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Document

# Executive Summary Report

## Deliverable to AO-1-10549 | Project PANORAMA

## Application of machine learning and artificial intelligence technologies for process data analysis

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# Table of Contents

# 1 Introduction

The Executive Summary Report (ESR) summarizes the project »PANORAMA«, which aimed to implement two AI/ML/Hybrid use cases in the production environment of the ArianeGroup (AGG), site Ottobrunn. The development and deployment of the use cases was led by the Fraunhofer IPT (IPT).

# 2 Applicable and reference documents

The Final Report aligns with the ECSS standard of the following documents:

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| ECSS-E-AS-11C | Definition of the Technology Readiness Levels (TRLs) and their criteria of assessment |
| ECSS-E-ST-40C | Space Engineering – Software |
| ECSS-M-ST-80C | Space Project Management – Risk management |
| ECSS-M-ST-40C | Space Project Management (Configuration and information management) |
| ECSS-Q-ST-10-04C | Space Product Assurance – Critical-item control |
| ECSS-Q-ST-10-09C | Space Product Assurance – NonconformaCnce Control System |
| ECSS-S-ST-00C | ECSS System – Description, implementation and general requirements |

# 3 Terms, definitions and abbreviated terms

The definition of terms and abbreviations is addressed in the glossary (AO-1-10549-GD).

# 4 Summary

### Introduction

Recent advancements in advanced manufacturing of parts for space applications have led to the development of new equipment, providing greater control and precision over processing variables. These processes generate large numerical, alphanumerical, and videographic Big Data sets, which can be analyzed using artificial intelligence (AI), machine learning (ML), and/or Deep Learning (DL) models. The use of these models can lead to substantial benefits in terms of process control, detecting relations between processing conditions and part performance, and identifying anomaly and failure modes. The data should be collected from internal or external IoT sensors to augment the quality and quantity of available data. Data management, handling, and storage should come from pre-existing solutions already implemented or ready to be used. This leads to the creation of Minimum Valuable products adapted for use case classes with specific capabilities, such as establishing quantifiable relationships between processing conditions, NDT measurements, and in-service parts performance, discovering relationships between advanced manufacturing processing conditions and defects in final parts, achieving a higher level of advanced manufacturing processing parameter control, and expanding the capability of defects identification with the help of Non-Destructive inspections and relating them with part's in-service performance.

After motivating the project, the goals will be laid out. Following, the work program that was undertaken to achieve these goals will be explained. Afterwards, the development approach will be detailed with the use-case selection, system architecture and system features. Lastly, both implemented use-cases will be introduced in more detail and respective results will be presented.

### Goals of the project

The overall goal of the project »PANORAMA« is the targeted expansion of knowledge about machine learning in the production environment of launch vehicles, mainly for the optimization of advanced manufacturing processes. This ensures immediate and future participation in European space transportation systems. For this purpose, two AI use cases were selected, and AI models deployed in the production environment. Both use cases were developed in collaboration between IPT and AGG in the planned project time from Nov 2021 until July 2023 and are applied in the process chain related to advanced manufacturing processes.
The proposal from ArianeGroup and Fraunhofer IPT supports the European space strategy by expanding knowledge about machine learning (ML) in the production environment of launch vehicles. This ensures immediate and future participation in European space transportation systems and paves the way for securing competitiveness through a comprehensive AI strategy. The proposed activities support today's issues and enable step-by-step development towards optimized and cost-effective production in the future. The work proposed in this project is a prerequisite for implementing acquired knowledge in usable products that are technically and economically stable.

The project "PANORAMA" aimed to expand knowledge about machine learning in the production environment of launch vehicles by analyzing the technical requirements, identification and evaluation of use cases, and the development and deployment of AI models in the production environment.

### Work Program Description

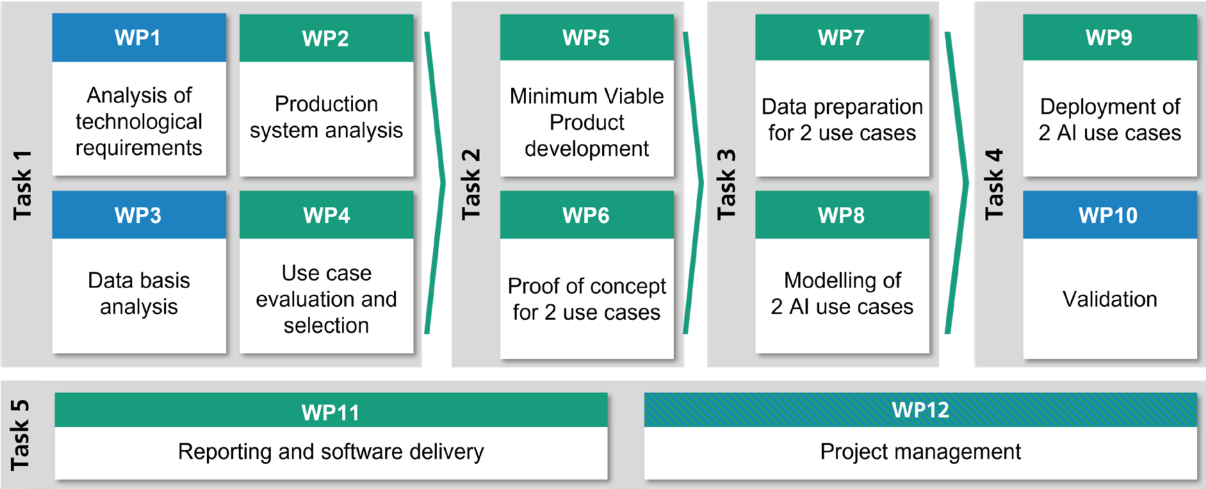


*Figure 1: Work programme*

To implement the proposed approach, the work followed the tasks and work packages listed in Figure 1. Based on a kick-off meeting, task 1 involved analyzing technological requirements and production systems (WP 1, WP 2). After analyzing the data basis, promising AI use cases were evaluated, and two AI use cases were eventually selected for further implementation (WP 3, WP 4). With a decision on the AI use cases, the development plan was finalized. The results of task 1 were reviewed in the requirements review meeting. In task 2, the proof of concept of the MVP was developed and further validated (WP 5, WP 6). At the end of task 2, a proof-of-concept review meeting took place to derive lessons learned for upcoming tasks. Based on experience from past AI projects, the duration of tasks 1 and task 2 was changed. In task 3, which focused on the detailed design and definition of the software architecture, the data was prepared, and the ML/DL algorithms were trained and evaluated in WP 7 and WP 8, respectively. In this iterative approach, software releases were generated to review all artifacts of all tasks. The software was implemented and integrated, which consisted of deployment and validation in WP 9 and WP 10. Continuous testing during deployment and parallel validation by ArianeGroup identified modifications in data preparation and modeling (i.e., task 3, as shown by the dashed line). This underpinned the iterative approach and the need for agile software development to react quickly to possible changes. Task 5 included reporting, software delivery, project management (WP 11, WP 12), and concluded with an acceptance review.

### Use Case Selection and System Architecture

Beginning with the design, the advanced manufacturing processes were identified first. These include the ALM process chain as well as the electronic valve process chain. Within these process chains, the characteristic process steps were identified, which helped to specify classes for machine learning applications. For this, a framework for the identification of machine learning use-cases was used, which is shown in Figure 2. For the individual application classes, AI/ML/DL/Hybrid AI use cases were identified regarding the specific challenges of the advanced manufacturing process. A preliminary selection was based on the risk of implementation and the available data basis and resulted in a longlist of 21 use cases along both process chains. Through a detailed selection based on the operational and strategic benefit as well as the effort of implementing the specific use-case, two cases to be implemented within the project were identified.

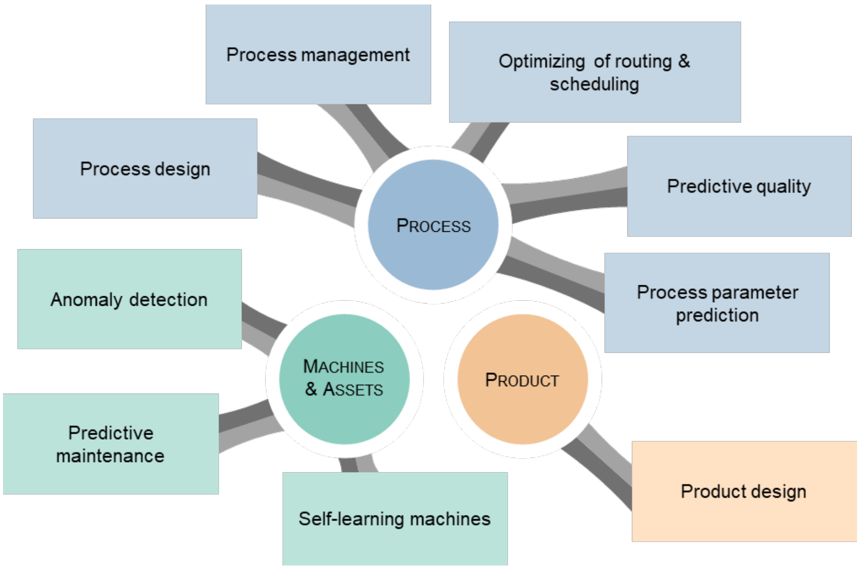


*Figure 2: Use case class overview by Krauss et al.*[1]

For the project PANORAMA, two use-cases in the production of partner Ariane Group were chosen together with Fraunhofer IPT, which could not yet be solved by regular statistics. The two use-cases had to have high operational and strategic benefit to be implemented.

For the first use-case, an automated live process monitoring for ALM process was chosen. The goal was to implement an early detection mechanism for process failures through automated live detection of errors. For this, all powder bed monitoring and optical tomography data as well as the data of quality-critical machine and environmental sensors are checked live during the build job. If a critical error is detected, the machine operator is informed.

For the second use-case, the goal was to analyze the manufacturability of product features based on the capabilities of past processes. Therefore, a model is trained to detect anomalies in the historical measurement data, i.e., identify tolerances and tolerance combinations that often lead to non-conformities and high-quality costs in production. This use-case was implemented in electronic valves and the ALM process.

Both resulting systems – MLsys1 and MLsys2 – are based on a three-tier architecture, which includes the tiers presentation, application, and data. Figure 3 shows an overview of the general system architecture. For increased modularity, portability and maintainability, the architecture is design in a containerized fashion.

[1] Krauß, J.; Dorißen, J.; Mende, H.; Frye, M.; Schmitt, R. H. (ed.): Machine Learning and Artificial Intelligence in Production: Application Areas and Publicly Available Data Sets, 2019

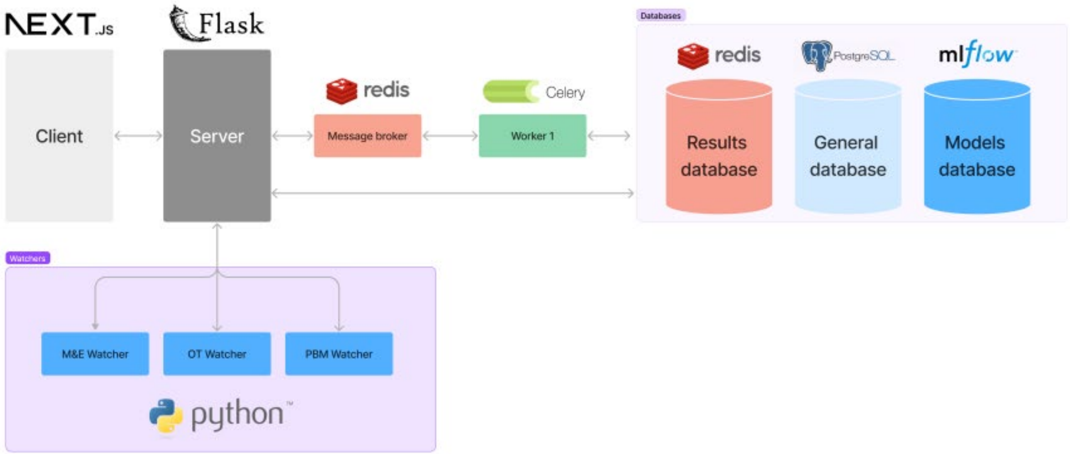


*Figure 3: Software architecture overview*

The main difference between the architecture of both systems is that the MLsys2 does not rely on watcher components for data inference. Furthermore, MLsys2 does not have a models database. Instead, the included clustering models are used for interactive analysis on changing input data with no benefit of storing specialized, fitted clustering models.

After this explanation of the use-case elicitation and model architecture, the configuration and modeling activities will be explained in more detail.
First, the main configuration items were specified in a software design. The results are depicted in Figure 4 and Figure 5 respectively. Specifically, the figures show the main elements of each system and how they are connected on a conceptual level.

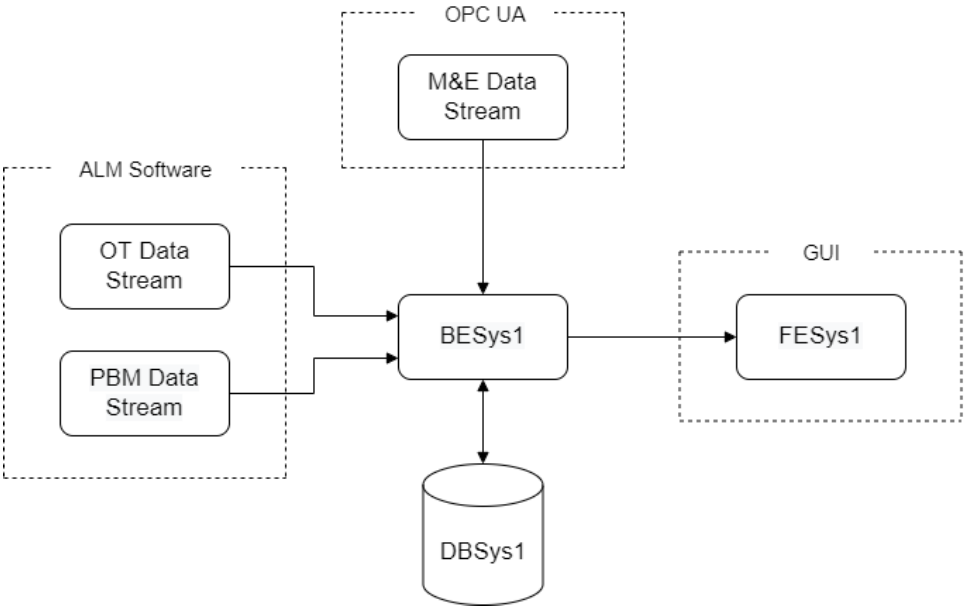


*Figure 4: Main elements connections of MLsys1*

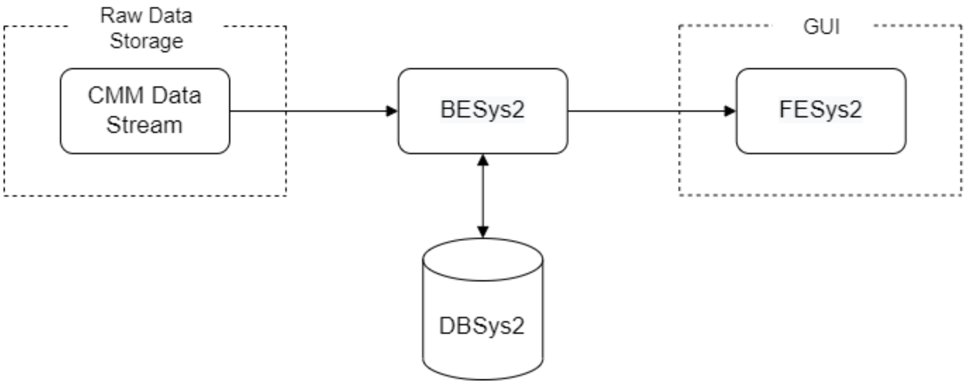


*Figure 5: Main elements connections of MLsys2*

Regarding requirements, user stories were used to assess the requirements baseline of the systems. These were then analyzed and specified into design requirements. These include provisions for the specific frameworks to be used for front- and backend components as well as other system aspects. The goal is to allow for a deployment of the system to the specified operational environment while realizing the requirements on the system capabilities.

The process of the system design and implementation is characterized by the use of traceability matrices, in which the requirements baseline in form of the system requirements are mapped to the software requirements. Furthermore, the software architectural design in the form of software components is traceable to the software requirements through a software design document. This offers transparency to the connection of individual software components to the applicable requirements and vice versa.

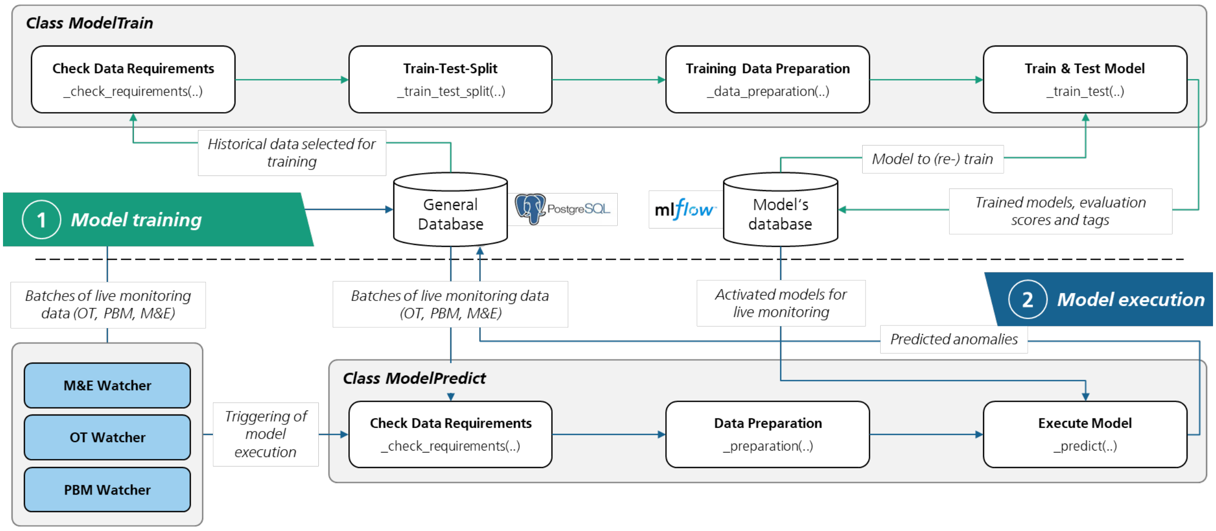


*Figure 6: Management of the model lifecycle (MLsys1)*

Next to the elicitation of requirements, also dependencies were used to learn about the correct architecture of the software system. For this, the dependencies within the software system lifecycle were mapped, so all necessary functions could be clustered into phases: Model training and models execution. From the descriptions of these phases, conclusions are drawn on the dependencies of the individual software components. It can be concluded that next to the missing watcher components and input data being fed by the user, the dependencies of MLsys2 are identical to the ones of MLsys1.

Lastly, the specific ML/AI/DL/Hybrid AI models needed to be chosen for each use case. Within the modeled use-case MVPs, different models were tested for their adequacy regarding the chosen use-case purpose. Models for the machine learning systems were selected by a comparative process in which the accuracy and performance of different machine learning models was measured. While this section gave a glace at the development activities of the two systems, the specific architecture and system features should be explained further in the next section.

## System Features

MLsys1 should be capable of monitoring an optical tomography image stream, a powder bed monitoring image stream, and a M&E (OPC-UA) data stream. There should be a notification in case of any error indications, while the decision making for the error detection should be transparent. This process from data sample collection to defect recognition should happen within less than 10 minutes. The retraining of the system should be possible within 12 hours. For this, the production capabilities per production step and the tolerance chains are analyzed.

For the described purpose, MLsys1 consists of a client, a server, a message broker, a worker, a M&E watcher, a PBM watcher, an OT watcher, a general database, a models database, and a results database. There are four main tasks the system needs to handle: the live monitoring of a running process, a retrospective analysis of monitoring results, the management of machine learning models and the management of training data.

MLsys2 is similarly structured and consists of a client, a server, a message broker, a worker, a general database, and a results database. There are three main tasks the system needs to handle: uploading raw measurement data, uploading parsed measurement data and the analysis of data (analyze measurements, create what-if analysis, export data and report).
Both systems interface their relevant data streams and provide means of authorization and authentication.

**Use-Case 1**

The first use case is an Automated Live Process Monitoring system for an ALM process using the ALM machine EOS-M290. Currently, only a manual and discontinuous process monitoring is performed during the ALM process. Errors are only detected during subsequent quality inspection steps or through a randomly manual process monitoring.
The target of this use-case is the early detection of process failures through automated live detection of errors and the according notification of the respective process expert. Due to the anomaly that occurs in about one in ten jobs, live detecting has the potential to save 2/3 of the build time. The early detection of failures reduces powder waste and machining time.

A comparative evaluation of use cases was conducted with scores in operational and strategic benefit as well as the implementation effort. The operational benefit of this use case is 4.0 on a scale from 0 to 4 and the strategic benefit is 2.54 on a scale from 0 to 4. This makes an overall benefit of 3.52 in a scale from 0 to 4. The effort for implementation is 1.81 on a scale of 0 to 4.

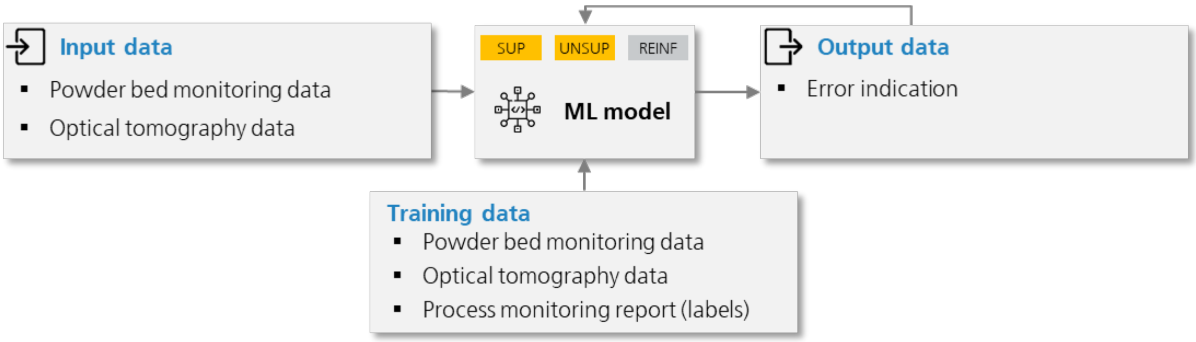


*Figure 7: Rudimentary Use Case 1 architecture*

For the **Optical Tomography Data**, a Detection of 95 from 100 defects on unseen test data (95% sensitivity) has been achieved. The detected anomalies can additionally be robustly classified into the known defect classes. For the **Powder Bed Monitoring Data**, a detection of 91 out of 100 anomalies on unseen test data (91% sensitivity) was achieved. Furthermore, 100% of non-defective instances were detected. Overall, this results in a robust binary classification / anomaly detection. For the **M&E Data**, the project resulted in full (100%) live detection of threshold violations for critical sensors. A time series forecasting was implemented as an aid to anticipate the progression of critical sensor values.
Overall, accurate live detection of quality-critical anomalies during running ALM processes on the EOS-M290 was achieved.

**Use-Case 2**

Over the two regarded process chains, strict tolerance limits lead to non-conformities in production. Numerous historical measurements are available but have not yet been analyzed in a comprehensive manner regarding the production capabilities and robustness of manufacturing and tolerance chains. So far, there is no existing solution in place at ArianeGroup with a comparable functionality.
The target of this use-case was to identify individual tolerance features and tolerances that cannot be robustly produced. In the long term, this allows for an optimization of product design and manufacturing processes. Due to more robust processes the estimated reduction of q-alerts is 20 percent.
For the comparative evaluation, the operational benefit of use-case 2 is 2.55 on a scale from 0 to 4 and the strategic benefit is 2.14 on a scale from 0 to 4. This makes an overall benefit of 2.41 in a scale from 0 to 4. The effort for implementation is 0.86 on a scale of 0 to 4.

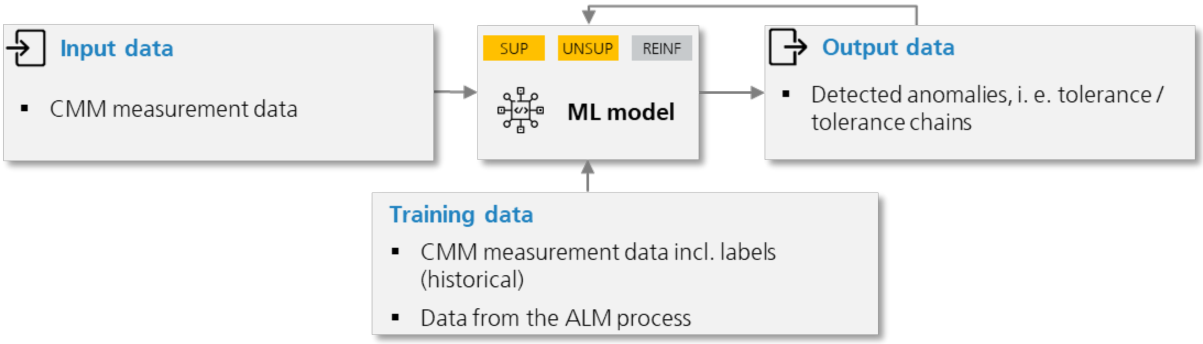


*Figure 8: Rudimentary Use Case 2 architecture*

For the **Data Upload**, automatic parsing of raw data, e.g. measurement protocols in .txt format, and augmentation with meta information were implemented. Preprocessed measurements are processed in the .csv-format. Regarding **Data Analysis**, measurement points can be clustered according to preselectable criteria in a clustering chart. Additionally, found clusters can be presented in a Pareto-chart. Furthermore, possible relationships can be represented in a correlation matrix. All performed analyses can be stored for later access. **The Robustness Assessment permits** different visualizations and combinations for the assessment of robustness. For the consideration of production capabilities, the adjustment of thresholds is facilitated. Based on the findings, reports can be created and considered data points can be exported as a .csv-file so share insights outside of the system environment.

All in all, the project "PANORAMA" successfully expanded the knowledge about machine learning in the production environment of launch vehicles. Promising use-cases were methodologically elicited and scored by their operational and strategic benefit. Additionally, the process of developing MVPs for these applications was laid out transparently and structured by state-of-the-art methods such as the CRISP-DM framework. This proves the possibility for ML/AI/DL/Hybrid AI use-cases in the space production environment.

**Signatures**:

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