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Early Prediction Methodology of Product Quality in Automotive Manufacturing Environment Using Data Analysis and Machine Learning

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Abstract

Growing competitiveness and enhancement of automotive industries to adapt to Industry 4.0 has led to the development of many innovative solutions to enhance the quality of production. This can be achieved through efficient use of data generated by various machines involved. Data from various sensors and controllers are stored in Programmable Logic Controllers (PLCs) which can then be retrieved and stored in a centralized storage location like shared drives, private servers or in cloud environments. A machine learning classification model, which is trained using the historic data retrieved from these PLCs, can predict the quality of the final product before it reaches the final stage. With this approach, a part or an assembly can be taken out of the line early, thereby reducing the scrap cost and achieving an improved efficiency of the production. This research provides a consolidated approach that can be used for predictive quality.

Keywords
Industry 4.0, Classification, Predictive quality, Machine Learning, Programmable Logic Controllers

1. Introduction
Industry 4.0 or Fourth Industrial Revolution (4IR) helps us to transition into the digital environment that provides enhanced capabilities like real-time decision making, increased productivity, flexibility, and agility. Artificial intelligence (AI) and Internet of Things (IoT) have proven to be the backbone in facilitating the adoption of the 4IR. Although the current state is in an adolescent stage, the actual potential of this technology has not gone unseen. Extensive studies are ongoing in the fields of deep learning, explainable AI, graph neural networks and many more, to overcome the existing challenges in this field (Kim et al. 2022). These concepts are being widely used in various kinds of industries including the automotive industry. It is believed that to be superior to the competitors, the elements of 4IR are a key factor. European manufacturers are being pushed towards digital transformations due to increasing operating costs and the rising need to have better quality products at a low price. Asian manufacturers have already gained an advantage by focusing more on knowledge and Research and Development. In entirety, research work has increased tenfold between the years 2015 and 2021 and is still increasing. This has been observed in various fields ranging from smaller applications like object detection to business management applications like manufacturing decision making (Mueller and Mezhuyev 2022).

Studies show that in the automotive industry, adapting to technological advancements would give good returns in the investments they make towards smart factories. AI, when applied to different manufacturing processes, is possible to have a positive impact in production and reduces waste and thereby costs related to scrap. It is also possible to be more flexible in make-to-order offerings, which increases customer demands as well. When these systems are used in compliance with the Personal Data Protection Act and other related laws, it is possible to realize the potential of AI in manufacturing industries (Chai and Nizam 2021). Along with all these efforts in compliance with Data Protection laws, there is an underlying pressure on the automotive industries due to the changing regulations to produce cars that can be emission-free. There is also an increasing demand for autonomous driving cars from the customer end. So, an increased investment in research and development is needed. On the other hand, since the COVID-19 pandemic, demand for new cars is comparatively less. This has led to the shrinking of the global market. To deal with these issues, automotive manufacturers are focusing on optimizing their operational costs, TQM, using automation tools like advanced robotics and other similar tools. In all these issues, AI has proven to be an effective tool. Despite resistance from many companies to adapt and use AI methods (26% to 39% between 2017-2019) there has been a slight increase in the number of companies who are able to use AI better than others (3% to 10% between 2017-2019). This contradictory trend is found due to a major reason that there was a clear lack of understanding and awareness towards AI tools (Demlehner et al. 2021). Among all the various possible use cases of AI in automotive manufacturing, we have focused on the predictive quality application in this research as this would help manufacturers to avoid eminent failures in the earlier stages thereby reducing scrap costs, raw material costs, labor costs and most importantly, saving time.

We start this paper by providing an overview of existing methods in which AI can be used in quality control, various data collection and processing techniques. This is then followed by a section that gives a framework that will help in selecting one of the data collection methods. The subsequent section contains the core of this research, which explains how the V-model approach can be used to develop the AI model, test and deploy for quality prediction and the results are included in the final sections.

2. Literature Review and State of Knowledge

This section comprises the existing research work as well as the current state of knowledge of major concepts involved in this research. It is further divided into 3 major subsections as given below:

2.1. Data extraction techniques from machines

The machines in an assembly line not only produce a product as an output, but also something much more valuable, ‘Data’. Just as there are 4 industrial revolutions, the data generated has also seen 4 revolutions as mentioned below (Tao et al. 2018):

1. Data in handicraft age (1st Industrial revolution): As the manufacturing methods were of low complexity and due to extensive use of the manual production process, data generated here was human experience that was passed on verbally.
2. Data in the machine age (2nd Industrial revolution): The then “new” manufacturing process using machine tools and interchangeable parts, there was a significant difference in the data and its analysis. It is in this period that manufacturers started focusing on terms like quality control, cost reduction, inventory management and so on by analyzing the data using scientific methods on the data extracted manually.
3. Data in the information age (3rd Industrial Revolution): The potential of using the data was realized more in this era, where manufacturers started focusing on flexible, intelligent manufacturing by leveraging the computing power of modern machinery.
4. Data in the big data age (4th Industrial revolution): This comprises the current revolution of data handling due to the rise of AI, IoT, cloud computing and big data. It is in this stage that manufacturers are realizing and starting to use the full potential of data.

A lot of data that is or that can be generated while manufacturing usually goes unused and we do not use it to its full potential. For example, something as small as the internal temperature in a machine can prove to be valuable when it comes to machine maintenance. Such valuable data can now be extracted and used because of IoT. in the context of manufacturing, it can be called Internet of Manufacturing things (IoMT) (Zhang et al. 2012).

Figure 1 shows a brief overview of how real-time data from the line can be extracted, stored, and processed. Every cell in a line has a network of sensors (as shown in levels 1 and 2) to capture different parameters involved in the manufacturing process. This rudimentary data is then processed into useful data using various rules and schemas in level 3. The processed data can then be visualized, analyzed, and monitored using independent tools or plug-ins provided by third party applications (Zhang et al. 2012).

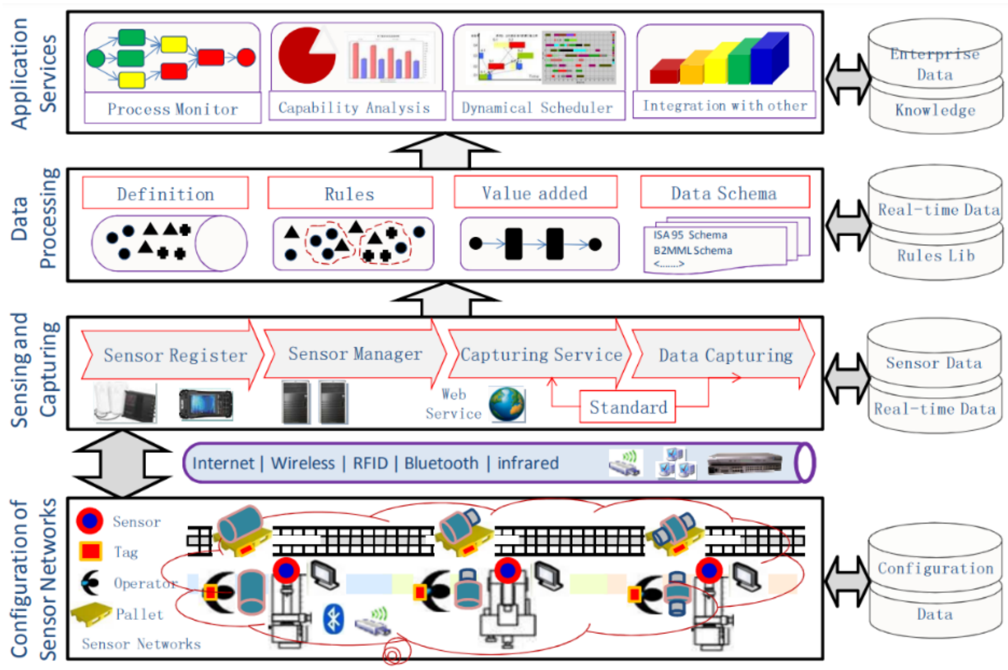

Figure 1. Overall Real-time Information Capturing and Integration Framework of the IoMT (Zhang et al. 2012)

The critical stage of data handling is selecting the correct method of data extraction and data transfer from level 1 to level 2 as it dictates the complexity of the latter levels. All the modern machines come with a PLC that is used to control the functionalities, store data, and monitor the processes. This PLC data can be extracted using different protocols, the widely used ones are explained below:

1. Modbus protocol: This is one of the widely used protocols in the industry. It is a master-slave type, quite robust and is compatible with different network architectures. Figure 2 shows the 2 different topologies (RTU and TCP) used by this protocol (KOTÁB 2023).

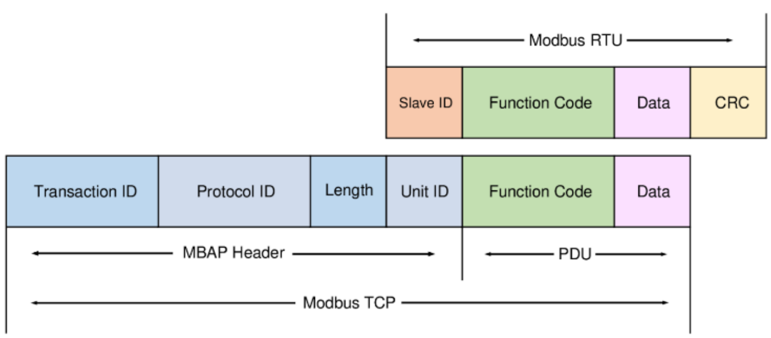

Figure 2. Modbus frame description (KOTÁB 2023)

2. MQTT protocol: Message Queuing Telemetry Transport (MQTT) protocol is a publish-subscribe type protocol which is designed for unreliable networks. Many IoT applications use this protocol that uses TCP/IP

for transport. It uses a star topology with data being pushed from client to the central server. Figure 3 shows the frame structure of this protocol (KOTÁB 2023).

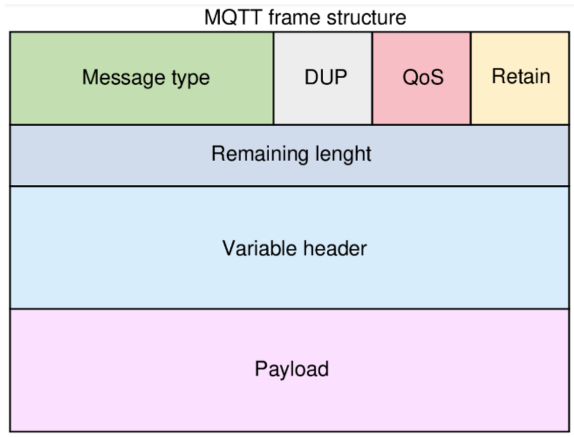

Figure 3. MQTT frame description (KOTÁB 2023)

3. OPC UA protocol: Open Platform Communication Unified Architecture (OPC UA) is used where an uninterrupted and smooth data transfer among the industrial devices is required. It uses a client-server to pull data from the machines and a publish-subscribe to exchange data banks and other systems that use this data for further applications. Figure 4 highlights 2 different methods used for this type of communication (KOTÁB 2023).

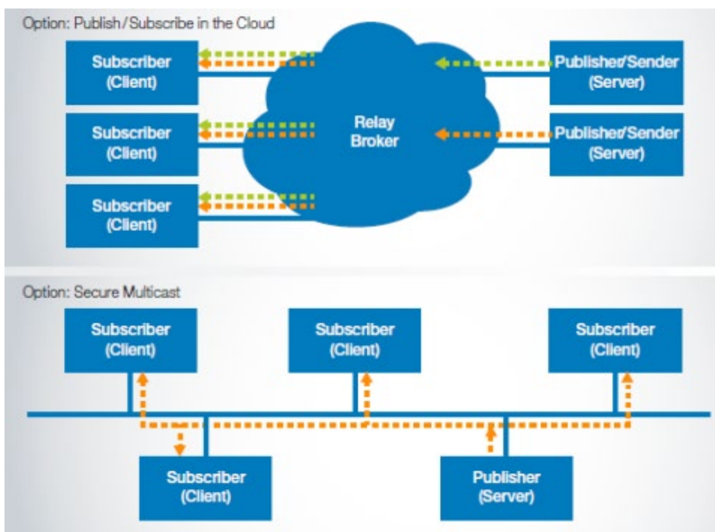

Figure 4. Different methods of communication using OPC UA protocol (Drahoš et al. 2018)

2.2. Data analysis in manufacturing

Making proper use of the data being generated in a manufacturing system can make us aware of the internal and external affecting factors as well as enable us to make decisions based on a scientific approach to increase the efficiency and reduce costs (Wang et al. 2022). There are 2 different techniques to analyze the data: model-driven and data-driven. Model driven approach focuses on analyzing the data based on a specific idea or a model. All the necessary parameters and conditions are determined based on this model. Whereas the data-driven approach depends only on the online measurements that are being collected. As it does not depend on any model, it can adapt to any uncertainties that may occur in the data (Benosman 2018).

The following factors, also called the 4Vs, need to be considered for data analysis: Volume, Velocity, Variety and Value. Volume, as the name suggests, indicates the quantity of data. Velocity stands for the frequency in which the data is being generated. Value indicates the economic value that the data might provide. Variety accounts for the inconsistencies in the data being generated (Babu et al. 2024).

2.3. AI in Predictive quality

Predictive quality can be defined as "enabling the user to make a data-driven prediction of product- and process-related quality with the goal of acting prescriptively on the basis of predictive analyses" (Schmitt et al. 2020b)

Since the 4IR began, many trends that deal with AI, especially Machine Learning (ML) and deep learning (DL) started taking root in the manufacturing industries to incorporate smart manufacturing driven by data. The major field that makes the most use of this technology is quality. There are a lot of research activities focusing on predicting quality as early as possible, also known as predictive quality. This approach is being used in multiple sectors and industries already, like predicting in-line faults (Mayr et al. 2019), automating the process of quality check (Schmitt et al. 2020a), detecting structural defects in additive manufacturing (Zhang et al. 2019), deep drawing (Meyes et al. 2019), and many more. Every use case mentioned above is different, yet the approach stays similar in terms of how the data is being used (Tercan and Meisen 2022).

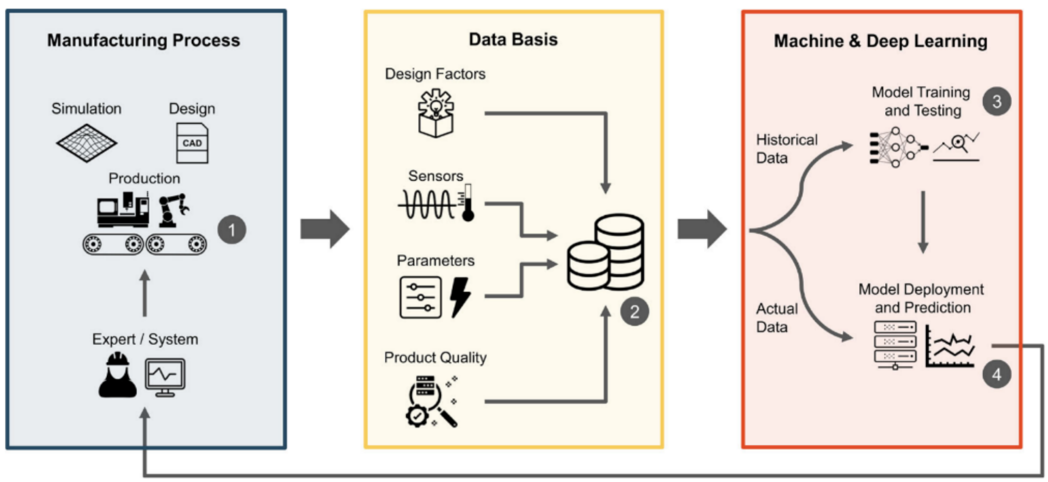

Figure 5. Predictive quality approach using AI (Tercan and Meisen 2022)

Figure 5 shows a basic schematic that explains how AI plays a role in predictive quality. There are 4 main steps in predictive quality:

1. Selecting the target manufacturing process and target quality.
2. Collection of process and quality data.
3. Developing and training a ML/DL model.
4. Deploying the model to make an estimated decision on the quality.

Depending on the application, the learning model can be selected between ML and DL. This learning model must be designed to perform these 3 primary tasks (Köksal et al. 2011 and Rostami at al. 2015):

1. Quality description: To gain required insights about how the processes are related to each other.
2. Quality prediction: To predict product quality as a numerical value (for example, chances of failure).
3. Quality classification: To predict product quality as a binary value (for example, determining whether product would pass or fail at any given stage).

3. Methodology

3.1 Selection of data transfer method using Pairwise comparison and benefit analysis

Pairwise comparison

To select the best protocol to communicate with the PLCs in manufacturing is important to efficiently get the data transferred, multiple protocols are compared, and the best protocol is selected. Pairwise Comparison is considered for analyzing the importance of different criteria used for comparison. This creates a cardinal scale of absolute numbers that is stronger than a ratio scale (Saaty 2008).

Following criteria can be used to assess the protocols (Tapia et al. 2023):

1. Performance requirements: This criterion takes care of factors like latency, throughput, determinism, etc.
2. Compatibility and interoperability: This criterion considers the use of the protocol with existing PLCs, sensors and other components involved and the capability to work with other systems or protocols.
3. Scalability: This criterion ensures that there are no significant negative changes in performance during operation
4. Ease of implementation and maintenance: This criterion considers the level of skill needed to install, use, and maintain the communication system.
5. Cost: This criterion takes care of overall financial aspects that includes licensing, maintenance, and other related costs.
6. Security: This criterion considers the security features as well as the risks that come with the protocol.
7. Support for Advanced Feature: This criterion considers the robustness of the protocol.

In this method of measurement, the criteria were compared against each other, to find their weights in view of their relative importance. As a first step, criteria were compared against each other in the comparison matrix and are rated as per the relative importance table. An example of a relative importance matrix is given in Table 1.

Table 1. Relative importance - rating matrix example

Rating	Level of Relative Importance of Parameters
2	More important than the other
1	Equally important
0	Less importance than the other

Once the ratings for the criteria in each row compared to the one in each column of the pairwise comparison matrix are assigned, the rating scores are summed, and the relative percentage weightage is calculated. An example of this calculation is shown in Table 2.

Table 2. Table illustrating Pairwise Comparison Matrix with 3 Criterion

Criteria	Criterion 1	Criterion 2	Criterion 3	Total	% Weightage
Criterion 1	-				
Criterion 2		-			
Criterion 3			-		
Sum	-	-	-		100%

So once the pairwise comparison is completed, the relative quantitative importance of the criteria in view of the use case is available.

Benefit analysis

The next step is to judge the different alternatives in this study – different use-cases, for each criterion compared in the previous step. For each criterion under consideration, each of the use-cases is rated with a score on a scale of 1-5. This score refers to a relative competence compared to each other and in view of the benefit compared to the conventional alternative, if the latter is having a higher rating if considered. This rating is specifically for the application or use case under consideration and is assigned based on literature and the author's understanding and expertise in the area. The competence rating matrix being considered is given in Table 3.

Table 3. Competence rating matrix

Rating	**Level of Competence**
5	Most Competent or the best option
4	Very good Competence
3	Average Competence
2	Weak Competence
1	Least Competent or the worst option

Once the use-cases are assigned with the rating for each of the criteria under consideration, based on the relative weights, a weighted score can be calculated for each of the alternatives. The best alternative for a specific use case can then be judged as the one with the highest total score. This total score is the summation of the product of criteria and its percentage weightage evaluated in pairwise comparison.

$$\text{Total score of Alternative 1} = \sum (Rating\ for\ i^{th}\ Criteria) \times (Percentage\ Weightage\ of\ i^{th}\ Criteria)$$

The protocol with the highest total score can be selected for data transfer.

4. V-Model

Having a structured approach to the development and deployment of an AI model is crucial. To set a structure to the process, an approach like software development can be used. Software development includes a set of activities from specifying the requirement to designing, implementing, and testing of the system. A software development model needs to be the framework which supports these basic steps in the development process:

1. Specification: Defining the exact requirement and expected outcome.
2. Design: In this phase, the specified requirements are converted into technical terms.
3. Validation: This is a step where the design is implemented, and the developer confirms that the requirements of the customer are met.
4. Evolution: In the evolution phase, the system is adapted as per the customer's further requirements.

Various software development models like Waterfall model, V-Model, Incremental model, Iterative model etc. can support software development. In this research, due to a closed loop nature, V-Model is opted for the development process. Here, the testing phase after coding is associated with a corresponding development phase and works using feedback loops (Visual Paradigm, 2022).

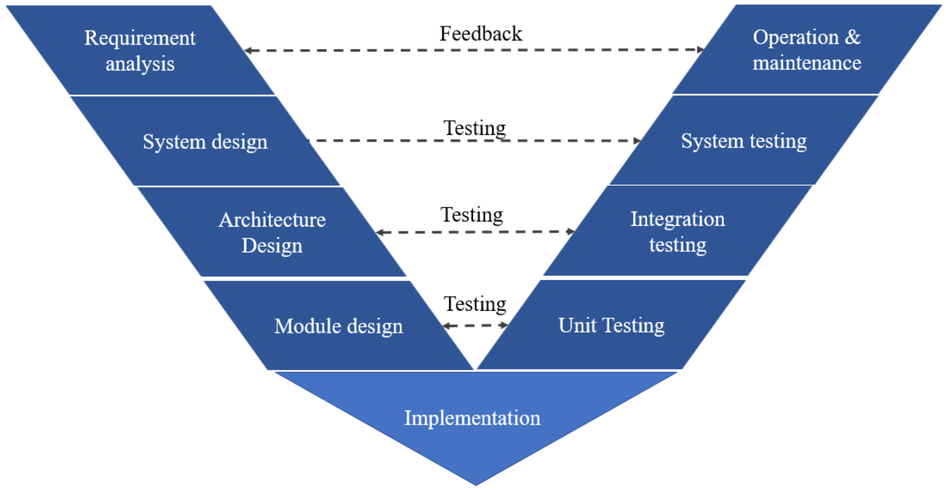

Figure 6. V-Model for software development (Gräßler et al. 2021)

Figure 6 shows a generalized form of V-Model which can be adopted for the effective execution of the software development project, which passes through 9 defined stages.

1. Requirement Analysis: In this stage, the business case is being defined. Here the business case or the project requirement is analyzed, and the need of automation is defined. In this application, the major requirements are reduction in costs and achieving an increase in efficiency (Gräßler et al. 2021).
2. System Design: In this stage, the inputs and outputs of the software under development need to be defined. In this application, inputs would be the data from different sensors and machines, and outputs would be prediction and classification of machine output (Gräßler et al. 2021).
3. Architecture Design: In architecture design, the required tools and equipment need to be specified. Here the protocol, data analysis architecture and predictive quality model architecture are finalized (Gräßler et al. 2021).
4. Module Design: Module design goes one step into architecture. Here, the different variants specified in architecture are broken down into specific modules or unit level functions, for detailed design. The logical loops for different modules are designed here. The output of Module design needs to be a completely logical diagram of the whole project for all the architecture and all the systems. The modules required for this application can be data transfer, data analysis, model development and model deployment.
5. Implementation: In implementation, the coding of the designed modules and architecture in the coding environment is executed. Along with the codes, required databases are created and the systems for its updating are established. Required equipment and tools are procured and made ready for usage and the codes are deployed. In implementation, in short, all the outcomes of design are implemented, and the software is ready for testing (Gräßler et al. 2021).
6. Unit Testing: Here the testing of the modules defined in module design is performed, and focus is given for verifying each activity or command implemented in each module. The RPA bot is given with specific inputs which affect each module and allowed to perform its task. Once the task is performed by the bot, the behavior of each command in input and output is verified. In case of any unintended output, Unit testing calls for the changes in the Module design which needs to be tested again until desired output is obtained (Xie & Wang 2013).
7. Integration Testing: Here, the testing is performed at a higher level in view of the effectiveness of the architecture design. In integration testing, the performance of all the variants of architectures is tested. All the variants need to be working effectively and without errors from start to result. In case of any feedback the required modifications will be made in the architecture design and retested (Gräßler et al. 2021).
8. System Testing: System testing deals with the testing of the developed software in real world applications. In case of any failure in this stage, retesting for integration testing and unit testing is performed and required changes are made in architecture and module design. In case of ineffectiveness of these changes, this calls for a change in system design.

Operation and Maintenance: Operation and maintenance are the part of software development project which addresses any future changes in the business requirements of the bot and the regular or periodic maintenance plan. This also includes the solving of any future failures, handling of errors and exceptions which cannot be solved by the customer themselves and the smooth operation of the bot till its defined lifetime. Here proper planning of these activities is expected to be performed (Gräßler et al. 2021).

5. Results

5.1 Numerical results

This research was primarily aimed to reduce the scrap costs of a manufacturing process. The impact of this research can be explained by the help of the following example.

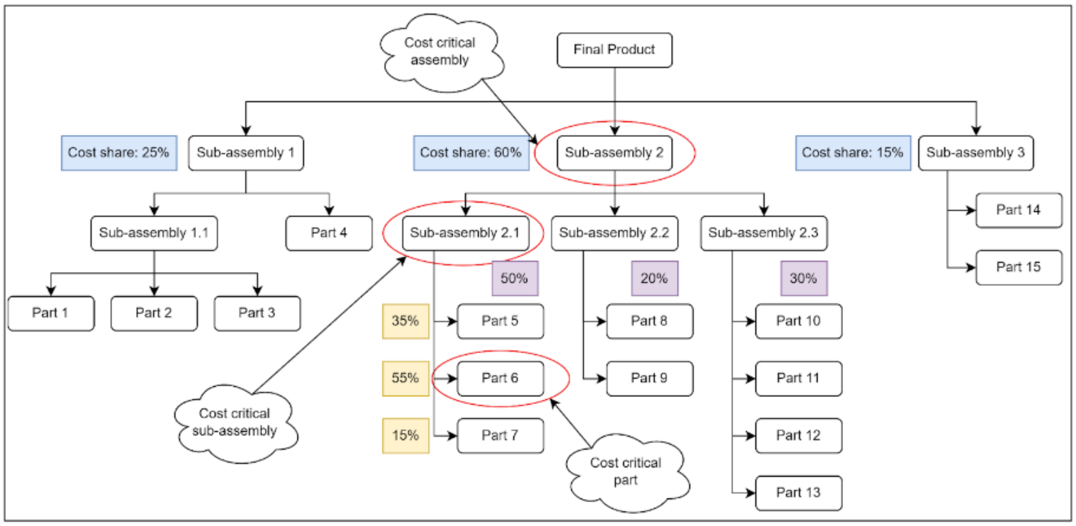

Figure 7. Example of a Product architecture

Figure 7 is an example of process flow for a product with the contribution to costs at required levels. As indicated, sub-assembly 2 contributes to major costs of the product. This makes it the most critical sub-assembly in the entire process. Going to the next levels, we can see that sub-assembly 2.1 and part 6 are the cost critical parts or assemblies in the subsequent levels. Assuming 'x' as the total production cost, the cost for the target parts and assemblies can be calculated using the percentage share. This gives the costs as:

1. 0.6x (60% of x) for sub-assembly 2
2. 0.3x (50% of 60% of x) for sub-assembly 2.1
3. 0.165x (55% of 50% of 60% of x) for part 6

This shows that part 6, among the 15 parts, has a 16.5% impact on total cost and scrap costs. Ensuring the quality of these target parts and assemblies would reduce the scrap costs and increase the cost efficiency of the line.

5.2 Proposed Improvements

This technique is not only restricted to cost effective parts but can be extended to higher levels as well. Moving up the flow as per the example given, the impact of this approach increases as well. While applying for higher levels, like sub-assembly 2.1 in this example, the size of the data handled increases, as the number of parts and processes considered increases as well. This leads to a more complex analysis of the data, an increase in the number of variables considered, thereby increasing the complexity of the model as well. But using concepts like Big Data Analysis and deep learning, it is possible to analyze for upper-level assemblies. To make this approach sustainable, a scheduled upgrade of this model can be used. A fresh set of training data can be used to re-train and re-deploy to avoid the model from giving inconsistent results.

6 Conclusion

The automotive industry is one of the competitive industries with growing technologies and innovations. This research focuses more on the tabular and structured data. But using this same approach, several types of data can be used, such as images, binary files, and other data and file types. For this purpose, the AI model can be tuned to perform multi-modal analysis. Also, contemporary trends show an increase in research Advanced Driving Assistance Systems (ADAS), autonomous driving and manufacturing (PYMNTS 2024). This has led to a major change from the conventional manufacturing methods and has introduced more complexities and additional costs. To tackle this issue, solutions like this research would prove helpful for making the process of incorporating these complexities more efficient, thereby ensuring cost effectiveness. This research would provide a helping hand to the automotive manufacturing industries in moving towards AI aided data-driven manufacturing.

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Biographies

Steffen Klarmann is an accomplished professional currently serving as the Advanced Development Director Manager at Valeo SA in Wemding, Germany. He has over seven years of experience in automotive project management, thermal design, Artificial Intelligence, Industrial Internet of Things and Cyber Security. Dr. Klarmann holds a Ph.D. in Electronic Engineering from the University of Chester, United Kingdom, where his research focused on enhancing PCB technology for automotive applications. Dr. Klarmann is highly recognized within his field, having received multiple awards for his contributions to AI and cyber security within Valeo. Throughout his career at Valeo, Dr. Klarmann has spearheaded numerous interdisciplinary projects aimed at integrating AI and digital tools into manufacturing processes. He has also played a pivotal role in introducing cyber security protocols in the production of the first automotive LiDAR sensor.

Anand Balaji is a dedicated student intern focusing on Data Analytics and Artificial Intelligence in Manufacturing Enhancement at Valeo SA in Wemding, Germany. Currently pursuing his master's degree at Technische Hochschule Ingolstadt, he is immersed in the intersection of technology and industry. In the year 2018, he co-authored a research paper previously in 2018 titled “Intelligent Unmanned Aerial Vehicles” which was his steppingstone into this field. After that, during his tenure at Valeo provides hands-on experience in real-world applications of data analytics and AI within the manufacturing sector, while his academic pursuit at Technische Hochschule Ingolstadt equips him with the theoretical knowledge and research expertise to innovate in this field. After joining Valeo in 2023, he has taken initiative and shown pro-active involvement in various projects that involve visualization of machine data, development of AI models, developing pipelines for integrating Google Cloud with manufacturing environments and many more.