Artificial Intelligence for Quality Assurance and Troubleshooting in Industry

Rudolf Hoffmann[1], Slimane Arbaoui[2], Léa Charbonnier[3], Amel Hidouri[2], Ali Ayadi[2], Franco Giustozzi[2], Thomas Heitz[4], Julien Saunier[3], Frédéric Pelascini[4], Christoph Reich[1], Ahmed Samet[2], Cecilia Zanni-Merk[3]

[1] Institute for Data Science, Cloud Computing and IT Security; Furtwangen University; 78120 Furtwangen, Germany
contact: {rudolf.hoffmann or christoph.reich}@hs-furtwangen.de
[2] ICube, CNRS (UMR 7357) INSA Strasbourg, University of Strasbourg, 67000 Strasbourg, France
[3] INSA Rouen Normandie, Normandie Univ, LITIS UR 4108, F-76000 Rouen, France
[4] CETIM – Centre Technique des Industries Mécaniques, 67402, Illkirch-Graffenstaden

Abstract.
This paper presents the new X-Quality conceptional framework, that applies Artificial Intelligence (AI) to contribute to the improvement of quality assurance and troubleshooting in manufacturing. The goal is to identify and resolve quality issues effectively using AI techniques, applying Explainable AI (XAI) and stream reasoning to ensure transparency and comprehensibility to find causes for predicted quality defects. There are mainly three approaches of the framework described, that are tackling typical industry challenges. The first approach combines Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) for time series quality prediction with SHApley Additive exPlanations (SHAP) to explain the LSTM-CNN. The second method combines Machine Learning (ML) and Fault Tree Analysis (FTA) methods for comprehensive fault detection and analysis. The third technique applies semantic reasoning for real-time contextualization and root cause identification.

Keywords: AI; Machine Learning; XAI; Time Series; Root Cause Analysis; Fault Tree Analysis; Stream Reasoning; Ontology; Quality Assurance; Manufacturing

1 Introduction

In the present globalized economic era, industry competition demands continuous quality and reliability. Monitoring manufacturing processes is essential to prevent failures and maintain product quality. Artificial Intelligence (AI) enhances quality assurance by automating tasks traditionally handled by humans, using Machine Learning (ML) and Deep Learning (DL) to improve accuracy and consistency in defect detection [1]. Traditional troubleshooting methods like Root Cause Analysis (RCA) are extended by AI techniques to analyze vast amounts of data from multiple sources, improving defect detection and prediction [2]. For the stable deployment of AI-based systems and their acceptance by experts and regulators, it is crucial that the decisions and results produced by these systems are comprehensible, interpretable, and transparent, in other words, “Explainable” [3].

Our work aims to leverage AI techniques to enhance quality assurance and troubleshooting processes in various industries by developing methods for precise defect detection, predictive maintenance, and effective RCA.

The rest of this paper is organized as follows. Section 2 presents the related work, discussing previous research and approaches relevant to our study. Section 3 introduces the proposed X-Quality conceptional framework, and section 4 details the approaches that are integrated within this framework. Section 5 provides a critical discussion, evaluating the strengths and challenges of this framework and provides an outlook for future work. Finally, Section 6 concludes this paper.

2 Related Work

Recent research in quality assurance and troubleshooting in manufacturing has increasingly turned to AI and data-driven approaches. This section reviews related works that explore these approaches. While many works focus on automation, predictive capabilities, and explanations, our X-Quality conceptional framework focuses on a holistic view of the production line for a more comprehensive explainability and traceability of quality issues to determine the causes of the occurrences.

Several studies have explored AI-driven approaches for quality assurance in manufacturing, addressing challenges like data complexity, lack of transparency, and adaptability. The work [4] reviews these challenges and proposes a functional software architecture using Automated ML (AutoML) for automated model training and advanced data preparation to handle diverse data sources. Similarly, the study [5] focuses on the potential of ML and DL techniques for predictive quality, clustering existing methods by manufacturing processes, data sources, and ML methods. [6] proposes the Hybrid Digitization Approach to Process Improvement (HyDAPI) methodology that utilizes key elements of the Six Sigma Define-Measure-Analyse-Improve-Control (DMAIC) and the CRoss-Industry Standard Process for Data Mining (CRISP-DM) methodologies to enhance decision-making and operational efficiency. [7] and [8] address the need for transparency through eXplainable AI (XAI), using various XAI techniques to enhance transparency of ML models and improve preventive maintenance.

While these studies contribute valuable insights into AI applications for quality assurance in manufacturing, our X-Quality conceptional framework differentiates by integrating inductive and deductive AI, XAI, and expert knowledge across multiple production stages. Unlike [4], who emphasizes automation, or [7], who focus on improving transparency of ML models, our approach provides a more holistic perspective. By using ontology-based analysis, it enables more effective RCA and proactive actions, in order to prevent quality issues throughout the entire manufacturing workflow.

3 X-Quality Conceptional Framework

In multi-stage manufacturing processes, such as milling, grinding, and assembly, various operational parameters, such as cutting conditions, tool wear, and surface quality, must be monitored. Failures at one process can propagate, affecting subsequent processes and the final product. The X-Quality conceptional framework provides a more comprehensive view of the manufacturing workflow by monitoring data across multiple processes rather than focusing on a single manufacturing

process, enabling the system to identify final product issues and trace them back to the process where the deviation occurred.
In traditional manufacturing production lines, each operator does manual inspection at their respective machine (milling, grinding, assembly) and a quality manager supervises the overall production process for total quality control (Figure 1a). In the X-Quality conceptional framework (Figure 1b) from each machine, data is collected and different AI/XAI methods are applied to the collected data, in order to predict the quality after the manufacturing process and additionally provide the explanation for the prediction for the corresponding operator. Data streams, predictions and explanations are used to enrich an ontology. When a quality issue is predicted, the ontology is used to trace the root cause by linking machine failures to the quality issue. The quality manager supervises the entire manufacturing process using this ontology. This allows the quality manager to take proactive steps to maintain the overall quality of the production line, ensuring more effective quality assurance and troubleshooting in manufacturing. For example, if a defect, like a misaligned component, is detected in the assembly stage, the system can trace this issue back through the earlier processes, identifying that the problem arises from surface roughness during milling due to excessive tool wear. By taking proactive actions, such as replacing worn tools, similar defects can be prevented from occurring in future production cycles.

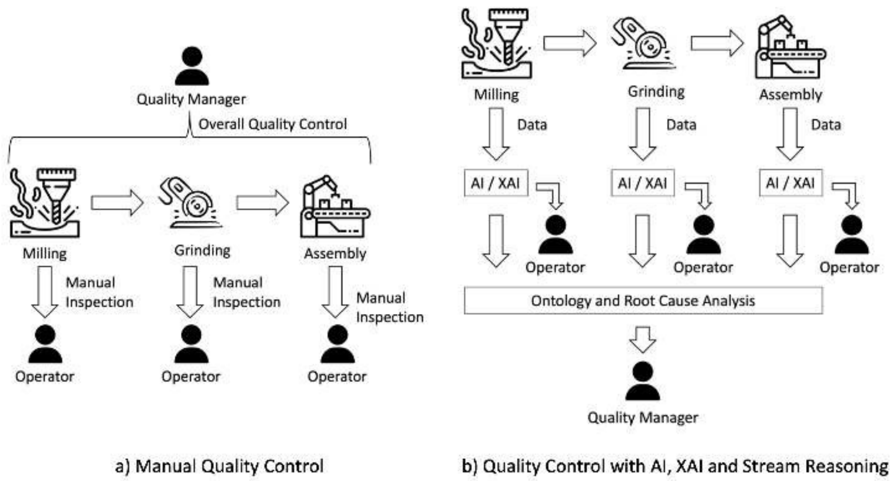

Figure 1: X-Quality Conceptional Framework

4 Three Approaches for X-Quality Conceptional Framework

The following sections introduce the approaches that are integrated in the X-Quality conceptional framework.

4.1 Time Series Data used for Quality Prediction

To predict product quality using time series sensor data, DL models such as Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) are commonly employed due to their ability to handle this type of data effectively. Combining these models can leverage their complementary strengths. CNNs reduce the dimensionality of the input data while capturing spatial features, whereas LSTMs excel at capturing temporal dependencies, leading to more accurate predictions of product quality.
The proposed model is expected to yield strong results in estimating product quality. However, like most DL models, it suffers from the "black box" nature, making its decision-making process difficult to interpret. To address the lack of transparency, a well-known post-hoc explanation model, named SHapley Additive exPlanations (SHAP) [9] is incorporated, which provides explanations in the form of relative importance values, being commonly referred to as SHAP scores. These scores highlight the features that most influence the model's predictions and reveal how each feature contributes to the final output. This enhances the interpretability of the model while maintaining its predictive power.
The important scores provided by the SHAP library will be used to select the features that most affect the prediction of our model. These features associated with their SHAP values that provide a link between the input and output, will be used as input to a Multidimensional Matrix Profile (MMP) [10] that allows to identify numerous structural elements within time series data, such as repeated behaviors, known as motifs, as well as anomalies, referred to as discords.
Our focus is on identifying discords which must appear simultaneously in both time series, named as natural anomalies, and represent data points that are most different among all the time series. Notably, the model is able to capture and explain these irregularities that correspond to product quality loss. The architecture of the proposed method is illustrated in Figure 2.

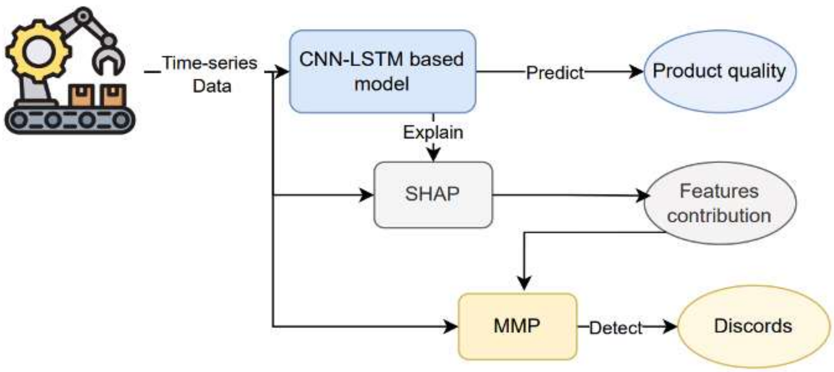

Figure 2: Quality prediction model with explainability for time series data

4.2 Combination of Artificial Intelligence and Fault Tree Analysis

The approach combines AI, specifically ML models, with Fault Tree Analysis (FTA) to enhance the prediction and understanding of system failures. ML models predict the probabilities of Basic Events (BEs) in a fault tree, which are then used to calculate the likelihood of the Top Event (TE). This enables the identification of underlying failure causes. The deductive structure of fault trees helps to determine the TE, thereby enhancing the explainability of the TE predictions.

Figure 3 illustrates the implementation of this approach. To implement this approach, an expert first constructs a fault tree based on their domain knowledge. ML models are then trained to predict the probabilities of the BEs within this fault tree. Once these probabilities are obtained, FTA is used to determine whether the TE will occur. If the TE is predicted to occur, the system can analyze the fault tree to explain which BEs or combinations of BEs are responsible for triggering the TE. Furthermore, it can provide recommendations on which BEs should be mitigated or eliminated to prevent the occurrence of the TE, offering actionable insights to improve system reliability.

The proposed approach offers several potentials, particularly in the context of explainability and understandability in the manufacturing domain. One strength is the ability of this approach to provide an explainable occurrence of the TE. Since fault trees are a well-established method in the industry for representing the logical relationships between different system states, stakeholders in manufacturing are more familiar with this explanation. This familiarity enhances the understanding in the prediction and makes the explanation more intuitive for stakeholders in the manufacturing. This understanding provides a better decision-making and intervention in manufacturing processes. However, there are also limitations that has to be considered. While the occurrence of TEs can be explained, the occurrence of BEs remains opaque due to the "black box" nature of the DL models that are used to predict these events. This lack of transparency in DL models is a significant challenge, because it restricts our ability to fully understand and interpret the underlying mechanisms that lead to BE occurrences. Additionally, the construction of fault trees requires expert knowledge and is highly time-consuming. This dependency on domain experts not only limits the scalability of the approach but also increases the required resource. The need for expert involvement in developing, refining, and validating fault trees can create bottlenecks, particularly in dynamic or rapidly evolving manufacturing environments where quick adaptation is crucial.

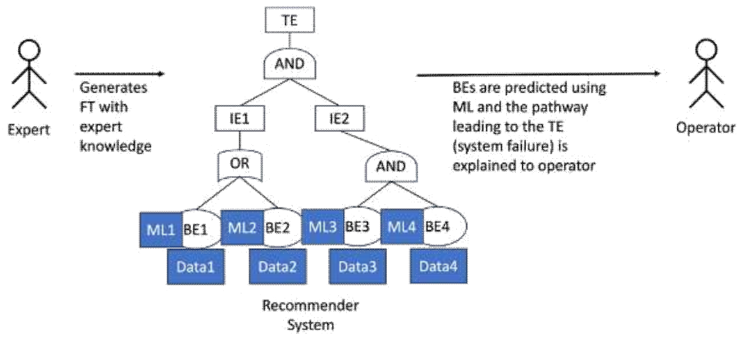

Figure 3: Combining ML with FTA for explainable TE occurrence

4.3 Stream Reasoning

Stream Reasoning is used to continuously query heterogeneous data streams from multiple sources in real time and apply logical reasoning to the data. The aim is to detect situations associated to quality problems in finished products and to understand the causes that lead to them. During the process, an ontology is populated to contain all the collected information to reason about the detected situations and causes.

To apply this approach in manufacturing, it is necessary to define the constraints that apply to the machines and products in question. This will enable the identification and categorization of abnormal situations. A constraint represents a rule on a property of a machine or a product and a situation is composed of sets of constraints. Defined constraints and situations are added into the ontology to support querying and detection. The ontology contains information on machines and sensors used in the production line. Indeed, as each query is composed of constraints representing one situation, numerous references are made to the ontology to obtain links between machines, sensors and values. Once an abnormal situation is detected, the ontology is updated with the related constraint values, sensor and machine or product. As quality issues are often from machine-related causes, identifying the origin of the problem is essential. Reasoning over the ontology helps trace quality issues back to the initial machine failures, providing insights into the root cause of the problem.

Since the input data is not formatted for use in an ontology, it is transformed into W3C standards such as Resource Description Framework (RDF). These statements exchange data on the web as triples: subject-predicate-object [11]. RDF statements can be combined into a dataset which can be queried using a query language such as SPARQL [12]. A SPARQL query is a tuple composed of a SPARQL algebra expression, an RDF dataset and a query form. As the data must be continuously treated in real time, it is therefore processed as streaming data. RDF streams, which are unbounded sequences of timestamped RDF statements, are used for this purpose.

The goal is to contextualize data streams composed of raw data and prediction results and explanations from predictive models (see Figure 4). Data processed by these models is collected and used in a Stream Generator to create RDF streams, which are continuously queried with a Stream Reasoner for pertinent information. An ontology containing expert knowledge is used to contextualize the streams. Since streaming data cannot be queried directly, the streams are parsed into finite pieces using time windows. A time window is defined by two-time stamps, such that any event within that interval is included in it [13]. To select a stream piece, the time window uses the timestamp of the events. Once parsed, streams can be queried like static data.

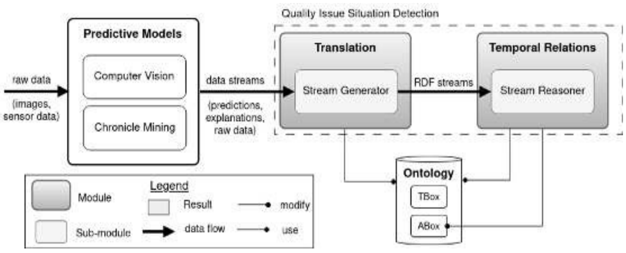

Figure 4: Quality issue detection with stream reasoning

5 Critical Discussion

The X-Quality conceptional framework presents a holistic approach to integrate inductive and deductive AI, XAI, and expert knowledge to improve quality prediction and RCA in manufacturing. However, several considerations arise when evaluating the framework, particularly in terms of practical deployment, scalability, and maintainability in real-world environments.

One of the key strengths of the X-Quality conceptional framework is its comprehensive integration of various methods. By using different AI/XAI methods for time series data, FTA, and stream reasoning, the framework is able to effectively address predictive maintenance, defect detection, and RCA. This approach ensures that the framework not only forecasts or detects potential issues but also provides actionable explanations and contextual insights, allowing operators and the quality manager to make informed decisions. This enhances both the product quality and the process reliability. Another strength of this framework is its adaptive capability, which is enabled by the use of stream reasoning. This enables the framework to continuously update the system based on data streams and to respond to changes in machine conditions or product quality. A further strength is the ontology that capitalizes expert knowledge to provide a structured formal model of the manufacturing environment. The ontology establishes a meaningful relationship between different machines or products, sensors, and related constraint values, enabling contextualized analysis and RCA.

Despite its strengths, the framework faces several challenges, particularly in terms of scalability and maintainability. The integration of this framework to larger manufacturing plants that provide high-frequency data streams, requires high computational resources. Moreover, the ontology requires continuous updates to remain relevant as machine configurations, sensor types, and production lines evolve. This maintenance and updating of the ontology present another significant challenge. In dynamic manufacturing environments the need for regular updates could become a bottleneck, since it requires expert dependence. Another challenge is to provide heterogeneous data streams, because they are coming from various sources and could also be perturbed by noise. A further potential challenge is the interpretability of the explanations provided by the framework, because the explanations may still be complex or difficult for operators or the quality manager to interpret.

Future work should focus on improving scalability by automating ontology updates to reduce the expert dependence, and improving the interpretability and comprehensibility of the explanations provided by the framework. Developing efficient methods for processing high-frequency data and simplifying complex outputs will be essential for real-world deployment in dynamic manufacturing environments.

6 Conclusion

In conclusion, the X-Quality conceptional framework combines machine data with AI and XAI methods to predict future quality issues and trace potential failures back to their root causes. By offering transparent explanations for these predictions, the system enables operators and the quality manager to understand and address the root causes of defects and thus provide more effective quality assurance and troubleshooting in manufacturing. This data-driven approach reduces downtime, improves operational efficiency, and contribute to cost reduction, leading to better product quality and more reliable production processes.

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