Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

VIRTUAL COMMISSIONING OF AI VISION SYSTEMS FOR HUMAN-ROBOT COLLABORATION USING DIGITAL TWINS AND DEEP LEARNING

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ABSTRACT

Virtual commissioning is the process of validating the design and control logic of a physical system prior to its physical deployment. Machine vision systems are an integral part of automated systems, particularly in perception-driven tasks; however, the complexity of accurately modeling these systems and their interaction with dynamic environments makes their verification in virtual settings a significant challenge. This paper presents an approach for the virtual commissioning of AI-based vision systems which can be useful to evaluate the safety and reliability of human-robot collaborative cells using virtual cameras before physical deployment. A digital twin of a collaborative workcell was developed in Tecnomatix Process Simulate, including a virtual camera that generated synthetic image data. A deep learning model was trained on this synthetic data and subsequently validated using real-world data from physical cameras in an actual human-robot collaborative environment.

1 INTRODUCTION

The rise of collaborative robots, or cobots, has elevated human-robot interaction to a new level in manufacturing facilities. Human-robot collaboration (HRC) can expand the level of automation in areas that have conventionally been difficult to automate, such as assembly (Malik and Brem 2021). This increase in human-robot interactions has created a need to analyze human safety in these collaborative environments. The HRC workspace design should ensure that no harm is caused to humans, either directly or indirectly, both during operation or if the system goes into a failure (Malik and Bilberg 2018). Integrating robots into shared workspaces introduces the risk of unanticipated collisions, excessive force application, and unpredictable human movement, making safety a critical concern in human-robot collaboration.

In order to make sure that human operators can work alongside robots without the risk of getting hurt, safety regulations were developed by ISO in response to the growing use of collaborative robots in industrial settings. The ISO/TS 15066:2016 technical specification provides safety requirements for collaborative operations based on the ISO 10218-1 and ISO 10218-2 standards (Standard, I.S.O. 2016). The guidelines stress the importance of safety, risk reduction, and controlled collaboration between robots and humans. The main emphasis of this is on risk assessment and hazard mitigation. As per these guidelines, the deployment of HRC work cells requires a comprehensive risk assessment to identify hazards such as unintended contact, collisions, crushing, or ergonomic risks.

Conventional methods for the development of manufacturing systems are time-consuming due to their sequential nature. A digital twin is an emerging technology that can offer a high-fidelity simulation of a real manufacturing system, including its kinematics, automation program, behavior, user interface, and production parameters (Malik 2023). Digital twins of HRC cells can be useful in hazard analysis by serving

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as virtual models of human-robot collaboration. Virtual environments can help to simulate various human-robot interaction scenarios for the purpose of identifying risks in a safe space before physical deployment.

Virtual Commissioning (VC) refers to the process of testing and evaluating a manufacturing system, such as a human-robot collaborative cell, prior to its physical commissioning. Virtual Commissioning helps in detecting the errors and inconsistencies in the manufacturing system and/or process beforehand and without the necessity of conducting experiments on the actual physical system. Therefore, VC can save cost and time of the physical commissioning process. Virtual Commissioning can enhance safety compliance in HRC workcells by pre-deployment risk analysis and safety validation. Manufacturers can design safer, more efficient, and regulation-compliant collaborative robot workcells by integrating VC with ISO/TS 15066 guidelines.

In this paper a novel framework for the virtual commissioning of AI-based vision systems within human-robot collaborative (HRC) environments by leveraging digital twins and deep learning has been proposed. Virtual camera was installed into a high-fidelity digital twin of an HRC workcell, and synthetic image data was generated to train vision-based detection models, which were then validated using real-world data. Through this work, we aim to bridge the gap between virtual and physical commissioning by transferring AI vision systems from simulated to real-world environments.

2 RELEVANT WORK

Research on virtual commissioning and human-robot collaboration has expanded in recent years, with particular attention to simulation environments, digital twins, and system integration. A strong emphasis has been placed on the use of simulation environments, digital twins, and virtual testing tools for early validation and safe deployment of HRC cells. This section presents a short overview of the existing work on virtual commissioning and human-robot collaboration.

2.1 Simulation-Based Human-Robot Collaboration

There has been steady progress in simulating HRC environments, particularly where safety is a concern. Rueckert et. al. (2020) explores the concept of Human-in-the-Loop (HITL) simulations for Virtual Commissioning of human-robot collaboration in order to enhance the safety and efficiency. Human-in-the-Loop refers to interaction between a human and a control loop, where human beings can be a component of the simulation. By integrating virtual human models in VC, it is feasible to test and validate the behavior of human-robot interactions in realistic situations, hence ensuring safety in case of any human error or malfunction. The authors suggest that using VC can be beneficial in meeting the safety requirements specified in standards like ISO/TS 15066, and can offer a comprehensive approach to the certification and design of collaborative robotic systems.

A different angle comes from Sun et. al. (2022) who proposed a digital twin-driven Human-Robot Collaboration assembly-commissioning method to enhance the efficiency and adaptability of complex product assembly processes. They introduce a virtual-physical mapping framework that synchronizes the virtual and physical processes in real-time. The authors used a task knowledge graph and Deep Deterministic Policy Gradient (DDPG) to adaptively adjust the robot's movement path. The authors performed a case study and the experimental results show that the digital twin-driven HRC method reduces assembly-commissioning time by 47.4% compared to traditional methods.

2.2 Digital Twin Frameworks and VC System Integration

A lot of effort has gone into bringing together the various tools needed to make VC actually usable in practice. Zhou et. al. (2024) proposed a virtual commissioning system based on AML(AutomationML) to address the challenge of virtual commissioning for human-robot collaboration assembly cells. Their system models physical objects such as workers, robots, and other devices, through the technology called Asset Administration Shells (AAS). Their approach integrates 3D models, human actions, robot motion, and PLC files into a single AML file for virtual commissioning in a software-in-the-loop setup. They validated the effectiveness of this system in a battery pack harness assembly cell case study.

Metzner et. al. (2020) present a simulation framework for industrial human-robot collaboration systems for improving productivity in flexible production through virtual commissioning. They integrated virtual reality (VR), motion capture, and object tracking into robot simulation software which was connected to PLCs. The framework combines motion-capturing devices, including a Microsoft Kinect, Leap Motion Controller, and HTC Vive, allowing for precise interaction with the simulation. The authors demonstrated the system's capabilities through two case studies: a cleaning process in power electronics and a handling application for printed circuit boards. The system was able to accurately simulate robot behavior and PLC logic.

In more industry-focused work, Ugarte et al. (2022) developed the application of digital twins for virtual commissioning in the machine tool manufacturing sector. The authors used Siemens NX MCD, Simit, and Sinumerik 840D software to develop and test a digital twin-based virtual commissioning model. De Oliveira et al. (2021) presented a structured approach combining digital modeling, simulation, and virtual commissioning to design and develop automation equipment. The authors created the digital twin model alongside the physical machine using Siemens 3D Simulation System NX MCD, TIA Portal, PLCSim Advanced, and Simit.

To improve simulation efficiency, hybrid approaches have also been proposed. Noga et. al.(2022) introduced the idea of Hybrid Virtual Commissioning which they referred to the commissioning process in which the cost of simulation is reduced by incorporating the physical devices into the system model which would otherwise be more costly to simulate. The authors implemented the method on a case study which consisted of a vision camera mounted pick-and-place robotic manipulator and a PLC. The digital twin of the system was created on NX MCD (Mechatronic Concept Designer). Scheifele et. al. (2019) emphasized on a real-time co-simulation platform for virtual commissioning of production systems. The platform's architecture is based on partitioning, parallelization, synchronization and data exchange mechanisms.

2.3 Application-Oriented Approaches in VC

Several studies have been conducted in order to take a more applied approach on how VC can be used in real-world automation scenarios. Alaameri et. al. (2024) used TIA Portal and FACTORY I/O software for creating and testing a virtual model of an automated system for sorting products based on color. The system's performance was monitored and controlled through SCADA and HMI interfaces. Sobrino et. al.(2019) explored virtual commissioning within the context of Industry 4.0 framework using the integration of Siemens software tools: Tecnomatix Plant Simulation (TPS), S7-PLCSIM Advanced, and STEP 7 TIA Portal. The authors showed how the simulation software Plant Simulation can be connected to virtual PLC controllers to simulate and validate manufacturing processes before physical implementation. Wang et. al.(2024) proposed a digital twin-driven method of virtual commissioning of machine tools by simulating the machining process in a virtual environment. The authors tested their method on a CNCMT spindle system. The results show a decrease in commissioning time and a 54% reduction in total systematic error.

After reviewing existing studies on virtual commissioning of manufacturing systems particularly human-robot collaborative cells, it’s clear that no significant efforts have been made on AI-based vision systems for safety assessments in virtual environments. Therefore, in order to address this gap an effort has been made in this paper to design a framework for virtual commissioning of AI-based vision system for applications in human-robot collaboration safety analysis.

3 METHODOLOGY

This research aims to develop a deep learning model using transfer learning for virtual commissioning of AI vision systems using simulation for a human-robot collaborative environment. All the work done in the past for safety analysis in human-robot collaboration have been done by using images and videos of the physical twin where the cobots and humans are detected by the machine vision and depending on how close or far the two bodies are from each other, the situation could be classified as dangerous or safe to avoid collisions. This paper will explore the idea of training such a model, but by using simulation images and videos, i.e. synthetic data, generated through a virtual camera installed in the simulation. This model will then be tested and evaluated on real data gathered from a real system using a real camera installed in the cell. The goal is to present a technique to enhance virtual commissioning by developing a ready to use safety model before the implementation of a real system.

There are four main parts of this research which are discussed in the following sections. Section 3.1 explains the process of simulation development, 3.2 describes the different type of datasets used, 3.3 is data pre-processing and augmentation, then section 3.4 presents the experiments with different datasets and development of object detection models. Figure 1 shows the pipeline of the methodology used to achieve the goals.

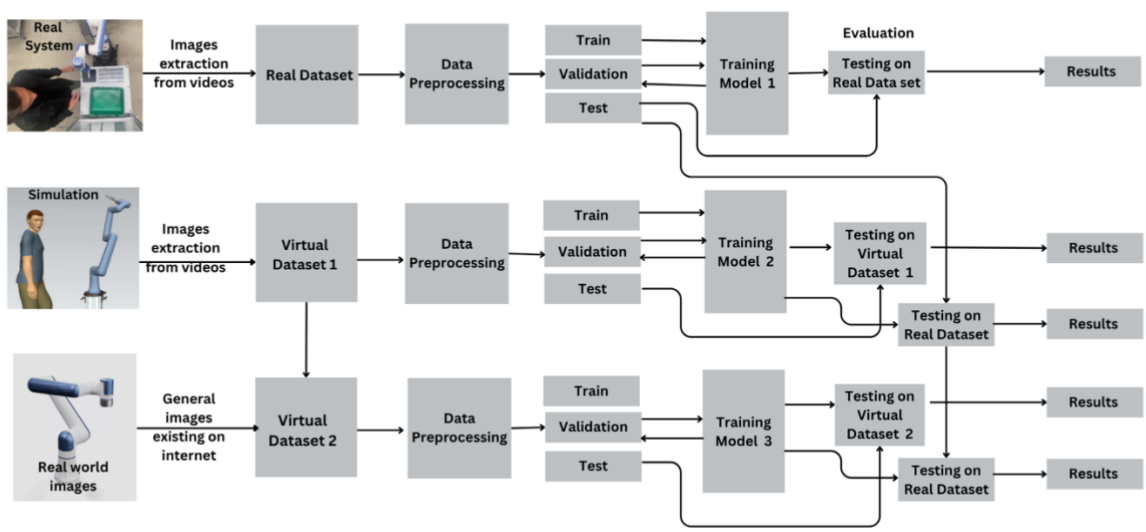

Figure 1: Virtual AI Vision System Pipeline for HRC

3.1 Simulation Creation

The digital twin of the HRC cell containing the Dobot Nova5 robot, a Jack human and a virtual camera, was created in Tecnomatix Process Simulate (TPS) software. The CAD models were imported into the software and the kinematics models were created. The camera was installed at various positions in order to capture the video of the virtual environment at different angles. Figure 2 shows the virtual environment setup for the HRC cell in Tecnomatix Process Simulate.

Figure 2: Virtual Environment in TPS

3.2 Datasets

3.2.1 Virtual Dataset 1

The initial set of training images were collected from simulation videos using the OpenCV library in python. From every 15 frames a single frame was extracted out of three simulation videos, each approximately two minutes in duration. Rather than relying on a large dataset, this work aims to demonstrate that a minimal amount of data can still be effective for developing such a model. In total, 211 images were extracted, with sample images shown in Figure 3(a).

3.2.2 Virtual Dataset 2

Virtual Dataset 1 is modified by adding some general images of humans from the COCO dataset and robots (Dobot nova 5) images from internet videos. Dataset 2 was introduced to improve the accuracy of the model. The COCO dataset contains about 330k images of humans, but it is not right to add all of those images into our Virtual Dataset 1 for two reasons. One because the data for this research is kept small on purpose. Secondly, it is not possible to get the same number of images for robots, which will result in an imbalance dataset. Hence, to avoid this problem only 300 random images were added from the dataset. Robot images were collected from several different sources from the internet as direct images and as extracted images from Dobot nova videos available on YouTube. Constituting to around 124 images. Hence, Virtual Dataset 2 consists total of 636 images. Sample images of this dataset are shown in Figure 3(b).

3.2.3 Real Dataset

This is the dataset that comes directly from the real system with a human and a robot using a real camera installed in the system. As it is assumed that the real system is not developed yet, hence this is the target dataset and all the models that are to be developed will be tested on this dataset. The purpose of this dataset is to test the model that will be trained and enhanced using other datasets. From a total of three videos, 719 images were extracted. Sample images of this Real Dataset are shown in Figure 3(c).

(a) (b) (c)

Figure 3 Example Images: (a)Virtual Dataset 1 (b)Virtual Dataset 2 (c)Real Dataset

3.3 Data Pre-Processing and Augmentation

First and the most important preprocessing step before training for object detection is image annotation. All these three datasets Virtual Dataset 1, Virtual Dataset 2 and Real Dataset were annotated using an open-source tool Roboflow. Every single picture of all three datasets is manually marked with a bounding box into two classes as class-0 for human and class-1 for robot.

Afterwards all these images were resized into 640x640. The resizing of images dataset is important before starting the training for consistency as it ensures that all images have the same dimensions, which is necessary for batching and efficient computations.

Since the dataset is small in size i.e. the number of images for training and testing is less, different data augmentation techniques were applied to increase the number of images. These techniques include flipping, rotating, brightness, hue, saturation and exposure. All these augmentation techniques were applied to the pictures to produce variations in the images. Therefore, images in all datasets were increased in number. Refer to Table 1 for the final number of images in each dataset.

At last the three datasets were subsequently split into training set, testing set and validation set with 70 percent of images in training set, 20 percent in validation and 10 percent in testing set. With all these steps the dataset is all set to be fed to the machine learning model.

Table 1: Dataset Images.

Dataset Name	Total Images	Human Instances	Robot Instances
Virtual Dataset 1(only simulation)	411	386	561
Virtual Dataset 2(simulation+real)	797	798	813
Real Dataset(real)	604	586	654

3.4 Development of Detection Model

In this section, the training of the object detection models has been done and all datasets discussed in the previous section has been experimented one by one as shown in Figure 1. Transfer learning is a technique where a machine learning model, which is already trained on a huge dataset, is modified and trained to do some other specific but related task. In this research, a well known pre-trained model YOLO version 11 is used which is already trained to detect about 80 different objects. This model has been fine-tuned and trained with our image datasets to detect humans and robots with 150 epochs, batch size of 32 and input image size of 640x640. The exact same procedures are followed for all the three datasets. Model1 was trained with Real Dataset, then Model2 was trained on Virtual Dataset 1 and then finally Model3 was trained on Virtual Dataset 2. All the three models are developed using similar libraries and configuration and all these models were evaluated on their own test data. After that Model2 and Model3 were tested on validation set of Real Dataset.

4 RESULTS & DISCUSSION

Table 2 shows the results of the detection models. Model1 was trained on a Real Dataset, this dataset is the target dataset hence this model is the ideal model to which all other models can be compared. This model demonstrates high performance with near to perfect precision of 0.998 and recall of 0.994. The precision signifies that model rarely detects false objects and recall signifies it misses almost no true objects contributing to overall exceptionally high performance. It can be seen in Figure 4(a), that human and robot detection is quite accurate.

Model2 was trained on Virtual Dataset 1 which contains images from the simulation. As shown in Table 1 overall precision and recall are high, where human detection is perfect in accuracy and the model only misses 0.5% of the humans while the robot detection lacks in all parameters. Although, robot detection has somewhat high precision and recall, it detects 6.3 false robots and fails to detect 12.9% of the actual robots. One important thing to be noticed is that overall mAP50 is high which indicates good basic detection capability but mAP50-95 is significantly lower, 0.714, indicating the model struggles with exact positioning of the object specifically in the case of robot detection with only 0.564 mAP50-95. This observation suggests that the model trained on the real world is better at detection than on the simulation data. The deep learning model struggles to detect humans and robots in simulation compared to the real-world data.

Model2 was then tested on Real Dataset. This is the first experiment towards the goal of developing safety system using object detection without using real world data. In this step a model which was trained on only simulation was tested with real world dataset in order to find how well the model performs for a real world scenario. The Model2 severely underperforms on real data, across all metrics showing very low numbers. Both precision and recall are low with 0.284 and 0.351 i.e it misses about 65 % of objects, while the localization capability is extremely low with 0.09 percent making the model is practically unusable for the real world. It can be observed from Figure 4(c) that the model detects false humans and fails to exactly localize the robot. The model has a low F1 score of 0.32, which indicates that there exists a great domain gap between real world and simulation visuals in terms of detection using machine learning models.

Model3 was trained on the Virtual Dataset 2 which is a combination of simulation images and real-world images. It demonstrates excellent performance when tested on its own data, particularly for human detection with perfect recall and near perfect precision, which can be observed in Figure 4(d) . The high F1 scores confirm balanced precision and recall. The mAP50-90 score of 8.36 reveals that model lacks little in localization of humans and robots.

When Model3 was tested on Real Dataset it showed significantly stronger performance than that of Model2 on Real Dataset. It achieves high precision of 0.945 overall, which indicates few false detections were made. Meanwhile, recall has also improved but still remains a critical weakness at 0.462. It can be observed form Figure 4(e) that the model misses two out of four robot instances. The F1 score of 0.621 reflects a moderate balance between precision and recall. Notably, its mAP50-95 score of 0.505 shows reasonable improved localization capability, especially for humans (0.553), while robot detection also improved a little with a score of 0.457. This model proves that the performance of a simulation-data-trained model can be improved on real world data if mixed with real world images during training phase.

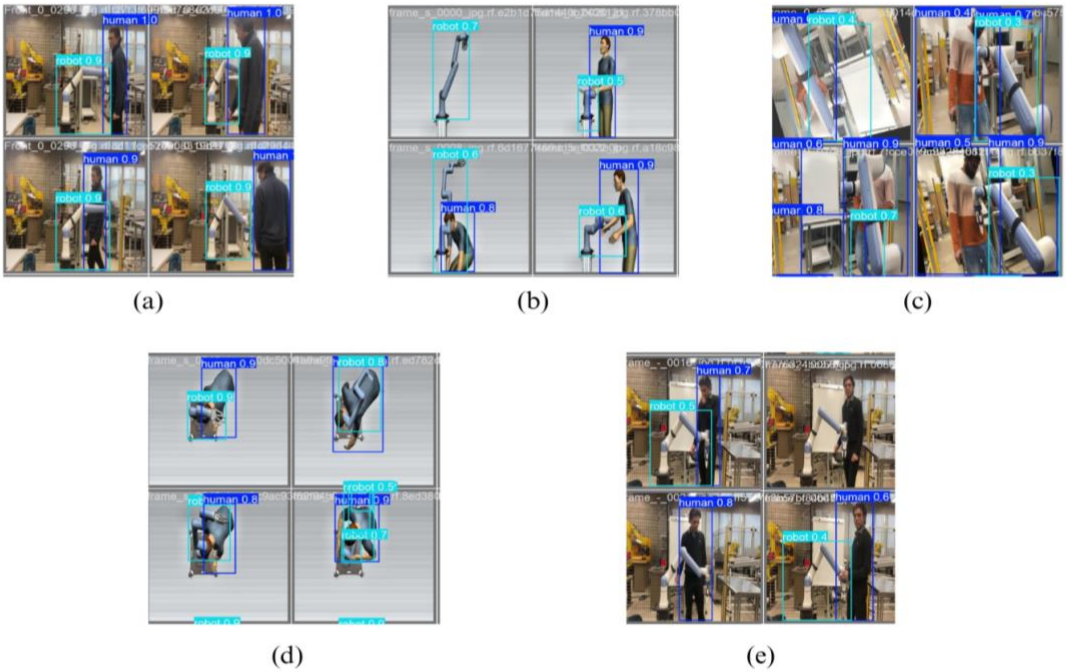

Figure 4 Sample Images Detected (a)Model1 on Real Dataset, (b)Model2 on Virtual Dataset 1, (c)Model2 on Real Dataset, (d) Model3 on Virtual Dataset 2 and (e)Model1 on Real Dataset

Table 2: Results

Model and Test	Class	Precision	Recall	F1 Score	mAP50	mAP50-95
Model1 (Tested on Real Dataset)	All	0.998	0.994	0.995	0.995	0.932
	Human	0.998	1.0	0.999	0.995	0.96
	Robot	0.997	0.987	0.992	0.995	0.903
Model2 (Tested on Virtual Dataset 1)	All	0.968	0.933	0.950	0.974	0.714
	Human	1.0	0.995	0.997	0.995	0.864
	Robot	0.937	0.871	0.903	0.953	0.564
Model3 (Tested on Virtual Dataset 2)	All	0.997	0.993	0.995	0.995	0.922
	Human	1.0	1.0	1.0	0.995	0.946
	Robot	0.993	0.987	0.990	0.995	0.897
Model2 (Tested on Real Dataset)	All	0.284	0.351	0.314	0.254	0.091
	Human	0.234	0.398	0.295	0.209	0.054
	Robot	0.335	0.303	0.318	0.299	0.129
Model3 (Tested on Real Dataset)	All	0.945	0.462	0.621	0.709	0.505
	Human	0.938	0.612	0.741	0.784	0.553
	Robot	0.952	0.312	0.471	0.635	0.457

5 CONCLUSION AND FUTURE WORK

This paper presented a novel approach to virtual commissioning of AI-based vision systems for safety analysis in human-robot collaborative (HRC) cells. A digital twin of a collaborative robot cell was developed using Tecnomatix Process Simulate, and synthetic data was generated using virtual cameras to train object detection models. The key goal was to explore whether a model trained on synthetic images could perform adequately in real-world scenarios. Three different datasets were used to train and evaluate the models: purely synthetic data, hybrid synthetic data augmented with COCO and online robot images, and a real-world dataset captured from a physical system. Although the model trained on real data showed good performance, the synthetic-data-trained models underperformed when evaluated on real-world inputs. The results clearly demonstrate the feasibility of using virtual data for preliminary model training; however, a significant domain gap remains between virtual and real-world images, particularly in robot detection accuracy. This confirms that the visual gap between simulation and real environments is a major limitation.

To bridge this domain gap and improve the model's real-world applicability, future research should focus on generating higher-fidelity synthetic images using more advanced 3D rendering software such as OpenUSD and Unreal Engine. These platforms can provide more photo-realistic simulations, which can significantly enhance model training quality. Once the detection model's accuracy is improved using higher-quality synthetic data, the next step would be to classify the workspace into dynamic safety zones based on the improved model's output. These zones could act as an early warning system for collision risks in collaborative workcells before their physical deployment.

Apart form this, there was another observation that opens the doors to a research topic worthy of investigation. The synthetic data was low quality in terms of visual representation and the model which was trained on it lagged behind in robot detection in comparison to human detection. This gives idea that rather than using a pre-trained model, a deep learning model, specially designed to handle this kind of quality data, can be developed from scratch. Furthermore, research could explore how to develop a deep learning model which trains on low quality simulation data for object detection but enhances itself to be applicable for real world.

In addition to these directions, an important consideration is the scalability of the proposed approach for broader industrial applicability. Extending this methodology to an entire production line presents both opportunities and challenges. To support scalability across larger and more complex systems, additional work could focus on developing modular digital twins. This modularity would allow for flexible replication and integration of individual cell models into entire production lines.

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