VIRTA-Yoke: A Virtual-Integrated Poka-Yoke System for Error Prevention and Operator Training in Manufacturing Processes

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Abstract: This paper introduces VIRTA-Yoke (VIRTA: Virtual Integrated Reliability and Training Assistant), a proof-of-concept virtual Poka-Yoke platform developed to increase reliability and efficiency in manufacturing processes for aluminum engine components. In contrast to traditional mechanical Poka-Yoke systems that require custom fixtures for each part, VIRTA-Yoke employs a low-cost webcam and a virtual reality (VR) headset to guide operators through each assembly step, verify correct placement in specific control areas, and provide real-time feedback when deviations occur. The system uses a convolutional neural network (ConvNet) to detect errors in coil insert placements. This information appears on the VR headset, minimizing operator distraction, optimizing operation times, and improving process adherence. In addition, the VR headset serves as a training environment, allowing new personnel to learn assembly procedures through a virtual component model before working on the factory facility. Preliminary tests indicate an accuracy exceeding 90% in overall defect detection, suggesting that VIRTA-Yoke is a scalable, cost-effective method for streamlining quality control, improving operator training, and eliminating the need for multiple custom mechanical fixtures across a wide range of parts.

1 INTRODUCTION

Poka-Yoke, a term coined by Shigeo Shingo in the 1960s, represents a fundamental concept in the Toyota Production System aimed at preventing and detecting human errors before they manifest as defects (Shingo, 2021; Martinelli et al., 2021; Martinelli et al., 2022). Initially, Poka-Yoke solutions were simple mechanical devices—such as guides, pins, or limit switches—designed to halt the progression of defective products through the manufacturing line. Over time, these measures have evolved well beyond their original scope, demonstrating effectiveness in correcting errors, as well as anticipating and preemptively eliminating potential process failures (Prabowo and Aisyah, 2020; Hetmańczyk and Michalski, 2013; Vinod et al., 2015).

This orientation aligns closely with lean manufacturing principles, which aim to minimize waste, streamline processes, and continuously improve quality (Hines and Rich, 1997; Bicheno and Holweg, 2008; Liker, 2004; Mor et al., 2019; Lekšić et al., 2020). By removing conditions that lead to errors, Poka-Yoke fosters a culture of ongoing improvement and increased reliability in production environments (Alves et al., 2012; Prabowo and Aisyah, 2020; Lekšić et al., 2020; Jiang et al., 2014). Shingo (Shigeo and Dillon, 1989) distinguishes between control type mechanisms, which halt the process at the detection of an error, and warning type mechanisms, which alert operators so that they may take corrective actions without stopping production entirely.

As manufacturing adopts more digital approaches, the concept of Poka-Yoke has expanded to virtual implementations. Instead of requiring mechanical changes to production lines, virtual Poka-Yoke systems rely on digital tools —such as computer vision, machine learning, and virtual and/or augmented reality— to identify anomalies and guide operators (Martinelli et al., 2021; Prabowo and Aisyah, 2020; Lekšić et al., 2020; Soares Alcalá, 2020; Kim et al., 2018; Saleem et al., 2020). These methods facilitate rapid adjustments to inspection criteria and reduce the need for extensive redesigns when products or specifications change.

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Studies have shown that applying convolutional neural networks (ConvNets) and advanced image processing can deliver high accuracy in defect detection (Huang and Kovacevic, 2011; El-Agamy et al., 2016; Kim et al., 2018; Saleem et al., 2020). Such approaches, along with VR- and/or AR-based training scenarios, allow operators to interact with virtual models of parts, practice identifying potential defects, and refine their inspection methods before working with actual components (Hedelind and Jackson, 2011; Jiang et al., 2014; Li et al., 2020; Siriborvornratanakul, 2016). This capability reduces reliance on costly physical resources and live production downtime, while operators gain familiarity with the process in a flexible, adaptable environment.

In essence, the evolution of Poka-Yoke —across mechanical, virtual, and VR- and/or AR-integrated solutions— reflects a broader trend in manufacturing toward greater flexibility, adaptability, time efficiency, and intelligence in quality assurance. Through continuous refinement and integration with advanced digital technologies, Poka-Yoke remains a key strategy for error prevention, contributing to more efficient and reliable production systems in an increasingly dynamic industrial landscape.

Based upon these concepts, this work presents VIRTA-Yoke, a Virtual Integrated Reliability and Training Assistant, which is a proof-of-concept system under development. This effort is positioned within a real industrial context, namely an aluminum parts foundry supplying the automotive sector. The primary challenge faced by the foundry involves a set of production steps where some mechanical Poka-Yoke devices have already been implemented, while other stages remain susceptible to human errors. Such errors impose significant costs, time delays, and operational inefficiencies, creating the need for additional, cost-effective strategies to mitigate quality issues.

To address these concerns, VIRTA-Yoke is presented as a system composed of two integrated layers, complemented by a dedicated training module for employees. The core solution is based on a standard webcam capturing images of specific sections of each manufactured part. These images are analyzed by a state-of-the-art computer vision algorithm that provides a probabilistic assessment indicating whether the processed part is correct or defective. The resulting information is displayed on a monitor, guiding the operator through repetitive verification tasks and improving overall decision-making accuracy. This virtual Poka-Yoke design aims to reduce hardware complexity and avoid substantial modifications to the production line.

In parallel, a virtual reality (VR) headset, adapted to provide augmented reality (AR) guidance[1], supplements the visual assistance by presenting the analysis results directly to the operator, in a manner such that no step is overlooked. This AR layer displays error outputs in a user-friendly manner and leads the employee through the entire process, preventing the skipping of critical tasks, as well as reducing the time needed to check each step, which is currently followed on a printed sign mounted on the wall. Additionally, the VR headset is employed off-site as a training tool, relying on a three-dimensional model of the workpiece to familiarize new employees with production procedures before they begin on-site work. By integrating image-based inspection, AR-guided verification, and pre-emptive training, this proof-of-concept system supports operational robustness, reduces human error, and provides a more reliable and cost-effective manufacturing environment.

2 VIRTA-Yoke AS A PROOF-OF-CONCEPT SYSTEM

VIRTA-Yoke is conceived as a proof-of-concept system that is introduced within the manufacturing process of an aluminum component destined for engine assembly. Its aim is to detect and prevent errors in specific physical sections of the workpiece, referred to here as *control areas*. These control areas are located on one face of the part and consist of a number of holes with two different sizes and two different depths into which coil inserts (called *helicoil* in this paper[2]) must be placed. A reference image for the helicoil is shown in Figure 1. A representative image of a control area is provided in Figure 2, although the complete geometry of the part cannot be displayed for confidentiality reasons. Nevertheless, this example of a control area illustrates the general principle, since similar control areas can be identified and examined across different workpieces.

An example of a placement error for the helicoil is shown in Figure 3, where the helicoil exhibits incorrect depth. Specifically, the tip of the helicoil pro-

[1]For clarity, the device is commonly known as a VR headset. However, we use its AR capabilities in this work. Therefore, we will use the expression *VR headset* when referring to the device itself, and the term *AR* when describing its application and functionality.

[2]In this study, the term helicoil will be used to refer to coil inserts. Although *coil insert* is the generic technical designation, the term helicoil corresponds to the commercial name commonly used by factory personnel and will be adopted throughout this paper for consistency with the terminology employed in the production environment.

trudes beyond the hole where it should be fully inserted. This is one of the multiple types of errors that can be found during the process[3]. For reference, a correctly placed helicoil can be seen in Figure 2.

Figure 1: Reference image for a helicoil.

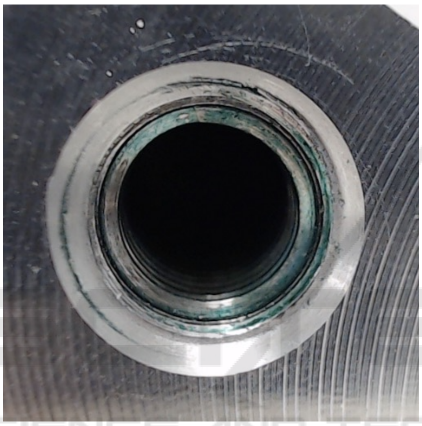

Figure 2: Example of a control area with a helicoil insert correctly placed.

Figure 3: Example of a control area with a helicoil insert placed incorrectly (incorrect depth: too high).

[3]Other errors include: no helicoil inserted; the tip of the helicoil (the section of metal that extends beyond the spiral structure) is not properly cut; helicoil too deep; helicoil too high.

It is important to note that VIRTA-Yoke does not aim to identify manufacturing defects on the aluminum part itself, such as dents, excess material, or dimensional deviations. Our system rather focuses on the verification of these specific operations involving control areas. By detecting errors in these controlled steps, the proposed VIRTA-Yoke system addresses a significant source of defects that currently arise in the production line.

The expectation for this proof-of-concept is that it can effectively address the majority of these insert-related and similar errors found in the facility. The intended approach would cover hundreds of pieces with a cost far lower than that associated with traditional mechanical Poka-Yoke devices, which must be custom-built for each individual part. Through the integration of a single webcam and a VR headset, the system leverages widely available and reasonably priced components, increasing its scalability and adaptability to a broad range of production scenarios.

3 THE PROCESS INVOLVING VIRTA-Yoke

3.1 The VR Headset Guidance

The first part of the proposed solution involves using the VR headset as a step-by-step guidance tool within the assembly process. Currently, operators follow a series of instructions displayed on a board at their workstation. The first step in the process requires placing helicoil inserts into designated holes in the aluminum part. The placement and the tools required for this task are described in printed signs mounted on the wall within the operator workstation. In addition, the order in which each insert must be placed is indicated on a custom-made plate that immobilizes the part, serving as a basic mechanical Poka-Yoke for this initial step. However, this plate must be manufactured to the exact specifications of the particular piece, a considerable drawback given the hundreds of different part types handled by the facility.

In contrast, the proposed method utilizes the VR headset to provide a dynamic and adjustable step-by-step guide. By wearing the headset, the operator receives clear, real-time instructions for each action to be performed. After completing each step, the operator sends a signal (e.g., using a controller or a simple input device, or even their own hand, recognizable by the device) to the headset, confirming that the task has been done. The headset then displays the next step. This approach addresses two frequent issues, namely operators occasionally skipping steps due to fatigue or distraction, and the additional delay caused by the movements that the operators have to make to check or review the following steps, provided that the correct sequence is always visible in a highly accessible manner. The AR-based guide can be easily adapted to new parts or modified procedures through software, thus eliminating the need to produce custom-made physical guides for each piece type. This represents a significant cost reduction and flexibility improvement compared to conventional mechanical Poka-Yoke solutions.

As an example of the process as well as the provided guidance, the operation guide for working with one of the components used in this research is provided in the supplementary material[4], including information up to the extent allowed by confidentiality constraints.

3.2 The Low-Cost Webcam

The next component of the system employs a machine learning-based approach, using a standard state-of-the-art algorithm in combination with a low-cost webcam. The device chosen for our proof-of-concept system is a Logitech C922 Pro HD Stream Webcam (1080p, 30FPS). By placing the workpiece in a fixed position, the camera captures images of the designated control areas and provides a high-confidence assessment of their status, indicating whether the helicoil insert has been correctly placed and whether the tip has been properly cut. Through this example, it becomes clear that control areas adhere to one defined correct shape and can exhibit multiple error types, all of which the algorithm is designed to detect.

The verification results are displayed on the VR headset, allowing operators to access critical quality checks without shifting their gaze or consulting separate monitors. This integrated feedback mechanism is currently the most practical solution to the challenge of efficiently verifying control areas, minimizing operator distractions, and reducing overall operation times.

A notable limitation at present (December 2024) is the inability to use the chosen VR headset, namely Meta Oculus Quest 3, to provide direct image input for the algorithm analysis[5]. Although the Quest 3 was selected for its availability and cost-effectiveness, the manufacturer currently restricts external video output from its camera feed. As a result, the webcam remains necessary to capture images, with the processed information subsequently transmitted to the AR environment. Within the AR interface, the system displays the number of correctly processed control areas compared to the total number required. If not all areas meet the specified criteria, the guidance system halts progress until the error is corrected. Once the issue is resolved, a signal is sent to the VR headset, enabling the operator to proceed to the next task.

In addition to providing immediate feedback to operators, the system generates notifications for supervisors, capturing a wide range of real-time information in detailed text-based records. These records will evolve in the next system version, scheduled for March 2025, into comprehensive back-office dashboards accessible to both mid-level and senior management. These dashboards will aggregate detailed logs of operator interactions, error detections, corrective actions, and real-time process metrics. Data will include start and end times for each process, the sequence and duration of steps guided by the VR headset, any downtime or delays encountered, and gaze-based attention estimates derived from eye-tracking metrics. The collected metrics will also log errors identified by the algorithm and warning messages prompted when mandatory steps are missing. This enhanced data environment aims to support advanced data-driven decision-making, enabling continuous improvement, better resource allocation, and improved quality management throughout the production workflow.

3.3 The Computer Vision Algorithm

This section focuses on the algorithm itself. The presented results emerge from the integration of a state-of-the-art convolutional neural network (CNN) architecture based on Conv2D and MaxPooling2D layers implemented using the TensorFlow/Keras framework. Preliminary tests conducted on a representative dataset with real images from correct and incorrect pieces indicate that the model achieves an accuracy exceeding 90% in overall defect detection. The ConvNet model, once trained and validated, is integrated into a dedicated software application installed on a workstation computer. The complete code is available in https://pastebin.com/9Yb05hrn.

The algorithm was developed following a structured methodology. The convolutional neural network (ConvNet) employed in this study consists of an architecture combining three Conv2D layers with ReLU activation functions and MaxPooling2D layers for feature extraction, followed by two fully connected layers to perform classification. The Conv2D

[4]Supplementary Material is available at https://tinyurl.com/virta-yoke

[5]For further information, see https://www.meta.com/blog/quest/new-safety-privacy-features-mr-headset-family-friendly/

layers include 32 filters in the first layer and 64 filters in the second and third layers, all with a filter size of (3, 3). The fully connected layers comprise 64 units with ReLU activation and a final softmax layer with 2 units to compute class probabilities. The model was trained using the Adam optimizer with an initial learning rate of 0.001 and sparse categorical crossentropy loss, over 15 epochs with a batch size of 1. Images were preprocessed by standardizing them to a resolution of 32x32 pixels and normalizing pixel values to the range [0,1]. Data augmentation, including random rotations and zoom, was applied to the training dataset to improve robustness. The training process was conducted on a MacBook Pro (M1, 8GB RAM), and required approximately 1 minute of processing time. The resolution of 32x32 pixels was selected to balance computational efficiency and model accuracy, as it is sufficient to capture the types of defects analyzed. While the dataset size (60 images) may limit generalization capabilities, this limitation was partially mitigated through data augmentation. In future iterations, we aim to expand the dataset to further enhance the robustness and accuracy of the model.

As indicated above, a set of 60 labeled images from 30 correct areas and 30 incorrect control areas was organized into training, validation, and testing subsets (80%/20% proportion between training and test, following standard machine learning practices), each containing examples of correct control areas and incorrect control areas in two defect categories. The webcam was placed in a fixed position, 20 centimeters above the workpiece, under white non-directional artificial light.

Following training, performance was evaluated using the validation and test datasets, reporting accuracy as a primary metric, as well as the standard precision, recall and F1-score metrics. Output results for these metrics can be seen in Table 1. Visualization functions were created to display predictions on sample images, allowing qualitative inspection of model behavior and detection of misclassifications. Finally, the approach validated the feasibility and accuracy of the computer vision-based quality control system.

Table 1: Output metrics for the algorithm.

Metric	Value
Accuracy	0.92
Precision	0.92
Recall	0.93
F1-Score	0.92

3.4 Training and Operator Instruction with VIRTA-Yoke

The training component of VIRTA-Yoke leverages a virtual environment that allows operators to become thoroughly familiar with the production part and its associated control areas before entering the actual factory facility. By employing a VR headset, the operator can manipulate a three-dimensional model of the component, inspecting it from all angles and identifying the operations required at each step. For this proof-of-concept, the control areas where helicoil inserts must be placed can be visually examined and virtually "marked" as inspected once the operator has verified their correct configuration. This immersive training environment reduces the reliance on real-world machine time and physical workpieces, effectively lowering training costs and minimizing disruptions to ongoing production.

In practice, this virtual training scenario enables off-site learning, allowing operators to become proficient in identifying correct and incorrect configurations without consuming factory resources. Rather than dedicating valuable time and materials to train personnel directly on the production line, the system provides a versatile and cost-effective solution. Operators can interact with a three-dimensional mock-up that mirrors the dimensions and complexity of the actual part. This virtual representation allows operators to gain confidence and agility in handling the component, mastering inspection techniques that will later be applied to genuine parts.

The training functionality of VIRTA-Yoke is further complemented by the inclusion of three demostration videos showcasing the proof-of-concept training module. These videos feature a dummy piece, which is designed to replicate the dimensions and operations of the actual component used in production. The dummy part contains several holes, within which the correct pladement of the helicoil insert must be verified. These holes are prominently marked in red, indicating the control areas that require inspection to assess whether the helicoid has been correctly inserted.

For training purposes, operators use the VR headset to manipulate the dummy part in a 360-degree mixed environment. One hand holds the piece, enabling it to be rotated and inspected from all angles, while the other hand is employed to point to the control areas and mark them as ”correct” or leave them unmarked if deemed incorrect. This step-by-step interaction reinforces awareness of the inspection process and the motor skills required to perform thorough inspections.

The three training videos provided cover distinct environments to replicate various production conditions: a) White artificial lighting: this video demonstrates the inspection process under controlled, optimal lighting conditions; b) Printed polygon overlays: this video introduces polygonal overlays to simulate a higher level of detail during the inspection; c) Dim lighting: this final video reproduces the typical lighting conditions found in real production facilities, where operators encounter lower visibility[6].

By using this pointer to signal that a particular control area has been inspected, the operator can simulate the exact steps of the verification process. Upon confirming the inspection via simple gestural inputs, the system registers that the control area has been checked, reinforcing the correct procedure and serving as an aid to improve muscle memory. This approach enhances the user's familiarity with the workpiece and reduces the learning curve associated with the real-world implementation of the VIRTA-Yoke system.

4 EXPERIMENT AND PRELIMINARY RESULTS

To assess the effectiveness of the VIRTA-Yoke system on operational efficiency, an experiment was conducted involving six volunteer operators selected across the company's three shifts (morning, afternoon, and night, two operators per shift) that collectively cover the full 24-hour production cycle. The tasks performed for the experiment included working with multiple control areas with varying hole sizes and depths, requiring the insertion of helicoil inserts, following the exact steps necessary to work on a specific workpiece within the manufacturing process. The step-by-step guide for the process used in the experiment is provided in the supplementary material[7]. The primary types of error targeted in this experiment were the incorrect insertion of helicoil inserts —specifically those with improper depth—, and the lack of insertion of helicoil inserts.

Completion times for each operator were recorded. These measurements were taken under two conditions: the traditional work setup and a scenario incorporating the VIRTA-Yoke system. In the first scenario, the operators performed the tasks following their standard procedures, without any additional guidance. The recorded times for each employee are presented in Table 2. Subsequently, the same operators were equipped with the VR headset and provided with dummy parts, which approximate the size, shape, and complexity of the actual components. Using the guidance interface provided by VIRTA-Yoke, including step-by-step instructions delivered through the VR headset, the operators repeated the procedures. The times recorded under these enhanced conditions are listed in Table 3.

Table 2: Scenario 1. Normal conditions. First 5 rows.

Operator	Shift	Operation Time (Seconds)
O1	Morning	79.26
O1	Morning	93.97
O1	Morning	88.83
O1	Morning	76.08
O1	Morning	82.80
...	...	...

Table 3: Scenario 2. Using VIRTA-Yoke. First 5 rows.

Operator	Shift	Operation Time (Seconds)
O1	Morning	75.52
O1	Morning	73.85
O1	Morning	62.95
O1	Morning	70.87
O1	Morning	69.04
...	...	...

A total of 30 data points were gathered for both conditions, comprising 5 observations for each operator. A two-way t-test was conducted to compare the mean completion times. With a 95% confidence level (p-value = 1.33×10^{-14}), the analysis indicated a statistically significant reduction in completion time when VIRTA-Yoke was employed. Although dummy parts were used for the VIRTA-Yoke condition and genuine parts for the traditional scenario, the pieces were comparable in dimensions and required operations. Additionally, the experiment was performed under a failure-free environment to avoid generating real defects, which could impact actual production. Following discussions with the production supervisor, it was agreed that these results provide a valid estimate of the potential time savings achievable through VIRTA-Yoke. The complete tables for both scenarios are provided as supplementary material[8].

[6] All three videos are available in https://tinyurl.com/virta-yoke

[7] Supplementary Material is available at https://tinyurl.com/virta-yoke

[8] Supplementary Material is available at https://tinyurl.com/virta-yoke

5 CONCLUSIONS AND FUTURE WORK

This work has presented VIRTA-Yoke, a proof-of-concept system integrating virtual Poka-Yoke methodologies, machine learning-based error detection, and AR-assisted operator training. The proposed solution aims to enhance reliability, reduce costs, and streamline the handling of control areas in the manufacturing of aluminum parts for engine components. By combining low-cost hardware (a webcam and a commercially available VR headset) with a state-of-the-art computer vision algorithm, VIRTA-Yoke guides operators through each step of a complex process, provides accurate feedback on insert placement, and allows off-site training that does not depend on physical resources or live production runs.

Preliminary tests have demonstrated encouraging results, indicating an accuracy exceeding 90% in overall defect detection in control areas. Operators can interact with a virtual model of the piece, familiarize themselves with the process, and practice identifying and verifying control areas. This approach reduces the risk of skipped steps or overlooked defects, thereby enhancing overall process quality and operational efficiency. The proposed system also plans to integrate extensive logging capabilities, ultimately enabling supervisors and managers to review detailed performance data via dashboards and make data-driven decisions to improve the quality control process.

While the VIRTA-Yoke system introduces a virtual Poka-Yoke approach, a direct quantitative comparison with traditional Poka-Yoke systems is not entirely feasible due to the current manufacturing process already utilizing basic mechanical Poka-Yoke mechanisms for individual steps. The proposed system integrates a virtual Poka-Yoke guide for the entire assembly process, serving as a proof of concept that can be generalized to other components. Traditional Poka-Yoke systems require custom-built fixtures for each specific part, leading to higher costs, whereas VIRTA-Yoke leverages low-cost webcams and reusable software, making it more cost-effective. Although error detection accuracy cannot be directly compared due to the absence of a controlled production environment with deliberate errors, the VIRTA-Yoke system demonstrates over 90% accuracy in overall defect detection based on machine learning metrics. Operator training times are expected to be similar to traditional systems; however, the VR-based training module allows training in a flexible virtual environment without consuming physical resources. Additionally, the scalability of VIRTA-Yoke far exceeds that of traditional systems, as it can be adapted to multiple parts by reconfiguring the software, whereas mechanical systems require custom fixtures for each component. These advantages suggest that VIRTA-Yoke offers a cost-effective, scalable, and flexible alternative to traditional approaches, despite the lack of direct performance comparisons.

However, several challenges remain. At present, the VR headset hardware restricts certain data channels, preventing a direct input feed of camera images into the headset, thus needing an external webcam for capturing real-time data. Future development efforts will focus on overcoming such limitations. The eventual inclusion of logging and dashboard functionalities is scheduled for March 2025, supporting continuous improvement and higher-level oversight.

Additionally, it is worth briefly discussing whether the use of VR headsets posed challenges for operators, particularly those with no prior experience using such technology. While no significant usability issues were reported during the initial tests, it is recommended that future studies incorporate usability surveys to assess specific metrics, such as comfort levels, ease of adaptation to the VR headset, and any potential impacts on performance or fatigue. These insights will help refine the system to make it both effective and user-friendly. However, certain limitations of the implementation must also be acknowledged. One key constraint is the dependence on lighting conditions, as variations in illumination can significantly impact the final accuracy for the model, making consistent and controlled lighting essential for reliable defect detection. Furthermore, the use of VR headsets may lead to visual fatigue or discomfort due to prolonged usage, as well as physical fatigue from the weight of the device. Another technological limitation is the battery life of most VR headsets, which typically lasts between two to three hours, which is substantially less than the duration of an operator shift. To address these challenges, the team has preliminarily discussed alternative VR solutions, such as X-REAL headsets, which offer improved ergonomics and do not rely on battery power. This alternative is under consideration for future iterations to enhance usability and reduce operator discomfort, while remaining practical and efficient in real-world applications.

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