (ZANCUL et al., 2024). The prototype can identify four different colors of an object that is handled by the experimental pneumatic setup, and can be integrated with a Digital Twin platform being developed.

The remainder of this paper is organized as follows: Section 2 reviews the extant literature on DT technologies, computer vision focusing on industrial applications, and also computer vision-enabled Digital Twins. Section 3 describes the methodology for the research, including the project and experimental setup for the prototype. Section 4 presents and discusses the results of the application. Finally, Section 5 concludes the study.

2. Literature Review

Digital Twin technology, first proposed by NASA, has become a cornerstone of smart manufacturing strategies. It enables virtual modeling of physical assets and processes, allowing for real-time monitoring, diagnostics, and predictive analysis (GRIEVES & VICKERS, 2017). The increasing use of DT in aviation, healthcare, and manufacturing highlights its potential for improving system design and operational performance (BARRICELLI; CASIRAGHI; FOGLI, 2019).

A critical advancement in this space is the implementation of DT-based Cyber-Physical Production Systems (DT-CPPS), where the physical and virtual layers of a shop floor are interconnected. Ding et al. (2019) demonstrated that such systems allow for real-time simulation, data-driven decision-making, and increased flexibility. These findings support the argument that DT provides a solid foundation for developing adaptive and autonomous manufacturing environments.

Furthermore, in the context of the Industrial Internet of Things (IIoT), Jiang, Guo, and Wang (2021) proposed a DMS (Data, Model, Services) framework that structures DT deployment to improve system scalability and synchronization. The approach has been applied to distributed systems such as smart grids and gas-insulated switchgear units, demonstrating its applicability across multiple domains.

DT applications are used in supply chain management to simulate operational and critical risk scenarios, allowing for more informed decision-making and increased system resilience (BARYKIN et al., 2020). Supply chains can respond to disruptions dynamically using scenario analysis and failure simulations, ensuring efficiency and profitability.

Computer vision has also established itself as a key pillar of Industry 4.0. According to Gill et al. (2024), CV uses AI techniques and image processing to enable applications such as tracking objects, safety inspection, quality assurance, and maintenance prediction. These features make it indispensable for automating repetitive and precision-based duties across multiple manufacturing domains.

CV enables robotic systems to recognize objects dynamically and adapt to changing situations. The use of DT and CV in robotic pick-and-place tasks, reduces the need for human involvement by automating spatial detection and simulation verification (CHIDDARWAR; JAKHOTIYA; RAHUL 2024). This dramatically improves process accuracy and reactivity.

Ensuring product quality is crucial not only for customer satisfaction but also for maintaining a company’s reputation in the marketplace in contemporary manufacturing environments. Traditional quality assurance methods often struggle to meet the demands for greater efficiency and effectiveness. The integration of computer vision with real-time object detection marks a new era in quality control, promising enhanced accuracy, speed, and automation. This technology employs advanced algorithms and state-of-the-art hardware, potentially transforming quality control processes across various industries. Real-time object detection in computer vision involves identifying and locating objects of interest within a live video feed, using sophisticated techniques (AHMED; DESAI, 2024). These objects can range from defective components on a production line to integral parts of complex assemblies.

Historically, manual inspection has been the standard for quality control in manufacturing, despite being labor-intensive and prone to human error. Automated systems utilizing real-time object detection can significantly improve the accuracy and efficiency of these processes. By integrating cameras and sensors throughout a production facility, computer vision systems continuously analyze and interpret visual data (GILL et al., 2024). This capability allows for the immediate detection of quality discrepancies, enabling rapid responses to any arising issues. The ability of these systems to provide real-time alerts and facilitate immediate corrective actions offers a significant competitive advantage, reducing waste and enhancing operational efficiency.

The primary objective of this research is to explore the potential of real-time object detection in computer vision for improving quality control processes in industrial settings. This research seeks to promote enhanced quality control practices, ensuring continued exceptional product performance and a competitive edge for manufacturers. Implementing real-time object detection systems in quality assurance can significantly reduce costs and increase production efficiency, underscoring the value of this advanced technology in modern manufacturing environments (AHMED; DESAI, 2024).

Learning Factories help integrate and test sophisticated technologies in educational and prototyping settings. According to Abele; Metternich; Tisch (2019), Learning Factories provide a real-world environment in which DT-CV systems can be tested prior to widespread application. Durão et al. (2019) emphasized their function in reducing technical uncertainty and promoting adaptive learning.

The most recent developments have also emphasized improved knowledge integration in DTs via the use of Knowledge Graphs and Function Blocks. In this regard, Zhang et al. (2024) proposed a Digital Twin framework for robotic machining of large-scale components that incorporates semantic modeling and adaptive process methods to improve real-time control and decision-making. These methodologies enable more accurate representation of machining parameters as well as dynamic optimization during operations, showing that DT progress will lead to increasingly intelligent and autonomous systems (ZHANG et al., 2024).

3. Research Methods

This manuscript investigates the integration of Digital Twins (DT) and computer vision (CV) within industrial settings, focusing on optimizing their collaboration. An overview of the methodology is presented in Figure 1.

The project commenced with a thorough literature review aimed at gaining a comprehensive understanding of DT and CV concepts and their applications. This review not only offered valuable insights into the functionalities of both technologies but also pinpointed opportunities for cooperative integration. It emphasized the role of DT in enabling real-time monitoring and optimization by creating virtual replicas of physical systems while highlighting how computer vision enhances this process by facilitating object detection and analysis using advanced image processing techniques. These findings were instrumental in defining the objectives and scope of the project framework.

Afterwards, it progressed into a practical phase that involved the creation and evaluation of a technological integration through the definition of the architecture of a CV-DT and a code prototype. Color identification was selected due to fast validating real-time feedback in early-stage prototypes. The initial focus was on simulating industrial scenarios using distinctly colored physical objects as test cases. Custom algorithms developed in Python were employed to detect and analyze these objects via image processing techniques. A webcam was utilized to capture live video feeds, allowing for real-time detection based on color attributes. This interactive setup successfully connected physical objects with their virtual representations, resulting in a functional prototype of a DT that integrates computer vision capabilities.

The final phase comprised ongoing testing and evaluation to validate the system's performance. Various colored objects were assessed under different conditions to evaluate the accuracy and precision. The computer vision system accurately detected, analyzed, and represented physical objects in real-time. This underscores its potential applications in various industrial contexts, including process monitoring, quality control, and system improvement. The findings illustrate the practicality of merging Digital Twins with computer vision, laying a foundation for further exploration into advanced industrial automation solutions.

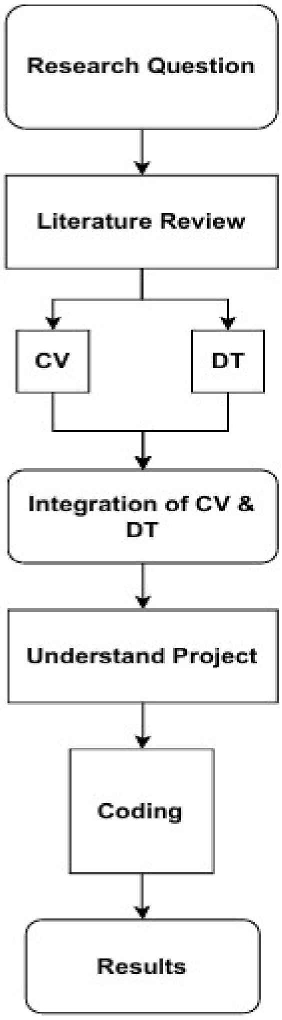

Fig. 1: Methodology of the overall project (2024)

4. Results and Discussion

The results of this paper can be organized into two main contributions: the definition of an architecture for a computer-vision-enabled Digital Twin, implemented in the project setting; and the software prototype, responsible for the image analysis and color identification, as well as Digital-Twin-ready integration.

4.1. Computer vision-enabled Digital Twin Architecture

A simplified view of the architecture is presented in Fig. 2, and explained afterwards.

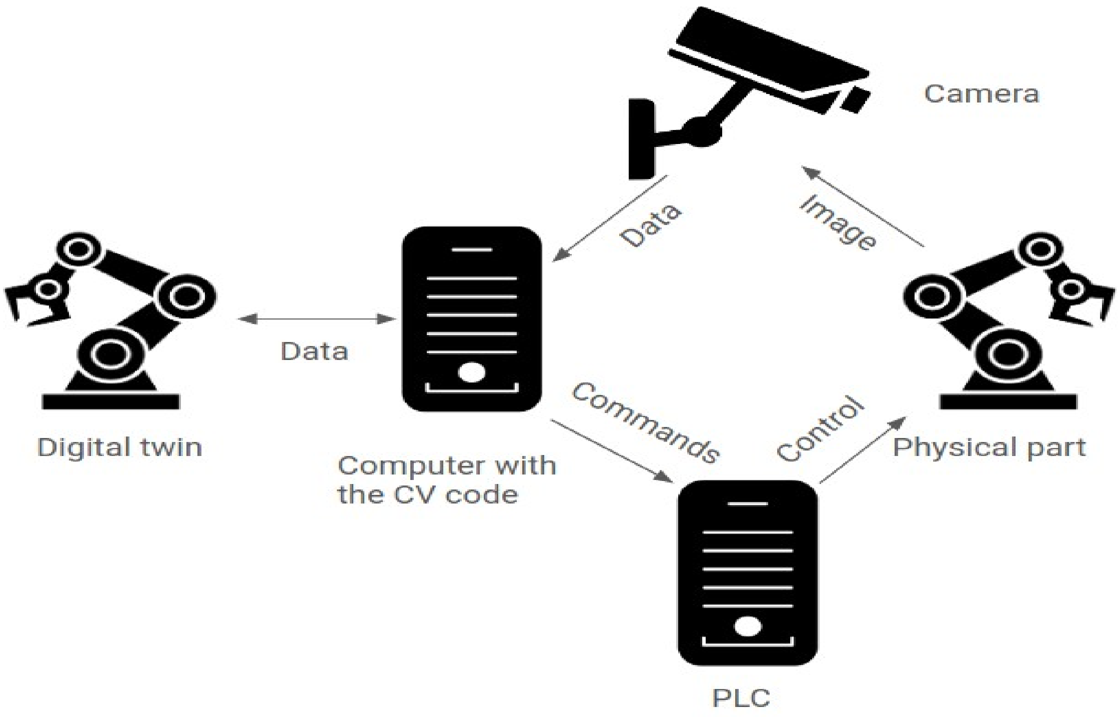

Fig. 2: CV-enabled DT implementation architecture

In this architecture, a computer is used to process the images of the physical part of the product. It could be used also to send commands to the PLC that controls the physical part of the Digital Twin and to communicate with the digital part, but this possibility is not in the scope of this work. The camera acquires the live image of the physical part and sends it as data to be processed by the computer running the CV code.

4.2. Computer vision software and test results

To validate the use of computer vision to complement the Digital Twin, a python code prototype was developed. It was made with a widely used open-source library for computer vision named opencv. More about that library can be found on the site https://opencv.org/. The program shows the image of the camera and the result of the detection in different windows. The user can select the color to detect by just clicking on the image shown in the “img” window, and the areas with the selected color will appear in the “results” window. The program identifies the values of red, green, and blue color in the pixel clicked and searches for similar values in the image, then shows the detected areas, by drawing a red rectangle out of them, as shown in Fig. 3.

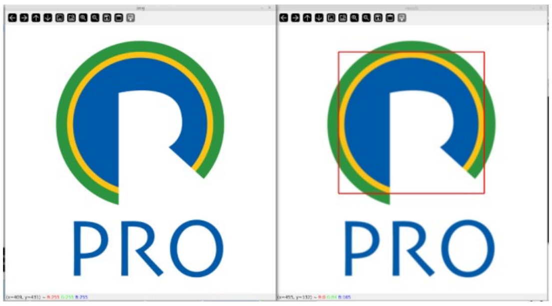

Fig. 3 (a) Identification of a blue color sample, with the red box drawn around the blue item. (2024)

Fig. 3 (b) Identification of green color sample, with the red box drawn around the green item.(2024)

To make the program simpler to use, the library pyinstaller was used to create a Windows executable file, and it reads a “variable.txt” file in the same directory to define the name of an image or the id of the camera to be accessed.

Some colored cubes were 3D printed to test the program applied to the physical equipment at the learning factory. A webcam was used to take images of them. The camera was fixed in the physical part of the Digital Twin, as shown in the Fig. 4.

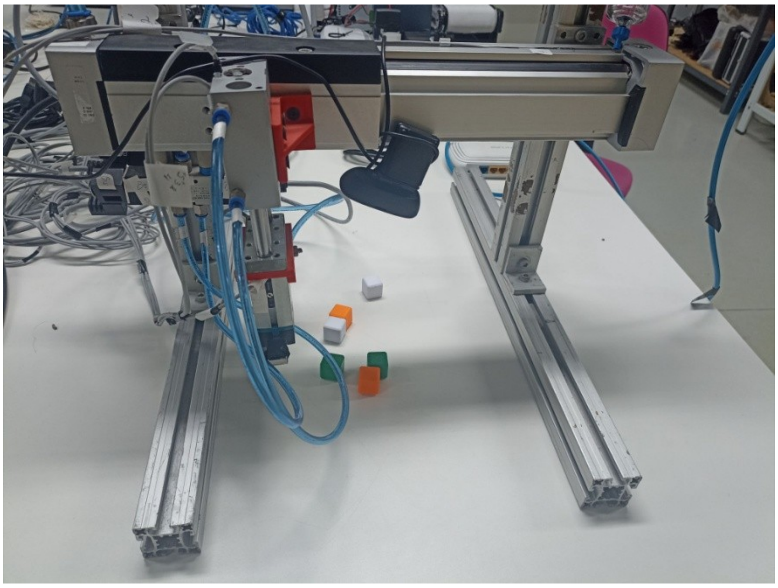

Fig. 4: Experimental setup, including 3D printed cubes and camera in testing position (2024).

The software was able to detect the color of the cubes, based on the sampling of a particular region. In this way, it could be used to “learn” different colors, depending on the application, as illustrated by Fig. 5. Note that the identified colors as RGB values are printed in the terminal, and are thus accessible to be integrated into the Digital Twin platform.

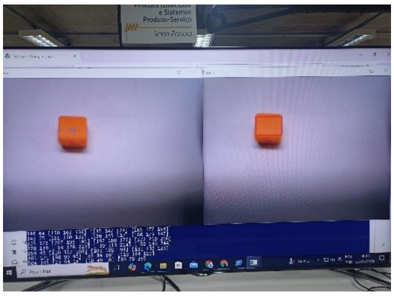
Fig. 5 (a): orange


Fig. 5 (b): green

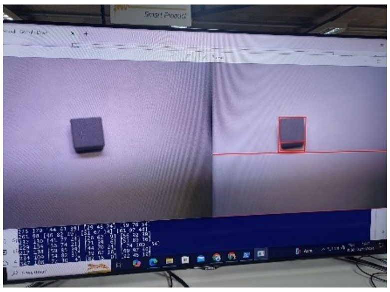
Fig. 5 (c): grey

Fig. 5: Proof-of-concept prototype identifying orange (a), green (b) and grey (c) parts (2024).

It was noted that in some cases (when the color of the cube is near to the color of the background) unwanted objects are falsely detected. It is a limitation in the use of color detection for object detection as presented in Fig. 6. In the case of the white cube, the program contours the background. When detecting the gray cube, the shadows were also detected because of having similar colors.

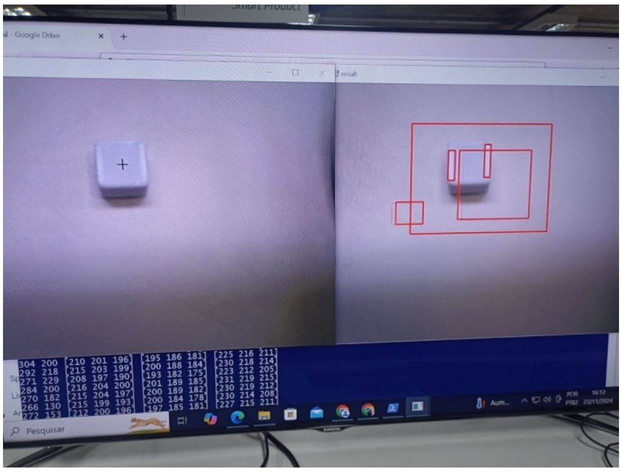

Fig. 6: False detection of white parts, including unwanted background objects (2024).

Given the initial results, more advanced algorithms for edge detection can help mitigate the false positives. Conversely, using objects with contrasting colors from the background may significantly improve the performance; masking regions of the final video feed can also help to detect and determine the position of objects manipulated by the physical prototype.

5. Conclusion

This study demonstrates the transformative potential of combining Digital Twins and Computer Vision technologies to detect object colors with precision and reliability to complement other sensors' data. The proposed system takes a structured approach following an architecture proposed by the project team. By feeding the processed data into a DT environment, the system allows for real-time simulation and validation of object color recognition tasks.

The preliminary experimental results validate the system's ability to detect and classify object colors under specific conditions. It was able to identify colors in images given an initial sample point, and tests performed with additive-manufactured sample cubes proved to be sufficiently accurate. However, the algorithm struggles to identify more complex situations, in which the object color can be confused with the background color.

From a theoretical perspective, the research supports and extends the conceptual foundations of Cyber-Physical Production Systems (CPPS), as discussed by Ding et al. (2019), by providing an empirical example of how Digital Twin (DT) and Computer Vision (CV) can interact to achieve a more comprehensive and detailed digital description of physical equipment. It aligns with the DT-CPPS architecture that promotes data-driven decision-making and system interoperability. Additionally, the study contributes to the broader Industry 4.0 literature (GRIEVES; VICKERS, 2017; BARRICELLI et al., 2019) by illustrating a modular and scalable approach to integrating AI-based perception through CV (GILL et al., 2024) with digital modeling. These results show that even low-cost computer vision solutions can meaningfully contribute to real-time synchronization in DT frameworks, supporting the CPPS model proposed by Ding et al. (2019). The use of a Learning Factory as the implementation setting also reinforces the educational and experimental relevance highlighted by Abele et al. (2019), and Durão et al. (2019).

From a practical standpoint, compared to existing pick-and-place implementations relying on manual input, the CV-DT prototype offers a scalable pathway toward automation with minimal human intervention and low-cost. The prototype validates the use of computer vision for real-time object identification in industrial testbeds, suggesting practical routes for implementing DTs in production environments. Learning factories emerged as platforms for testing such technologies due to their ability to provide controlled yet realistic conditions for experimentation and training.

However, the system has limitations. The reliance on color-based detection introduces inconsistencies depending on the background color and low data acquisition capacity occasionally resulting in false positives. These limitations highlight the need for more robust detection algorithms, such as shape detection, contours detection and filters. It will enable the software to detect and differ more objects and consequently collect more data to the Digital Twin.

Future work will aim to expand the framework to include multi-feature detection, such as object shapes and textures, as well as improve its applicability in more complex and dynamic environments. The integration of the vision module into the Digital Twin platform, currently under development, would further enhance the system's capabilities by adding more data acquisition capability to the DT. It could enable the identification of characteristics of what is going to be manipulated by the prototype, like shape, color, position, and size, as well as monitoring quality and detecting problems in the production.

Finally, for other DT-CV studies, the academia and industry should invest in the organized implementation of Learning Factories. These environments serve as effective testbeds for deploying and validating Industry 4.0 technologies, such as DT-CV. They provide a practical and controlled setting to mitigate uncertainties, train human operators, and refine system architectures before full-scale application (ABELE; METTERNICH; TISCH, 2019; DURÃO et al., 2019). It is equally crucial to encourage interdisciplinary collaboration in system design. DT solutions, particularly those that include CV components, benefit greatly from the convergence of skills in systems engineering, human-machine interface, and software development. Many DT implementations, particularly in user-centric systems, risk falling short of their intended value if socio-technical issues are not considered (BARRICELLI; CASIRAGHI; FOGLI, 2019).

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