AI for Human-Centered Industrial Automation: Case Study of Rubber Extrusion Optimization

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Abstract

The industrial landscape is rapidly shifting from complete automation to a more balanced approach: Industry 5.0. This new paradigm seeks not to replace humans, but to enhance their capabilities through advanced technologies, with Artificial Intelligence (AI) at its core. The HUMAI project, a collaboration between Halmstad University, National Gummi AB, Research Institutes of Sweden (RISE), HMS, and Connectitude, aims to make the rubber-making process smarter, more efficient, and more sustainable. The goal is to integrate predictive AI in rubber extrusion to reduce waste and improve quality. Additionally, leveraging explainable AI and Generative AI will facilitate communication with operators, providing them with explanations and model insights to help them better understand the process.

The work on the project involves developing AI models, starting from pre-processing for waste prediction to making the models' decisions interpretable. It will provide clear explanations to operators, facilitating better understanding and interaction with AI systems.

Keywords

Human-centric AI, eXplainable AI, Industry 5.0, Waste Prediction

1. Introduction

Bridging the gap between AI research and practical industrial application remains a critical challenge in advancing digital transformation. The HUMAI project addresses this gap by demonstrating how AI can be integrated into real-world industrial settings through a human-centered and sustainable approach. The project focuses on the rubber extrusion process at National Gummi AB, aiming to reduce production waste and enhance operational decision-making. AI models are developed to predict waste based on sensor data and recommend optimal parameter settings, enabling operators to make adjustments during production. By predicting potential waste early, the system minimizes material waste and reduces environmental impact[1].

To ensure that AI becomes a useful tool for operators rather than a black box, HUMAI employs explainable AI (XAI) techniques. These methods enable the system to provide clear reasoning behind the models' predictions, assisting operators in understanding why certain decisions are made[2, 3]. To facilitate communication with operators, HUMAI leverages Generative AI[4]. This also allows us to collect feedback from operators regarding the decisions made by the model and the explanations provided. This supports knowledge transfer in both directions:

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less experienced staff can learn from the insights provided by the models, while experienced operators can offer feedback that refines the models over time.

Through this interactive, human-in-the-loop approach, HUMAI not only minimizes waste but also establishes a foundation for trust and continuous improvement in industrial AI applications[5].

2. HUMAI Project

HUMAI consists of two technical tasks: T1 and T2. These modules facilitate two-way learning between AI systems and human operators (Figure 3.1).

2.1. T1: AI for Waste Prediction and Process Optimization

T1 uses machine learning models to analyze data collected from various sensors, such as those measuring temperature, pressure, and speed. This system not only processes incoming information but also predicts the amount of waste that will be generated based on current conditions. This allows for proactive measures to be taken before additional waste is produced.

2.2. T2: Generative AI for Waste Reporting and Support

T2 develops a generative AI interface to support operators in reporting waste and understanding how process parameters affect product quality. An iPad will be placed at the end of the rubber extrusion line to both send and receive data from operators. T2 also helps operators learn from the machine learning model by offering explanations of its decisions and collecting their responses. This feedback is used to improve T1, creating a human-in-the-loop system that continuously learns from both data and human knowledge.

3. AI in HUMAI

The main AI challenge in the HUMAI project is creating predictive models that are both accurate and interpretable. Traditional machine learning methods often prioritize performance at the expense of interpretability. However, in industrial settings where decisions can impact safety and costs, it's crucial to understand the reasoning behind a model's predictions, particularly when predicting faults[6]. In the HUMAI project, we aim for a collaborative learning process between the model and the operators. Therefore, it is vital to clearly explain the model's predictions to operators, especially those who are inexperienced.

To achieve this goal, the project uses XAI techniques, specifically the SHAP (SHapley Additive exPlanations) framework[7], to identify the key features that influence model decisions[8]. Furthermore, counterfactual explanations are utilized to suggest minimum adjustments that could change the predictions[9, 10].

3.1. AI Pipeline

The AI pipeline in this project consists of several key steps:

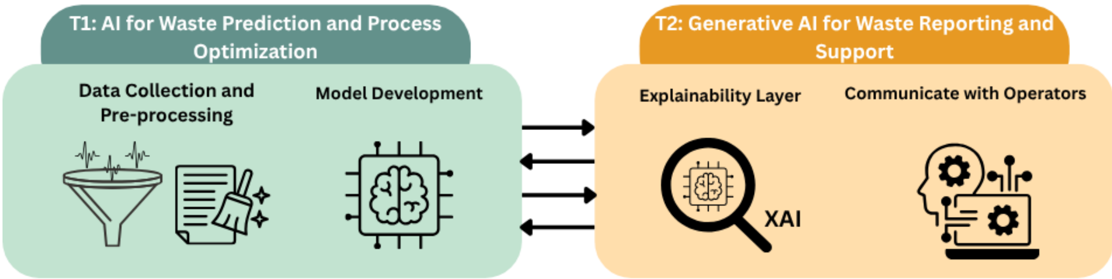

Figure 1: AI pipeline integrating T1 and T2 at the HUMAI project.

- **Data Collection and Pre-processing:** Time-series data is collected from multiple sensors that measure various parameters, including pressure, temperature, and speed. This data is aligned and cleaned to ensure quality and consistency.
- **Model Development:** Multiple models, such as Random Forests and LSTM, are evaluated for their performance in predicting waste. These models are trained to forecast waste levels and to identify optimal strategies for waste reduction.
- **Explainability Layer:** The SHAP method is applied to the trained models to extract explanations for individual predictions. This enables operators to understand which sensor readings significantly influenced the model's predictions, helping to identify the root causes of waste. Additionally, generating countermeasures specifies the minimum changes in inputs required to achieve a change in output, guiding operators on which adjustments can lead to waste reduction.
- **Communicate with Operators:** The explainable outputs are visualized on dashboards that assist operators in taking corrective actions and learning from the model's predictions. Operators' feedback and comments regarding the predictions and explanations are also collected, which will be used to improve the model further.

3.2. Challenges

- **Data labeling complexity:** Sensor data and daily production information, including waste, are collected, but there is currently no precise method to link sensor logs to the production time of the products. To effectively utilize supervised learning, this connection needs to be established manually, which may introduce some inaccuracies.
- **Temporal misalignment:** Data from sensors is recorded at varying frequencies, which complicates the processes of data pre-processing and modeling.
- **Data imbalance:** Significant wastes are rare compared to successful runs, making model training skewed.
- **Limited data:** The current dataset is small, restricting the use of deeper models until more production data is collected.
- **Adaptability to Operator Expertise Levels:** Different levels of operator expertise need different levels of explanation, which increases the complexity.

Table 1
Summary of raw material and waste types (kg) from January to April.

Raw Material	Start-up waste	In-process waste	End waste
305838	8121	4112	2221

4. Current Progress

In the first phase, sensor data is logged for AI development. Currently, operators also manually record some information; however, this process will be automated in the future through scanning. The recorded data includes the product number, material number, amount of product, amount of raw materials, the amount of waste, and other relevant details.

To assign each batch of production recorded by operators to sensor data, a framework is designed to partition the data based on features related to speed. However, this process is prone to error and should be supervised by a human, which is time-consuming. This highlights the need to record additional information for automatic data labeling and using supervised methods.

In the production process, waste is categorized into three types:

- **Start-up waste:** Material discarded before the first acceptable product is produced.
- **In-process waste:** Material discarded between the first and last acceptable products.
- **End waste:** Material discarded after the final acceptable product.

Table 1 provides a summary of raw material usage and each waste type from January to April. However, the timing of the first and last acceptable products is not specified, making it difficult to identify the temporal relationships between different waste types and their corresponding data.

The availability of labeled data is currently limited, making it difficult to model the waste. However, various data exploration techniques can be employed to gain data insights. Additionally, to implement an explainability layer, it is necessary to have an accurate, trained model.

5. Conclusion and Future Work

In this paper, we present the HUMAI project, which includes a case study of the National Gummi AB. The aim is to assist operators in minimizing waste within a complex production process. The primary objectives of this project are to reduce waste through a predictive model, to explain the predictions in a way that operators can easily understand, and to communicate with them using generative AI. This will support process optimization and facilitate the collection of operators' insights to further refine the model.

The project is currently focused on data collection and model development. A requirement for the explainability layer is the existence of an accurate predictive model, which will be the next phase of the project.

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