# The Challenge

Forecast of maintenance duration for production tools: Each incoming tool is inspected before the maintenance and repair activities begin. This is done by skilled workers. The inspection results are documented according to specific levels for certain specific categories (condition of paint, dirt, missing parts, etc.). To document the condition of incoming equipment photos are taken by the worker. In order to reduce the effort for inspection and enable even non-experienced workers to conduct this task it is intended to semi-automate the inspection activity by using photos of the incoming assets and to determine their condition automatically.

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## Main Requirements

* Optimize the production planning and scheduling;
* Optimize the maintenance operations based on ML and AI;
* Optimize number of operators based on performance.

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## Other Requirements

N/A

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## Key Performance Indicators

N/A

**Industry Sector:**  
Provider and integrator of solutions for manufacturing and logistics

**Challenge classification:**

Real-time process monitoring and optimization; Smart planning and scheduling of processes.

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## Other informations

What competence does the company have with this project?

Operational as well as technical know-how.

Use manufacturing execution systems (MES) or enterprise resource planning (ERP) systems?

No

Use of any existing cloud vendor (AWS IoT, Microsoft Azure, etc.)?

No

Number of machines to be connected:

0

Configuration of each machine and the operation of each:

N/A

Machines are equipped with PLC/PAC or CNC controllers and can provide data?

0

Machines are not equipped with any digital controller (Legacy Machines)?

0

Communication protocols, sensors or devices with which the solution needs to integrate?

Barcode readers indicating start and end of maintenance activities. Central database storing and providing further information related to incoming tools (condition, repairs, ...).

# Research Phase

*Taking into account the challenge description, its requirements and its information, elaborate at least 5 questions that can lead your research for a solution.*

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## Research questions:

1. Should the proposed technological solution work even without connectivity in the industrial environment?
2. Should the condition of industrial equipment be monitored at any time, from any place, or should the data remain at the local level for security reasons?
3. What is your budget?
4. Is your system Cloud-ready or not?
5. What is the level of knowledge and skills of current employees?

*Given the questions and the main requirements of the challenge previously listed:*

* *identify the technologies that will be utilized for the proposed solution;*
* *identify and analyze the sources (papers, articles, etc.) of those technologies that best suit the challenge;*

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## Used Technologies:

* Data Visualization Tools and Platforms
* K Nearest Neighbour (KNN)/Case-Based Reasoning (CBR) (Machine Learning)
* Deep Learning
* Computer Vision
* Cloud Data Storage and Computing
* Embedded Computing
* Connectivity (5G, WiFi, etc.)
* Augmented Reality (AR)
* AR and VR Software development, Platforms and Technologies

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## Sources of those technologies that best suit the challenge:

1. Mourtzis, D.; Boli, N.; Fotia, S. Knowledge-Based Estimation of Maintenance Time for Complex Engineered-to-Order Products Based on KPIs Monitoring: A PSS Approach. Procedia CIRP 2017, 63, 236–241, doi:10.1016/j.procir.2017.03.317.

2. Mourtzis, D.; Angelopoulos, J.; Panopoulos, N. A Framework for Automatic Generation of Augmented Reality Maintenance & Repair Instructions Based on Convolutional Neural Networks. Procedia CIRP 2020, 93, 977–982, doi:10.1016/j.procir.2020.04.130.

3. Remote Support | 4REMOTE | Zerintia Technologies. (<https://zerintia.com/en/industry-4-0/4remote/>)

4. Fieldbit - Fast AR and Spatial Computing for Remote Assistance Available online: <https://helplightning.com/solutions/fieldbit-share-know-how-instantly/> (accessed on 18 June 2022).

5. Aschauer, A.; Reisner-Kollmann, I.; Wolfartsberger, J. Creating an Open-Source Augmented Reality Remote Support Tool for Industry: Challenges and Learnings. Procedia Computer Science 2021, 180, 269–279, doi:10.1016/j.procs.2021.01.164.

6. Richard, K.; Havard, V.; His, J.; Baudry, D. INTERVALES: INTERactive Virtual and Augmented Framework for IndustriaL Environment and Scenarios. Advanced Engineering Informatics 2021, 50, 101425, doi:10.1016/j.aei.2021.101425.

7. Masood, T.; Egger, J. Adopting Augmented Reality in the Age of Industrial Digitalisation. Computers in Industry 2020, 115, 103112, doi:10.1016/j.compind.2019.07.002.

*In light of the discoveries made:*

* *report the answers for the questions above;*
* *Perform a side‑by‑side technical evaluation of at least two solutions that could satisfy the challenge (What are the possible benefits/issues in such a use of these technologies?);*
* *draw initial conclusions on which path you want to take in proposing a solution. Your deliverable must justify an optimal architecture (which can be a hybrid) by weighing measurable trade‑offs.*

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## Answers:

1. The proposed solution, to be reliable, should work with the same performance either in case of lack of connectivity or limited connectivity.
2. Managers should oversee the manufacturing system at any time and from anywhere, having applied the appropriate techniques for secure data transfer and minimization of cyberattacks.
3. The proposed solution should be characterized by the optimal trade-off between benefit and cost. That is a solution through which the goal will be achieved without requiring high operating costs or sufficient training time for this new operating mode.
4. No.
5. For non-skilled workers to be able to handle it, it must be user-friendly without the need to develop high-level skills such as computerized systems handling or programming.

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## Comparison:

Using the taxonomy, we identified various technological solutions for predicting the maintenance time of a failed production tool. The company's leading requirement was to create an AI-based system that uses photos of the incoming assets as input data. Therefore the basic technologies of all possible solutions are ***Computer Vision***/***Deep Learning***, which allows us to create knowledge-based models that can extract useful information from digital images, videos, and other visual inputs. Furthermore, all solutions use the ***Case-Based Reasoning (CBR) machine learning technique*** to estimate maintenance time.

The solutions' differences concern how the AI-powered system develops and the interaction between the worker and the system. For the development of the AI-powered system, two possible solutions were identified. The first one concerns the implementation of the system on a remote server (local or ***Cloud-based***). In this method, the worker captures the images and sends them (through ***IoT protocols*** or ***radio communication technologies*** such as ***5G*** or ***WiFi***) to the remote server for processing. Then the AI-powered system sends the output back to the worker. The second solution concerns implementing the AI-powered system in a local device (i.e., an ***embedded device***). The first approach is generally faster since it can process more data in less time due to the high computational power of the server and its ability to do several parallel computations. On the other hand, using a local device is more convenient and flexible, needing however lighter AI algorithms to be implemented efficiently; otherwise, both time and precision should be sacrificed.

Regarding the interaction, it is suggested to use ***Augmented Reality*** to take photos and display the results intuitively or use vision sensors (i.e., cameras) in conjunction with a web application (in which we have deployed the AI system) and ***Data Visualization Tools and Platforms***. However, using a web application requires more digital skills. On the contrary, Augmented Reality (AR) facilitates natural interaction between the worker and the system as it allows to send commands (gesture or vocal) and receive a fast response via an AR device (***AR glasses*** or ***mobile devices***), enabling an intuitive way to perform the inspection.

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## Comparative Matrix:

*Create a single table that highlights advantages and drawbacks of the analyzed solutions*

| **Feature/Aspect** | **Cloud/Remote Server** | **Local Embedded Device** |
| --- | --- | --- |
| Processing Speed | High | Medium |
| Connectivity Dependence | High | Low |
| Flexibility | Medium | High |
| Development Complexity | Medium | High |
| Suitability for AR | High | Medium |

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## Conclusions:

The final choice of the solution is based on the comparison made before, the industry's requirements and the answers to the questions asked. Initially, we chose the computation platform (local server or Cloud-based server or local device) in which the AI-powered system will be developed. For the proposed solution to remain reliable even in the case of lack of connectivity or limited connectivity, we have to choose between a local server or an embedded device where the images of the failed production tool are collected and used to estimate maintenance duration. For this choice, the fact that the system is not Cloud-ready also played a role as the networking of the manufacturing ecosystem requires enough time. Although mobile devices have become more powerful to handle computations near real-time, the need to use a central database led us to decide not to use embedded systems but a ***local server/data center***.

Regarding the interaction, it is suggested to use Augmented Reality technology because non-skilled workers can operate the system without needing to develop digital skills. Finally, regarding the AR device used, although ***AR glasses*** are a relatively expensive choice, they combine smartphone features with a hands-free operating mode, thus ensuring the industrial task's fastest and highest quality execution.

# Proposed Architecture and Solution Design

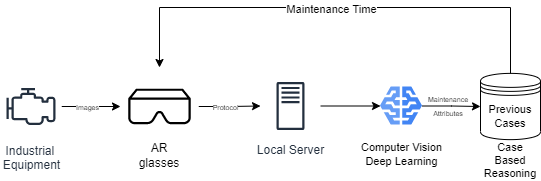
*Based on the technologies identified through source analysis, propose a potential solution to the challenge. Additionally, provide a flow diagram illustrating the architecture of the proposed solution.*

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## Solution Description

*Describe the solution and its details*

When a production tool fails, a worker captures images of it through ***AR glasses*** (equipped with vision sensors) and sends them (***IoT protocols*** or ***radio communication technologies*** such as ***5G*** or ***WiFi***) to the ***local remote server*** for processing by the AI-powered system [3]. There, the ***Computer Vision***/***Deep Learning*** model (e.g., MobileNet‑V3, YOLOv8, ViT) extracts the maintenance attributes (MA) from the images of the failed production tool (e.g., condition of the paint, dirt, missing parts, etc.) [2]. These attributes are qualitative and quantitative (i.e., linguistic and numerical variables). In order to avoid text processing, the qualitative attributes are encoded. Furthermore, based on the feedback we take (from semi-structured questionnaires and interviews) and the knowledge of expert engineers, a weight for each MA is assigned. These weights represent the relative impact of these features on the maintenance time (i.e., the higher the weight value, the higher its impact). Having completed this procedure, the newly entered maintenance task is compared through a similarity mechanism against previously solved cases retrieved from the ***central database***. Except for MA values, data regarding actual maintenance time are available for the past cases. The actual maintenance time for each task has been calculated with the help of ***barcode readers***, indicating the start and end of maintenance activities. The comparison is performed by calculating the distance of the attributes using specific equations [1]. As a result, the most similar past case, as well as the similarity degree between the new task and the past one, are identified. In the final phase of the CBR methodology, the resulting similarity degree is adopted to estimate the maintenance duration of the failed production tool. This methodology has presented promising results since the maintenance time has been estimated accurately based on past knowledge reuse [1]. To implement the Case-Based Reasoning system, the pyCBR library could be used. Finally, the AI-powered system sends the output back to the worker’s glasses.



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## Implementation and Technical Considerations

*Describe technical limitations of your chosen architecture and future directions for addressing them.*

The deployment of the proposed AI-powered inspection system requires a phased implementation plan alongside the identification of key technical constraints and future improvement directions.

**Development Phases**

* Phase 1: Design and development of the AR interface for image capture, integrating with barcode readers to align with current maintenance workflows.
* Phase 2: Training and optimization of Deep Learning models (e.g., YOLOv8, MobileNetV3) for automated defect recognition from captured images.
* Phase 3: Integration of the Case-Based Reasoning module, linking extracted maintenance attributes with historical cases stored in a central database.
* Phase 4: End-to-end system testing in a real-world industrial environment to evaluate accuracy, usability, and latency.

**Technical Limitations and Mitigations**

* Barcode tracking limitations: The use of barcodes as visual markers for AR tracking may result in reliability issues when markers go out of view. This can be mitigated by implementing model-based tracking, aligning physical tools with their 3D CAD representations.
* Wireless communication issues: Industrial environments may introduce signal interference. A redundant Wi-Fi network with multiple access points is recommended to ensure stable communication between AR devices and the local server.
* Computational constraints of edge devices: Although mobile and embedded devices have grown more powerful, the system prioritizes reliability and accuracy, leading to the choice of a local server over purely embedded solutions.
* Model adaptation over time: Continuous data collection and expert feedback should be used to refine the machine learning models and update the CBR knowledge base, enhancing prediction precision and system robustness.