

Robot Capability Assessment in Manufacturing Using Semantic XAI and Neuro-Symbolic Reasoning

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Abstract

Robot selection in manufacturing is challenging because advertised specifications do not always reflect operational performance under real-world task conditions. Existing approaches often rely on isolated prediction or ranking mechanisms and provide limited support for semantic interoperability, formal reasoning, and explainability in assessing robot suitability. This work presents a Semantic Explainable Artificial Intelligence (S-XAI) framework that integrates neural-network-based operational capability prediction, robot capability ontology, RDFox-based semantic reasoning, Datalog rules, simulation analysis, and explainable user interfaces. The framework evaluates industrial robots according to operational repeatability and precision capability for a given manufacturing task. The proposed system demonstrates how predicted robot operational capabilities can be transformed into semantically explainable reasoning outcomes. It supports the classification of best-suited, least-suited, and optimal robots, while providing graph-based visualization, semantic traceability, counterfactual simulation, neural explanations, and interpretable decision support for manufacturing within a unified S-XAI framework.

Keywords

Knowledge Engineering, Manufacturing Common-Sense knowledge, Semantic Explainable AI,

1. Introduction

Evaluating and selecting industrial robots for manufacturing tasks is a complex activity, particularly when capabilities such as repeatability and precision vary under real-world execution conditions [1]. Existing robot evaluation approaches often rely on isolated numerical prediction methods and provide limited support for semantic interoperability, machine-understandable representation of robot knowledge, formal reasoning, and explainability. To address this gap, we present a neuro-symbolic robot capability evaluation and explanation framework that integrates neural-network-based operational capability prediction, robot capability ontology

Posters, Demos, Blue Sky, and Tutorials at SEMANTiCS 2026, Sep 2026, Ghent, Belgium

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(RCO), Manufacturing Commonsense knowledge (MCSK) graphs and reasoning, Datalog(DL) rules, simulation analysis, and explainable user interfaces. This demonstration introduces a human-centred Semantic Explainable Artificial Intelligence (S-XAI) framework for assessing robot suitability in manufacturing tasks.

The system enables a user to submit a new manufacturing task defined in Cartesian coordinates X,Y,Z obtain predicted repeatability and precision values for multiple robots, update a knowledge graph with these values, infer robot suitability through DL rules, and inspect the resulting decisions through multiple explanations. These include KG-based explanations, counterfactual simulation, local neural explanations, natural language explanations, ontology and rule inspection, SPARQL query transparency, and system-level logging. The objective of the demonstration is to show how neural prediction and symbolic reasoning can be combined in an interactive Neuro-symbolic workflow to support transparent robot capability evaluation.

2. Related Work

Industrial robot selection has been widely studied as a multi-criteria decision-making problem, where robots are ranked using criteria such as payload, reach, accuracy, repeatability, cost, and task suitability [1-3]. Capability and skill based models, together with ontology-based approaches, support more structured descriptions of manufacturing resources, robotic functions, capabilities, constraints, and semantic relations [4-9]. Robotic knowledge representation systems and surveys further show the relevance of semantic reasoning and ontology-based representation in robotics [10,11]. This demonstration builds on these directions by combining neural prediction, semantic knowledge representation, RDFS/DL reasoning [12], and XAI methods such as LIME, SHAP, Integrated Gradients, and permutation-based importance [13-16]. Unlike approaches that focus only on ranking, modelling, reasoning, or neural interpretation separately, the proposed S-XAI framework integrates these components into one interactive workflow for explainable robot capability assessment.

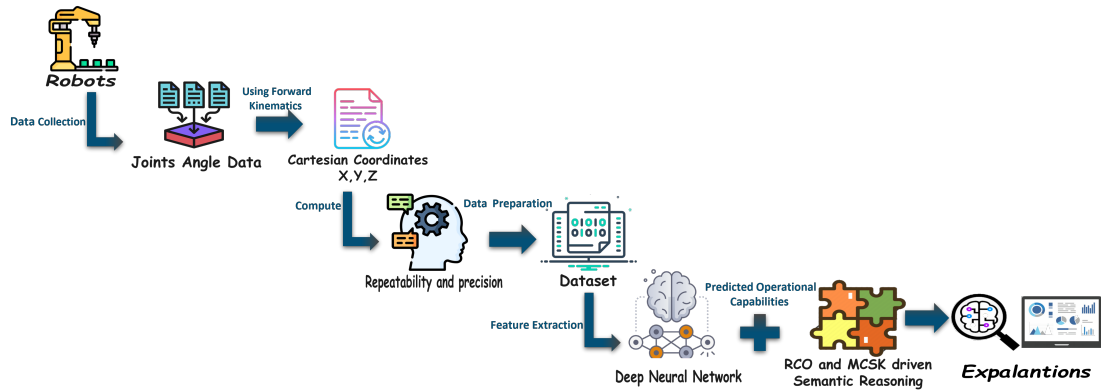


Figure 1: Workflow of the proposed S-XAI framework for robot capability assessment.

The overall workflow of the proposed S-XAI framework is illustrated in Figure 1. It shows how a manufacturing task is processed through neural capability prediction, semantic knowledge

graph update, RDFox/DL reasoning, and explanation generation.

3. Demonstration of the S-XAI Framework

The demonstration ¹ is organized around three interface views: the Main page, the Explanations page, and the System Logs page. The Main page supports task configuration and neural prediction, the Explanations page exposes the symbolic, graph-based, neural, and Natural Language (NL) explanations, and the System Logs page records the execution trace of the demonstration.

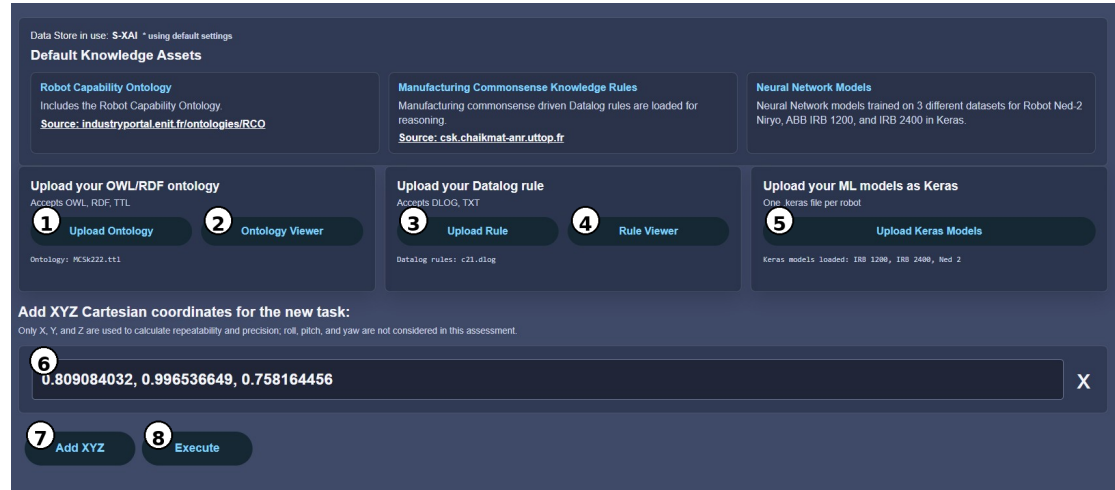


Figure 2: Main page of the S-XAI framework.

Figure 2 shows the Main page of the S-XAI framework, which serves as the entry point for evaluating a new manufacturing task. The interface loads the default S-XAI datastore, including the RCO, MCSK rules, and Keras neural network models for the robots. The user can replace these assets using the ontology upload ①, ontology viewer ②, rule upload ③, rule viewer ④, and Keras model upload ⑤ functions. For a new task, the user enters Cartesian coordinates in the XYZ input field ⑥; roll, pitch, and yaw are not considered in this demonstration. The Add XYZ button ⑦ adds the task coordinates, and Execute ⑧ sends them to the Flask API, where the neural network models predict repeatability and precision for each robot. The predicted or simulated values are then written to the RCO driven KG as `RCO:hasMeasurementValue`, and the Datalog rules infer the suitability of each robot for the task. Figure 3 shows the Explanations page, which presents the outputs generated after task execution. The Reasoned Facts tab ⑨ lists the inferred suitability facts, including the best and least suitable robots according to repeatability and precision, as well as the optimal robot. The Graph tab ⑩ visualizes the semantic evidence behind a selected fact, while the Simulated / Counterfactual Comparison tab ⑪ compares the baseline reasoning result with results obtained from hypothetical user-defined values. The XAI tab ⑫ explains the neural predictions using methods such as LIME, SHAP, Integrated Gradients,

¹<https://github.com/MRNaqvi/Semantic-XAI-Framework-for-Robot-Capability-Assessment>

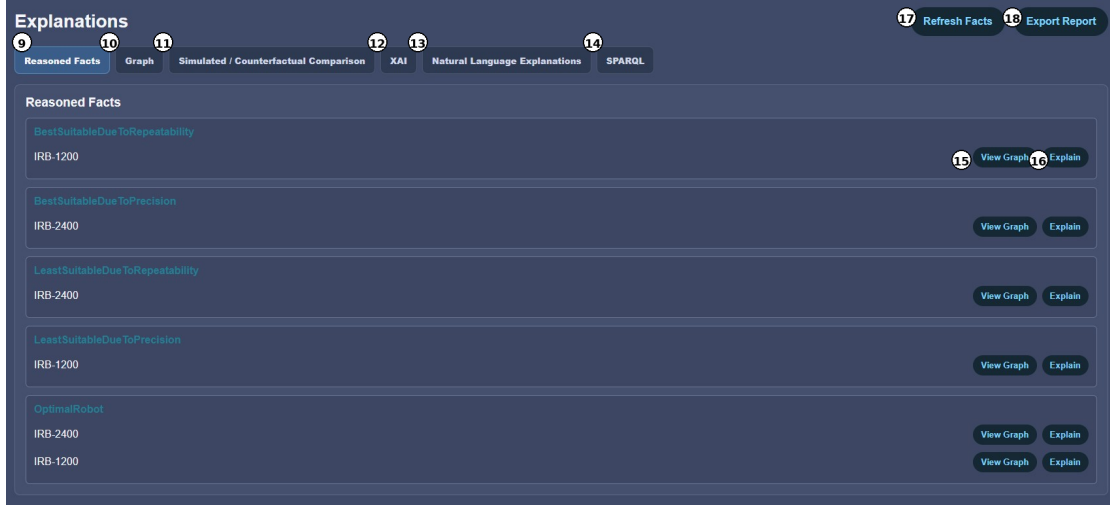


Figure 3: Explanations page of the S-XAI framework.

and Permutation Importance. The NL Explanations tab (13) generates an NL explanation of the selected fact, and the SPARQL tab (14) exposes the queries used to retrieve and update the KG. For each inferred fact, the user can inspect graph evidence through View Graph (15) or generate an NL explanation through Explain (16). The page also allows the user to refresh inferred facts (17) and export the explanation report (18). The System Logs page records the operational trace of the demonstration. It displays timestamped log entries in reverse chronological order and shows the interaction between the browser interface, Flask model service, .NET API, and knowledge graph. These logs indicate which assets were loaded, which predictions were executed, whether the knowledge graph was updated, which facts were refreshed, and which explanation methods were run. This view supports traceability and helps verify that the demonstration was executed correctly. Overall, the demonstration illustrates how neural prediction and semantic reasoning are integrated in a human-centered explanation workflow. The neural models estimate robot operational capabilities for a new Cartesian task, the KG stores these values using the RCO, and the DL rules derive robot suitability facts. The interface then presents these results through multiple explanation modalities, including graph-based explanation, counterfactual simulation, neural feature attribution, natural language explanation, ontology inspection, rule inspection, SPARQL transparency, and system logs.

4. Conclusion

This demonstration presented a Semantic XAI framework for assessing robot capabilities in manufacturing using a neuro-symbolic approach. By integrating neural prediction, ontology-based knowledge representation, MCSK driven RDFox/DL reasoning, and multiple explanation modalities, the system enables transparent and interpretable evaluation of robot suitability

Declaration on Generative AI

We acknowledge the use of the OpenAI API to generate experimental content and the use of GraphDB and the RDFox rule engine as the underlying graph database and reasoning engine, respectively. Grammarly and ChatGPT were used to assist with language related tasks. However, the authors take full responsibility for the scientific content and research ideas presented in this study.

Disclaimer

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