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RESEARCH ARTICLE

PIA - A Concept for a Personal Information Assistant for Data Analysis and Machine Learning of Time-Continuous Data in Industrial Applications

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Date Received:
2023-02-14

Keywords:
Machine Learning, Data Analysis, Measurement and data planning

Data availability:
This publication uses no data.

Software availability:
The concept demonstrator can be found on GitHub: https://github.com/ZeMA-gGmbH/-PIA

Abstract. A database with high-quality data must be given to fully use the potential of Artificial Intelligence (AI). Especially in small and medium-sized companies with little experience with AI, the underlying database quality is often insufficient. This results in an increased manual effort to process the data before using AI. In this contribution, the authors developed a concept to enable inexperienced users to perform a first data analysis project with machine learning and record data with high quality. The concept comprises three modules: accessibility of (meta)data and knowledge, measurement and data planning, and data analysis. Furthermore, the concept was implemented as a front-end demonstrator on the example of an assembly station and published on the GitHub platform for potential users to test and review the concept.

1 Introduction

Data and their analysis play a crucial role in research and science. In recent years, especially with steadily increasing computational power and the advances in Artificial Intelligence (AI), the importance of high-quality data has continued to grow. In this context, entire research fields and committees exclusively focus on improving data and their quality to maximize the potential of their use. However, using AI in the industry also offers enormous benefits for companies. In typical condition monitoring tasks, for example, early detection of damages or wear down of machine parts can avoid unplanned machine downtime costs. Instead, maintenance can then be scheduled, and downtimes can thus be minimized. Especially small and medium-sized

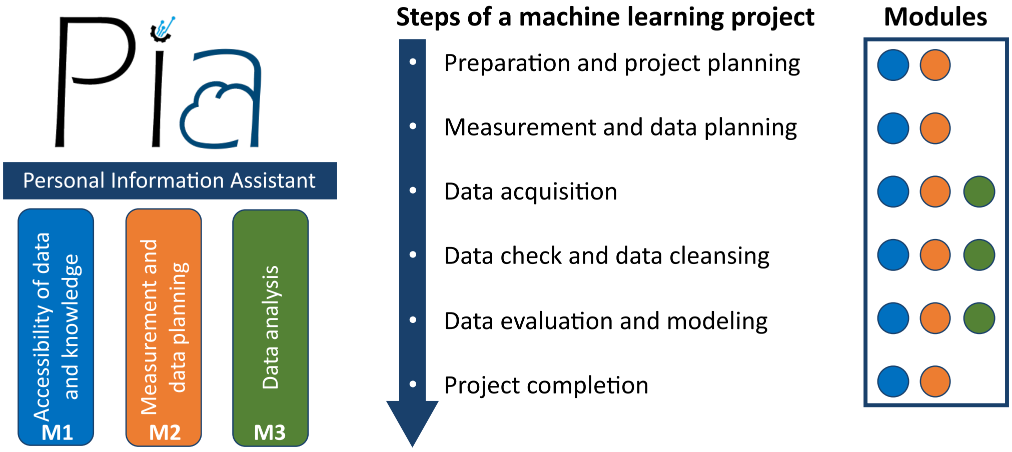

Pia
Personal Information Assistant
Accessibility of data and knowledge
M1
Measurement and data planning
M2
Data analysis
M3
Steps of a machine learning project
Preparation and project planning
Measurement and data planning
Data acquisition
Data check and data cleansing
Data evaluation and modeling
Project completion
Modules

Figure 1: Concept of the Personal Information Assistant PIA, with its three modules and their contribution to the six steps of a machine learning project.

enterprises (SMEs) often have no dedicated department, skilled staff, or resources for analyzing their data and performing machine learning (ML) [1]. For these cases and to retain the obtained knowledge, the concept "PIA – Personal Information Assistant for Data Analysis" has been developed. PIA is an open-source framework based on Angular 13.3.4, a platform for building mobile and desktop web applications, which runs locally on a server and can be accessed via the intranet. PIA is developed following the in research widely accepted FAIR (Findable, Accessible, Interoperable, and Reusable) data principles and aims to transfer and apply these principles in the industry as well [2].

The concept for PIA consists of three complementing modules that support users in different stages of the machine learning project:

- **Module M1**: Accessibility of data and knowledge
- **Module M2**: Measurement and data planning
- **Module M3**: Data analysis

Figure 1 shows the three modules (**M1-M3**) as pillars of PIA. Furthermore, the steps of a machine learning project are shown with the involved modules in their respective color. It can be seen that **M1** and **M2** cover all steps of a machine learning project and are therefore closely connected to each other in the concept of PIA.

In **M1** (*Accessibility of data and knowledge*), PIA provides an easy interface to access knowledge and data through the intranet. Here, two well-established methods in project management for lessons learned were combined and implemented as a knowledge base into PIA. Furthermore, an intuitive user interface (UI) enables users to easily find and access relevant (meta)data. In **M2** (*Measurement and data planning*), PIA provides a checklist that was developed by Schnur et al. [3], [4] in a previous project on brownfield assembly lines to increase data quality. An English checklist version can be found in [5]. **M3** (*Data analysis*) is based on the automated ML toolbox of Dorst et al. [6] and Schneider et al. [7], [8], which was developed in previous projects and successfully applied to industrial time-continuous data.

To the authors' knowledge, the concept PIA is a novel concept that covers a holistic approach to enable inexperienced industrial users to perform a first data analysis project, focusing on the domain of measurement and data planning. Here, the three modules are combined in a complementing manner and brought into an interface that assists users in data analysis and ensures the recordings of high-quality and ”FAIR” data. Furthermore, a demonstrator for the concept has been developed as a front-end in Angular 13.3.4 and tested on an assembly line as a use case, which assembles a specific product in several variants, focusing on bolting processes.

The structure of the paper is as follows: In the next chapter, the theoretical background and methodology will be explained, starting by pointing out the flaws of data in the industry, followed by the three modules **M1-M3**. In the chapter *Implementation and Results*, the use case *Assembly Line* is introduced, and details about the environment and structure of PIA are given. Thereafter, the implementation and application of the concept to each module is shown. The chapter *Conclusion and Outlook* summarizes the presented concept and what future research of PIA will cover.

2 Theoretical Background and Methodology

In the chapter *Theoretical Background and Methodology* first, data in an industrial context and its common problems will be elaborated on. Thereafter, each of the three modules (**M1-M3**) with their respective methods will be explained.

2.1 Data in Industry

In their empirical study, Bauer et al. [1] found that the lack of sufficient employees (with ML knowledge) and limited budget are part of the most frequent significant challenges for SMEs. This can lead to rushed approaches, which end in a database with low-quality data. However, an essential requirement for a successful application of AI in the industrial context is a database with high-quality data, e.g., from production and testing processes. The practical application of AI algorithms often fails due to

- Insufficient data quality due to missing or incomplete data annotation
- Incomplete data acquisition
- Problems linking measurement data to the corresponding manufactured products
- Lack of synchronization between different data acquisition systems

as shown in [9]. Furthermore, industrial data are typically acquired continuously without saving relevant metadata. In addition, this often leads to a brute force approach, which tries to use all acquired data. Large data sets are subsequently challenging to manage, and their use is computationally expensive. A knowledge-driven approach can efficiently use resources and increase the information density within the data, e.g., by reducing the amount of used sensor data due to process knowledge. By recording data in a targeted manner, redundancies can also be avoided. The necessary process knowledge to analyze data, especially in SMEs, is often limited to a few employees and cannot be easily accessed by colleagues. Those specialists might also not be willing to share their knowledge in fear they lose their distinctiveness against other employees [10]. In the worst case, the (process) knowledge is lost if the specialist leaves the company.

2.2 Module 1 - Accessibility of Data and Knowledge

Due to the specific challenges in the analysis of industrial data mentioned by Wilhelm et al. [9], the accessibility of the data itself and the accessibility of domain-specific knowledge play a crucial role in obtaining robust ML models or further insights and knowledge about, e.g., products or processes. Module 1 of PIA, therefore, consists of a UI to access easily (meta)data and knowledge as well as a knowledge base in the form of a lessons learned register. **M1** can be seen as a complementing add-on component to internal knowledge repositories like company wikis [11] and databases like *InfluxDB* [12] or *MongoDB* [13]. Guidance on recording and structuring data and metadata can be found in the checklist [4] presented in chapter 2.3 as well.

To learn from previous projects and retrieve knowledge to use in future projects, lessons learned are a well-established method in project management [14]. In the context of the framework PIA, the lessons learned register is organized and structured like the checklist presented in **M2** and contains high-quality lessons learned for each specific chapter of the checklist. Rowe et al. [14] structure the formulation of lessons learned into the five subsequent steps: identify, document, analyze, store, and retrieve. Moreover, they describe these steps in more detail and provide a template for lessons learned. The technical standard DOE-STD-7501-99 [15] suggests that each lesson learned should contain the following five elements:

- Understandable explanation of the lesson
- Context on how the lesson was learned
- Advantages of applying the lesson and potential future applications
- Contact information for further information
- Key data fields increase the findability

Additionally, Patton [16] distinguishes lessons learned into *lessons learned hypothesis* and *high-quality lessons learned*. While a *lessons learned hypothesis* is a lesson learned with one supporting evidence, *high-quality lessons learned* could be approved in multiple projects. To ensure the quality of the lessons learned, Patton [16] further formulated ten questions in his paper for generating such high-quality lessons learned. Moreover, he recommended reviewing lessons learned periodically regarding their usefulness and sorting out obsolete lessons learned to maintain high quality.

Figure 2 shows the approach proposed in this contribution. After analyzing a given use case, specific results were achieved. The whole project is evaluated in a retrospective, and lessons learned are formulated according to the five steps of Rowe et al. [14]. If the lessons learned (hypothesis) can be validated in further projects, they get added to the lessons learned register. The lessons learned register is reviewed regularly to ensure relevance and actuality.

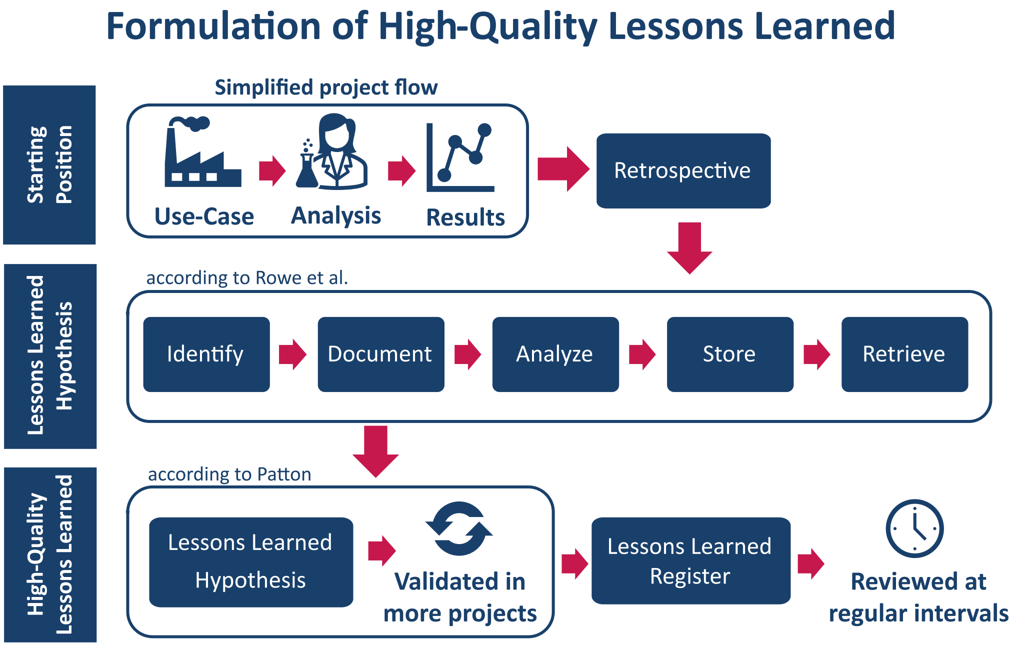


Figure 2: Formulation of high-quality lessons learned through combining the approaches of Rowe et al. and Patton [14], [16].

2.3 Module 2 - Checklist for Measurement and Data Planning

The foundation for successfully applying AI in industry is a high quality of the underlying data. The research field measurement and data planning can be seen as an early part or requirement of data mining, which is the process of extracting knowledge from data sets using computational techniques [17]. For industrial data mining, the *Cross-Industry Standard Process for Data Mining* (CRISP-DM) established, which divides data mining into the six non-sequential and independent phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment [18]. Since data mining consists of several disciplines, each of which has its own research area, inexperienced users can feel overwhelmed and demotivated mainly because the industry's focus is not to record high-quality data but to use data to increase efficiency and margin. A guide or checklist can help users to orientate and access the field of data mining. Here several approaches can be found in literature like, e.g., *A Checklist for Analyzing Data* of [19] or the *Analytical Checklist – A Data Scientist' Guide for Data Analysis* [20]. The checklists mentioned are universally applicable but lack information for the realization of a data analysis project and assume that data sets are already recorded. Other concepts, like, e.g., *FAIR* of Wilkinson et al. [2] ensure high-quality data and offer practicable solutions like *The FAIR Cookbook* that guide new users but are primarily focused on research data.

The *Checklist - Measurement and data planning for machine learning in assembly* of Schnur et al. [3] tries to find the sweet spot between having a broad scope, transferring knowledge from research data management but still being clearly structured and not overwhelming for an inexperienced user. Within PIA, the checklist enables the users of PIA to perform a machine learning project from the beginning to the end and record high-quality FAIR data. It covers the following chapters:

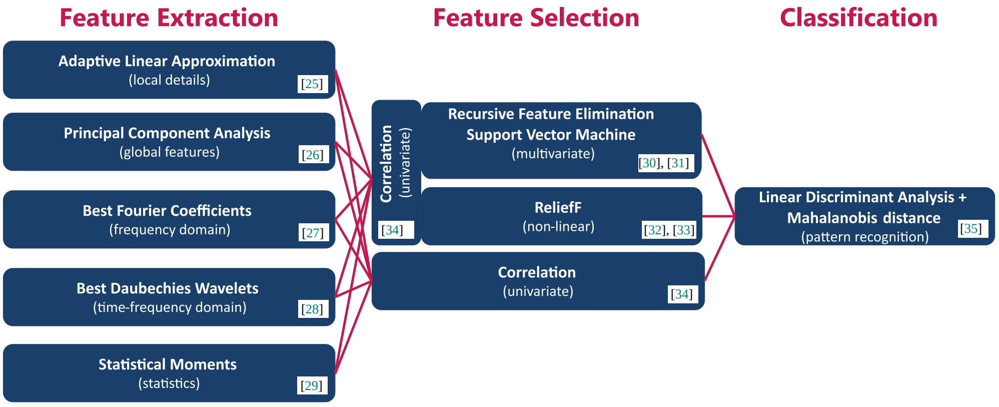


Figure 3: Algorithms of the automated ML toolbox for classification with their corresponding literature (adapted from [6]).

- Preparation and project planning
- Measurement and data planning
- Data acquisition
- Data check and data cleansing
- Data evaluation and modeling
- Project completion

Each chapter begins with a short introduction, followed by checkpoints that guide the user. Here, two types of checkpoints exist: necessary and best-practice checkpoints. While the best-practice checkpoints are optional but highly recommended, the necessary checkpoints must be executed. Furthermore, the checklists provide tips and notes derived from high-quality lessons learned from previous ML projects and further literature suggestions. The checklist is based on a revised version of the CRISP-DM mentioned above. Therefore, some parts of the checklist are iterative.

The checklist was initially published in German on the file-sharing platform Zenodo and has been translated for integration into PIA to English, which also increases accessibility and re-usability [4].

2.4 Module 3 - Data Analysis

In nowadays industry, an extensive range of tools and software for data analysis exists. Some well-known and established examples are the software library *Pandas* for Python [21], Power BI [22], the *Statistics and Machine Learning Toolbox* of MATLAB ® [23] or the open platform *KNIME* [24]. All the solutions mentioned are powerful data analysis tools and offer a broad spectrum of algorithms.

Within the concept of PIA, the focus lies on time-continuous data. However, potential users can implement every ML tool or algorithm that suits their use case and data into **M3**, starting from traditional approaches like feature extraction, selection, and classification/regression to modern approaches like deep learning with neural networks. However, it could be shown by Goodarzi et al. [36] that traditional approaches could perform similar to modern approaches while being less complex and have a higher interpretability. To cope with the heterogeneous data sources in industrial applications, especially as an inexperienced user, a set of different feature extraction and selection methods can be beneficial [37]. For the implementation of PIA within this study, the authors use the existing automated ML toolbox for time-continuous data of Dorst et al. [6]and Schneider et al. [7]. This toolbox automatically tests different combinations of feature extraction and feature selection methods with linear discriminant analysis and Mahalanobis distance as the classifier. This automated ML toolbox combines five complementary feature extraction methods with three feature selection methods, as shown with their corresponding literature in Figure 3. A 10-fold cross-validation automatically determines the best of the resulting 15 combinations by ranking the combinations according to their resulting cross-validation error on the test data [38], [39]. Due to the different focus of each algorithm (shown in Figure 3), the toolbox could achieve good results in a broad application range ([37], [40]).

Users can perform a first ML analysis with the toolbox by running five lines of code:

```
addPaths; %Adds folders and subfolders to the path
load dataset.mat %Load data set
fulltoolbox = Factory.FullToolboxMultisens(); %Build object
fulltoolbox.train(data,target); %Train model with data and target as input
prediction = fulltoolbox.apply(data); %Apply trained model on data
```

Listing 1: Code to run the complete toolbox.

For further analysis or regression tasks, the methods can be modified, changed, or applied separately.

3 Implementation and Results

To evaluate the methods presented in the chapter *Theoretical Background and Methodology*, the use case *Assembly Line* will be first introduced in this chapter. After that, PIA's chosen environment and structure will be shown, followed by the implementation of the three modules regarding the given use case.

3.1 Use Case: Assembly Line

As a validation use case for this contribution, an assembly line with two stations was chosen (Figure 4 a) that produces a device holder (Figure 4 b). In the first station, a robot picks up the individual parts of the device holder from a warehouse and places them on a workpiece carrier. The product is transported to station 2 by a belt conveyor for the next step. There, a worker assembles the two components by a bolting process. In addition, the device holder can be produced in another variant (Figure 4 c). The use case is presented in more detail in [41].

The combination of two different stations with different processes and different degrees of automation, as well as the opportunity to produce a second variant of the device holder, make

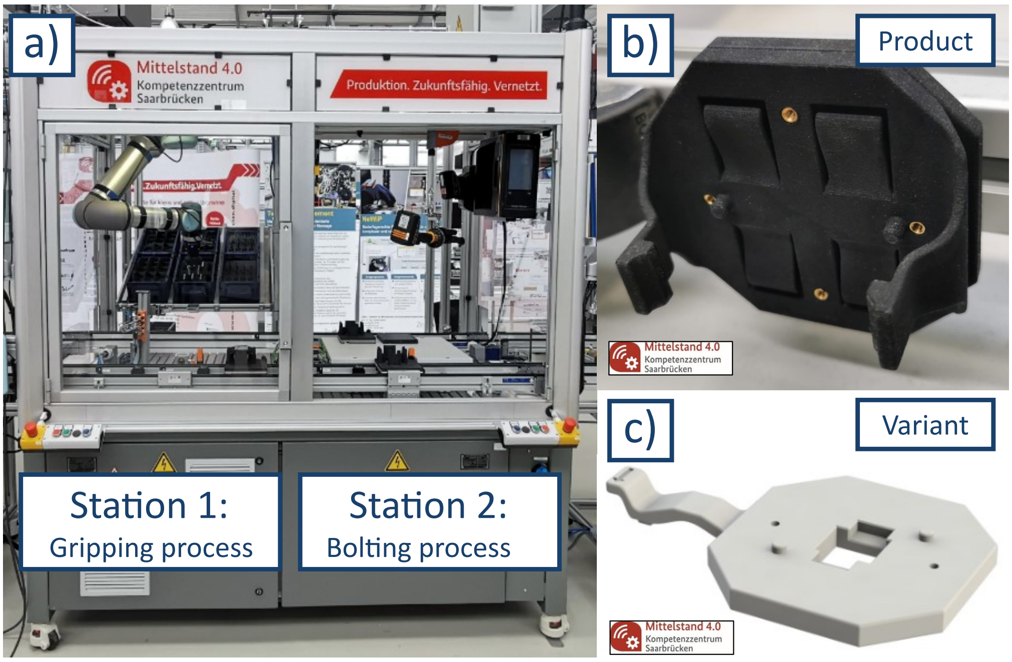

a)
Mittelstand 4.0 Kompetenzzentrum Saarbrücken
Produktion. Zukunftsfähig. Vernetzt.
Station 1: Gripping process
Station 2: Bolting process
b)
Product
c)
Variant

Figure 4: Picture of the assembly line with its two stations (**a**), the produced device holder (**b**) and a variant of the device holder (**c**).

this assembly line a good use case for demonstrating the flexibility of PIA while keeping the complexity low (compared to more extensive assembly lines).

3.2 Environment and Structure of PIA

The Angular framework, an open-source single-page web application framework, has been chosen to demonstrate the concept of PIA. Angular 13.3.4. allows fast development of the demonstrator and gives the possibility that, once the demonstrator is hosted on the web, PIA can be easily accessed from any device within the intranet.

Figure 5 shows a schematic representation of the development environment of PIA. For simulating the user experience, the type-2 hypervisor Oracle VM VirtualBox (https://www.virtualbox.org/) from Oracle Corporation was used with Ubuntu as the guest operating system (OS). However, in general, Angular can also be used on Microsoft Windows or Apple macOS.

Table 1 gives an overview of the used environments and Table 2 of the used libraries, each with their corresponding sources.

Value	Package	Source
E1	Angular CLI	https://www.angular.io/
E2	Node JS	https://www.nodejs.org/en/
E3	Node Package Manager	https://www.npmjs.com/

Table 1: Overview of the used environments.

Besides Angular (E1), the environments Node JS (E2) and Node Package Manager (E3) are used. Angular's primary architectural features are a hierarchy of components. Using this structure,

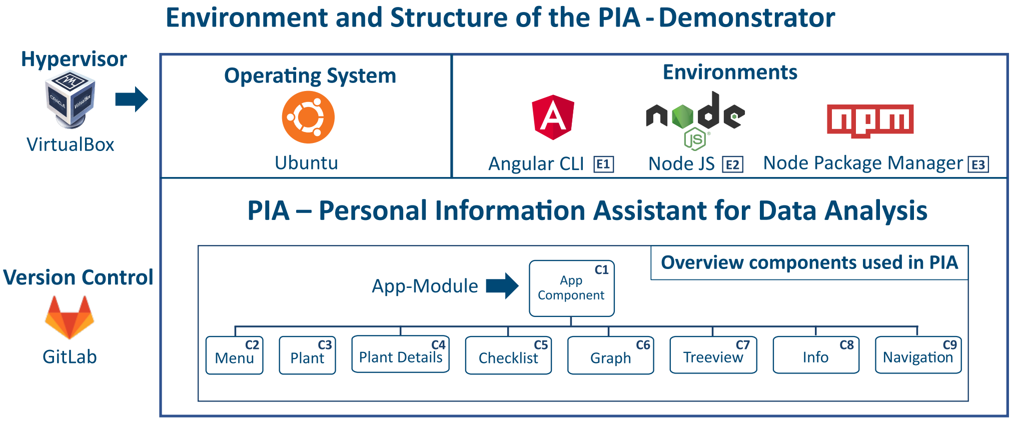


Figure 5: Schematic representation of the environment and structure of the PIA-Demonstrator.

Value	Package	Source
L1	Angular Forms	`https://www.npmjs.com/package/@angular/forms`
L2	Angular Material	`https://www.material.angular.io/`
L3	Bootstrap	`https://www.npmjs.com/package/bootstrap`
L4	Charts js	`https://www.npmjs.com/package/chart.js`
L5	Flex Layout	`https://www.npmjs.com/package/flex-layout`

Table 2: Overview of the used libraries.

the various PIA functionalities have been separated into components for ease of use and reuse. Table 3 provides an overview with a short description of the components used in PIA. This structure also allows to easily add new components to the application without interfering with existing ones. The Angular Material library (L2) provides a consistent experience across the website. Specific dynamic components have also been made responsive using Bootstrap and Flex-Layout libraries (L3, L4). To make it easier for future developers to add new information to the website, data about each process has been saved in JSON format and then queried to display the relevant information in the UI. Users or developers can easily add more plants or tools to the application by editing the relevant JSON file, which will be dynamically displayed in the UI.

Figure 6 shows the landing page of PIA. Over a menu, the user can navigate through the four menu points:

1. Plant
2. Knowledge base
3. Checklist
4. Data Analysis

3.3 Module 1 - Accessibility of Data and Knowledge

The implementation of **M1** contains two parts, accessibility of data and metadata (menu-point: *Plant*) and a lessons learned register (*Knowledge base*). The plant module displays information, data, and metadata about various plants. Figure 7 shows an example flow-through of the use case

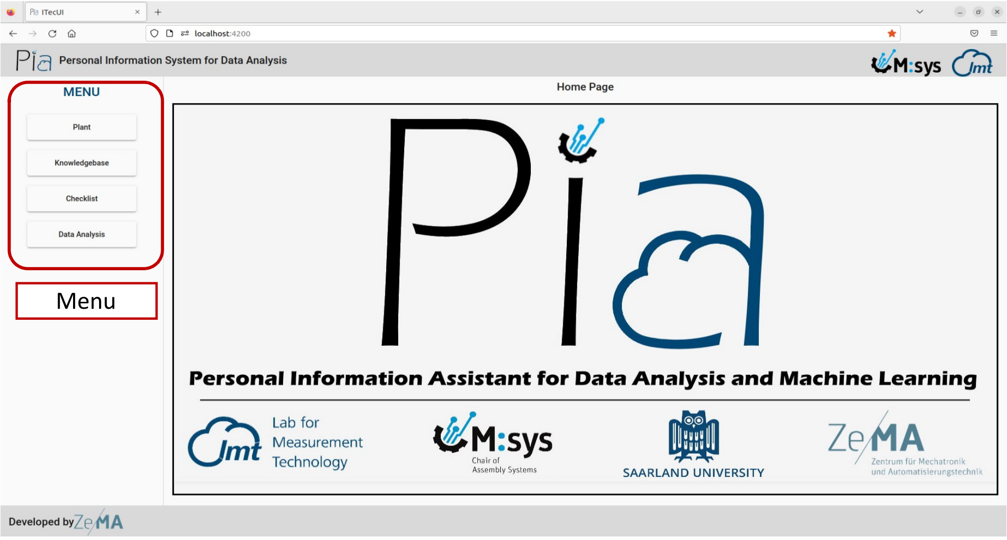

PIA ITecUI
localhost:4200
Pia Personal Information System for Data Analysis
M:sys
Jmt
MENU
Plant
Knowledgebase
Checklist
Data Analysis
Menu
Home Page
Pia
Personal Information Assistant for Data Analysis and Machine Learning
Lab for Measurement Technology
M:sys Chair of Assembly Systems
SAARLAND UNIVERSITY
ZeMA Zentrum für Mechatronik und Automatisierungstechnik
Developed by ZeMA

Figure 6: Landing page of PIA with its four menu points (red box): Plant, Knowledge base, Checklist, and Data Analysis.

in this study. After clicking on the *Plant* button, the available stations of the plant are displayed: *Gripping Process* and *Bolting Process*. After selecting a process (Figure 7, green box), the user can select between the following options:

- **Product**: Displays all available products with their variants containing further information like CAD files and technical drawings.
- **Resources**: All process resources are displayed with a picture (Figure 7, red box) and contain sub menus (Figure 7, blue box) with further information.
- **Measurements**: Data can be loaded as a CSV-file into PIA and plotted through the *charts.js* (L4) library.
- **Video**: A video of the process that shows the procedure and allows the user to develop a better understanding and link the data of a process. The video was embedded using the *HTML iframe tag*.
- **Sensors**: Contains an overview of all used sensors and their metadata (like sensor type, sensor position, sampling rate, etc.).
- **Shift book**: Displays the digital version of the shift book. Using the entries of the shift book can support the user, e.g., to explain outliers or shifts in data.

All information is contained in an array of JavaScript objects. Therefore, a new plant, station, or resource can be easily included by adding new objects to the array in the same format and assigning it on the front-end. Here, Angular material cards (L2) are used to display further information, e.g., process resources. An example of the basic structure of the array of objects for a *Station* with one process which includes a robot and relevant metadata, e.g., technical data or technical drawings, is shown in list. 2 (Section A).

Further instances of the resources, e.g., a gripper for the robot, can be easily added by creating a new object with ID, name, and paths corresponding to the documents and images in the assets

Nr	Component Name	Description
C1	App Component	The application's root component is defined in the *app.module.ts* file and bootstrapped to the *main.ts* file to start the application. It acts as a container for all other components in the application.
C2	Menu	It provides a menu in the application to navigate through the various features. It appears on the left-hand side of the UI and has buttons for navigation through components.
C3	Plant	Implements the navigation to select the specific plant described in the application and provides buttons to navigate through the various embedded components.
C4	Plant Details	Implements the information about a specific plant and contains an array of objects, which saves information about the specific plant. Each object in the array contains properties that describe the plant. The main array of the plant has further arrays embedded inside, with similar properties describing the processes/stations inside a plant.
C5	Checklist	Implements the checklist with a navigation pane to move to different nodes inside the checklist. It has a JSON implementation that contains the description and other relevant information about each node in the checklist.
C6	Graph	Implements the plotting of graphs in the application with the Charts js library. It allows users to plot data from an uploaded CSV-file.
C7	Treeview	Implements the tree view of available or used processes. Furthermore, it implements the domain-specific knowledge of those processes or related tools in so-called cards.
C8	Info	Implements a card that displays specific text information regarding a particular process in the plant.
C9	Navigation	Header component, which implements the logo and name of the application

Table 3: Overview of the used components.

folder and providing the relative paths to the corresponding documents. The new instance will automatically be displayed in the UI after recompiling. Furthermore, the button *Knowledge base* (Figure 7, blue box) contains specific knowledge about each resource.

The second part of the knowledge base contains the lessons learned register and a simple example of the link to general knowledge. The general knowledge was implemented illustratively as a graphical representation of the assembly processes in the form of a tree. Here, the user can expand the tree by selecting the respective nodes to access the sub-nodes that describe the next steps of the process described in the parent node. The information component has been integrated with the nodes, which can provide further descriptive information about each node.

The implementation of the lessons learned register is shown in Figure 8. In the suggested version of a lessons learned register, each lesson learned is generated by the process shown in Figure 2 and grouped by their respective project step (chapter) of the checklist (Figure 8, blue box). After selecting a chapter, the lessons learned appear on the right-hand side (Figure 8, red box). Users can add criticism to existing lessons learned, lessons learned hypotheses, or additional files in the *Comment Section* (Figure 8, green box). The *Comment Section* is reviewed at regular intervals and, if necessary, transferred to the *Lessons Learned Register*.

Using the presented structured, high-quality lessons learned register allows the user to easily access domain-specific knowledge in a target-orientated manner and to avoid previously made mistakes in earlier projects. The presented GUI enables users to find relevant information intuitively rather than searching for information in multi-layered folder structures with restricted accessibility.

3.4 Module 2 - Checklist for Measurement and Data Planning

The checklist implementation uses the tree component of the Angular Material (L2) library, which allows the present hierarchical content as an expandable tree (Figure 9, blue box). Each node of this tree displays information about itself and additional tips or hints (Figure 9, red box). Furthermore, comments and files can be added to each checkpoint (Figure 9, green box). This helps employees who are new to the project to catch up and comprehend past steps. When the user ticks through all the sub-nodes, the primary process node is automatically ticked, indicating that all the sub-processes have been completed.

The *Checklist for Measurement and Data Planning* guides and supports users holistically through a data analysis project while highlighting trip points. Using the checklist in an implemented version rather than the printed version, the status and progress of ongoing projects can be tracked and understood by non-involved users in case a worker gets sick or leaves the company.

3.5 Module 3 - Data Analysis

Since PIA is implemented as a front-end demonstrator with no back-end, the data analysis is carried out in MATLAB ® Online™. Figure 10 shows the results of the data analysis with the ML toolbox for data of the example use case provided in [6]. The toolbox can be directly connected to GitHub into MATLAB ® Online™ (Figure 10). As shown in the blue box of Figure 10, the

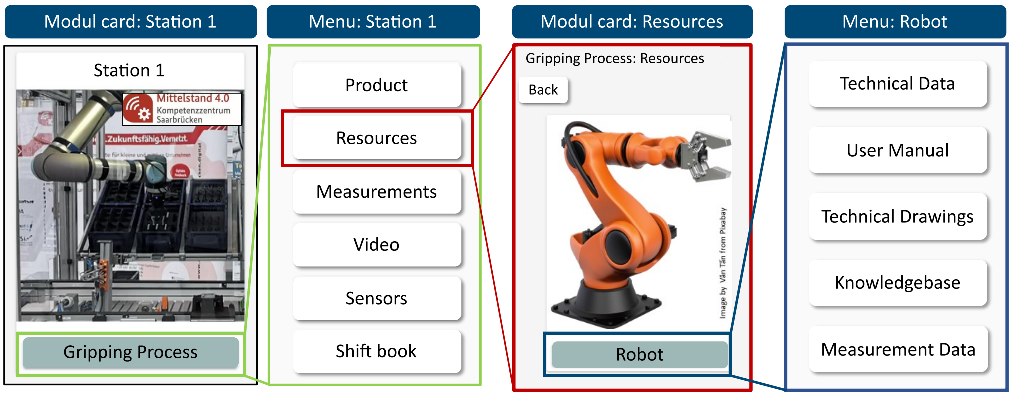
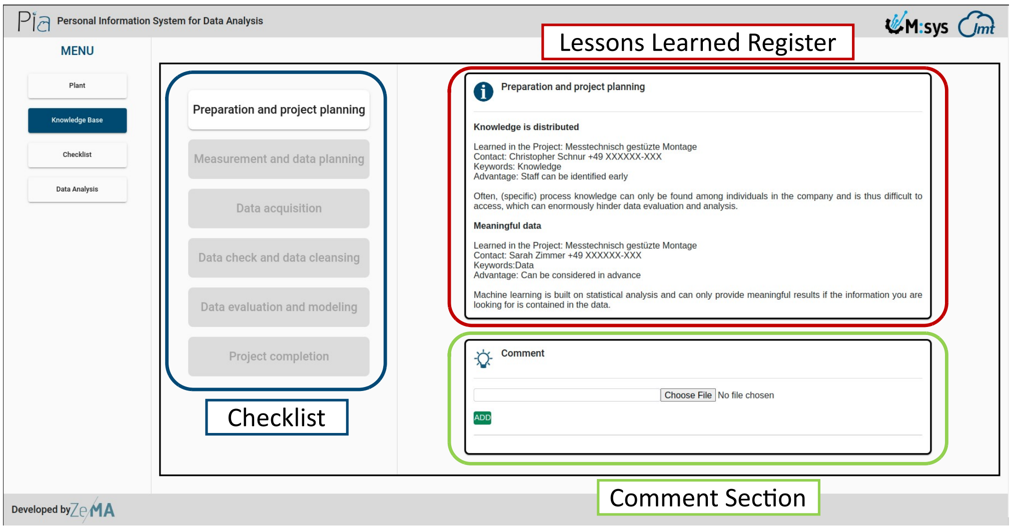


Figure 7: Schematic representation of the knowledge base with its single components.



Preparation and project planning

Knowledge is distributed

Learned in the Project: Messtechnisch gestüzte Montage
Contact: Christopher Schnur +49 XXXXXX-XXX
Keywords: Knowledge
Advantage: Staff can be identified early

Often, (specific) process knowledge can only be found among individuals in the company and is thus difficult to access, which can enormously hinder data evaluation and analysis.

Meaningful data

Learned in the Project: Messtechnisch gestüzte Montage
Contact: Sarah Zimmer +49 XXXXXX-XXX
Keywords:Data
Advantage: Can be considered in advance

Machine learning is built on statistical analysis and can only provide meaningful results if the information you are looking for is contained in the data.

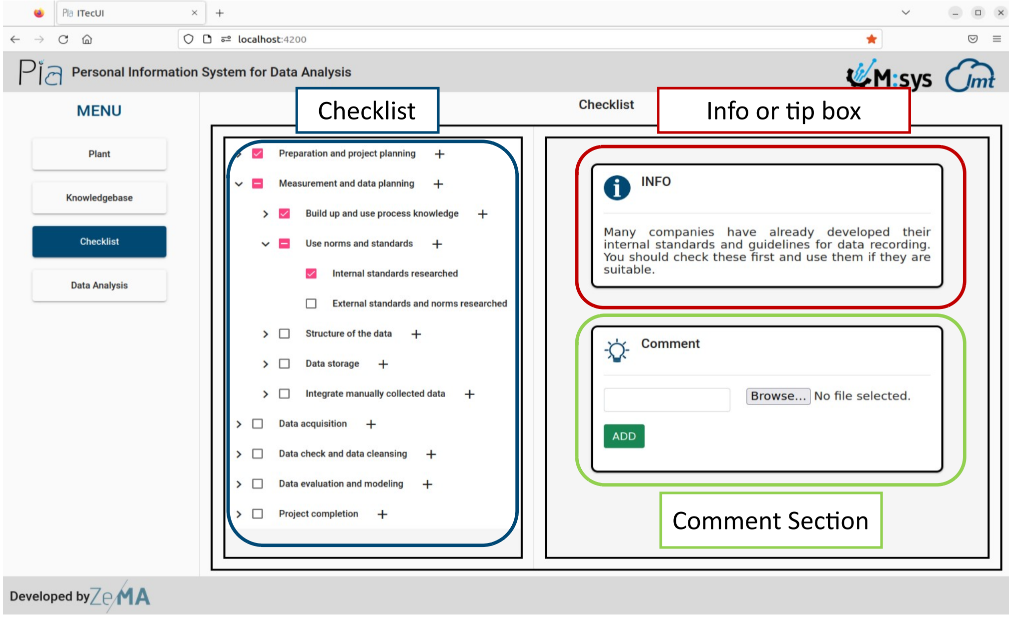
Figure 8: Implementation of the lessons learned register in PIA. Blue box: Chapters of the checklist. Red box: Lessons learned register. Green box: Comment section.

user can access other algorithms by clicking through the folder structure. After executing the code (Figure 10, green box), the user can plot the results (Figure 10, red box). For interpreting the results, the user can follow the subsequent steps of the checklist in **M2** while using the knowledge, data, and metadata provided in **M1**.

The implemented toolbox can be used by users with little programming experience while covering a broad range of algorithms for analyzing industrial time-continuous data with ML. However, the users can also embed other, e.g., use-case-specific algorithms.

4 Conclusion and Outlook

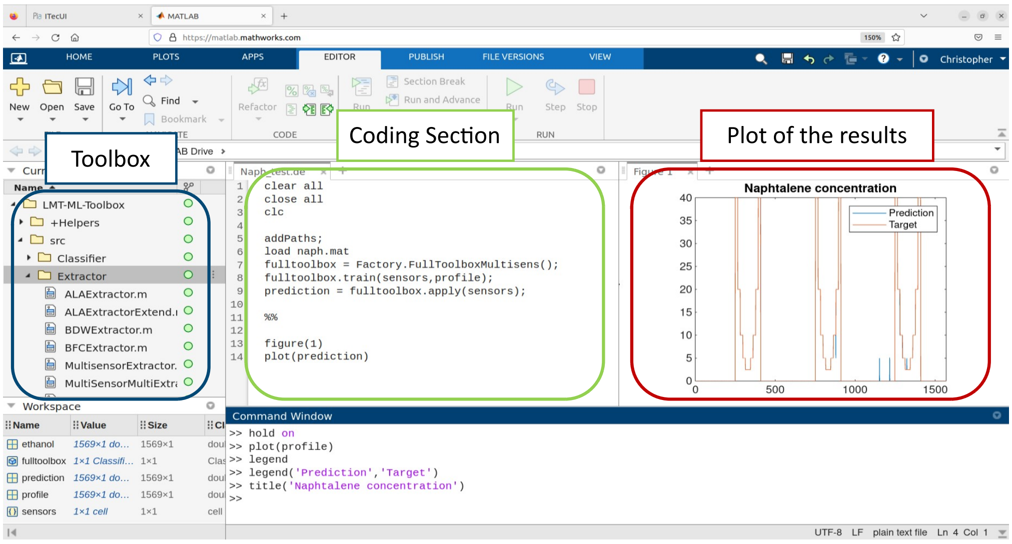
The personal information assistant PIA supports inexperienced users in performing an ML project and gaining further insights from data. For this, it consists of the three modules *Accessibility of Data and Knowledge*, *Checklist for Measurement and Data Planning*, and *Data Analysis*. *Accessibility of Data and Knowledge* allows the user to access relevant metadata and gain knowledge about the plant and processes through a lessons learned register. Using the concept, data, and metadata can be recorded and organized in a targeted and structured manner, creating appropriate boundary conditions for data analysis projects. In its current version, the PIA demonstrator is implemented on a front-end in a virtual machine. By adding an additional back-end, the progress of a project, attached files, comments, etc., can be saved and loaded properly. Furthermore, a direct connection to a database is conceivable. Implementing PIA in Angular was a time-efficient way to demonstrate its benefits. However, users can decide if they want to apply the concept in a different framework. Furthermore, the modules can be switched or customized to the specific needs of the users due to the open-source nature of this contribution and the PIA concept in general. The authors will further develop their concept in future research and test it on other use cases. Current development focuses on the integration of ontology's, respectively machine-readable metadata in **M1**, the generalization of the checklist in **M2**, and improvements regarding the usability for inexperienced users in SMEs and, in **M3**, the


ITecUI
localhost:4200
Pia Personal Information System for Data Analysis
M:sys
MENU
Plant
Knowledgebase
Checklist
Data Analysis
Checklist
Checklist
Info or tip box
☑ Preparation and project planning +
▬ Measurement and data planning +
☑ Build up and use process knowledge +
▬ Use norms and standards +
☑ Internal standards researched
□ External standards and norms researched
□ Structure of the data +
□ Data storage +
□ Integrate manually collected data +
□ Data acquisition +
□ Data check and data cleansing +
□ Data evaluation and modeling +
□ Project completion +
INFO
Comment
Browse... No file selected.
ADD
Comment Section
Developed by ZeMA

Many companies have already developed their internal standards and guidelines for data recording. You should check these first and use them if they are suitable.

Figure 9: Implementation of the checklist in PIA. Blue box: Chapters of the checklist with their corresponding sub-chapters and checkboxes. Red box: Info- and Tip-boxes. Green box: The comment section.

integration of a data pipeline to evaluate the data quality as well as the usage of algorithms that consider measurement uncertainty.



```
clear all
close all
clc

addPaths;
load naph.mat
fulltoolbox = Factory.FullToolboxMultisens();
fulltoolbox.train(sensors,profile);
prediction = fulltoolbox.apply(sensors);

%%

figure(1)
plot(prediction)
```

Name	Value	Size	Cl
ethanol	1569×1 do...	1569×1	doul
fulltoolbox	1×1 Classifi...	1×1	Clas
prediction	1569×1 do...	1569×1	doul
profile	1569×1 do...	1569×1	doul
sensors	1×1 cell	1×1	cell

```
>> hold on
>> plot(profile)
>> legend
>> legend('Prediction','Target')
>> title('Naphtalene concentration')
>>
```

Figure 10: Screenshot of the automated ML toolbox connected via GitHub in MATLAB ® Online. Blue box: Folder structure of the toolbox. Green box: Coding section. Red box: Plot of the results.

A Code sample

```
const Station = [
  {
    id: '1',
    title: 'Station 1',
    img: "path/station_1/picture_station_1.jpg",
    process_1: 'Process XY',
    resource_1:[
      {id: '1',
      name: 'Robot XY',
      technicalName: 'process 1 technical name',
      img:"path/station_1/Process_1/Robot_XY/Robot_XY.jpg",
      technicalData:"path/station_1/Process_1/Robot_XY/DataSheets/Robot_technical_details.pdf",
      manual:"path/station_1/Process_1/Robot_XY/DataSheets/DataSheets/Robot_manual.pdf",
      technicalDrawing:"path/station_1/Process_1/Robot_XY/DataSheets/Robot_technical_drawing.pdf"
      }]
   }]
```

Listing 2: Sample code for a station.

5 Acknowledgements

This work was funded by the European Regional Development Fund (ERDF) in the framework of the research projects within the framework of the research projects ”Messtechnisch gestützte Montage” and ”iTecPro – Erforschung und Entwicklung von innovativen Prozessen und Technologien für die Produktion der Zukunft”. Future development is carried out in the project ”NFDI4Ing – the National Research Data Infrastructure for Engineering Sciences”, funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 442146713.

Furthermore, the authors thank Anne Blum and Dr.-Ing. Leonie Mende for their profound input during conceptualization and the Mittelstand 4.0-Kompetenzzentrum Saarbrücken for the deployment of a use case.

6 Roles and Contributions

Christopher Schnur: Conceptualization, Writing & original draft

Tanja Dorst: Conceptualization, review & editing

Kapil Deshmukh: Programming & implementation

Sarah Zimmer: Conceptualization

Philipp Litzenburger: Conceptualization

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Lennard Margies: Coordination

Rainer Müller: Concept & Coordination

Andreas Schütze: Coordination, Concept & review

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