15th Model-driven Requirements Engineering Workshop

Assisting Stakeholders in Class Diagram Interpretation with LLMs

a Work in Progress

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Context and Motivation

- Growing interest in generative AI LLMs—, including within the MoDRE community
- Strong focus on diagram creation with LLMs
- The opposite direction deriving textual explanations from diagrams remains less explored

WHY THIS MATTERS

- Empirical evidence: application of a MoDRE-based method within interdisciplinary teams; development of an end-user modelling tool
- Literature: earlier work [Leopold et al., 2014] opening space to extend it with LLM-based methods



1. H. Leopold, J. Mendling, and A. Polyvyanyy, "Supporting process model validation through natural language generation," IEEE TSE, vol. 40, 2014.

Objective -LLM-generated interactive layer

Tooltip

local explanation, interactive

LLM-generated

send data

Class diagram

human-generated

access

Farmer

IoT vineyard monitoring system

Diagram description

general explanation, static

LLM-generated

Explanation

The diagram explains how a smart monitoring system is used to help manage a vineyard efficiently. At the center of this setup is the IoT vineyard monitoring system, which acts as the digital control point for the entire process.

Sensors are placed in the vineyard to measure key environmental conditions such as soil moisture, leaf wetness, and rainfall. These sensors automatically gather data from the field. The information collected by the sensors is then sent to a LoRaWAN

Device placed in the vineyard to measure soil moisture, leaf wetness, and rainfall, sending collected data to the gateway.

Sensor

→ Vineyard

send data LoRaWAN gateway **➤** Thingsboard platform

access

Technology provider

support

apply organic treatment

Advanced features

entities classification, interactive

LLM-generated

Highlight

Show/Hide Actors

Show/Hide Resources

Show/Hide Digital System

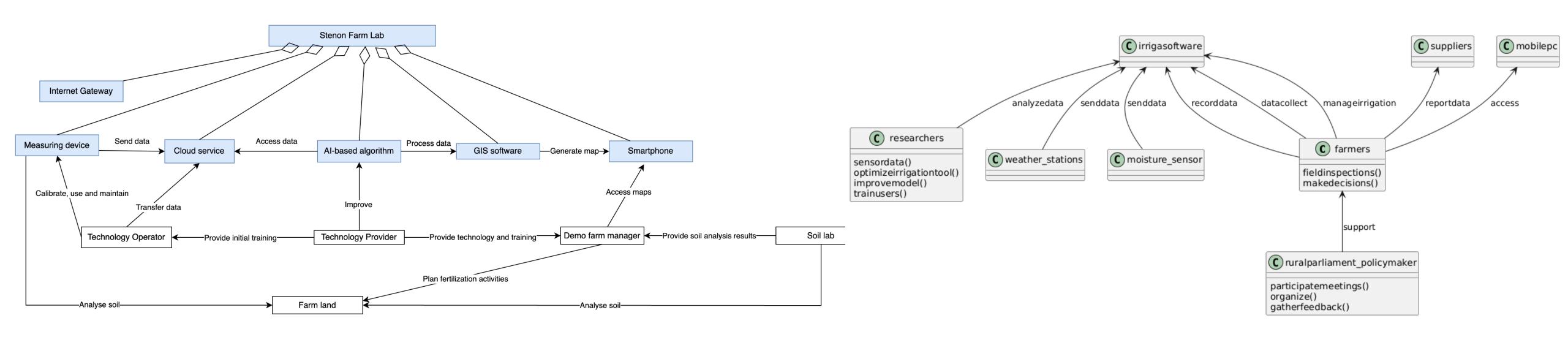
- soil moisture

measure

- leaf wetness
- rainfall

Technical evaluation - input diagrams

Case		Description	UML	Software	Format
1	IoT vineyard monitoring system	An IoT monitoring system based on sensors installed	No: nodes #9; arches #12		png
		on-field that measures several parameters in the	Types: class, aggregation,	StarUML	svg
		vineyard to optimize organic treatments.	direct association		xmi
2	Soil scanner	A soil scanner with sensors and AI-based software that measures soil parameters to optimise fertilisation.	No: nodes #12; arches #20		png
			Types: class, aggregation,	draw.io	svg
			direct association		drawio
3	Smart irrigation	An AI-based system to monitor field and weather conditions and manage irrigation	No: nodes #8; arches #9		png
			Types: class,	ModeLLer	PlantUML
			direct association		xmi



Prompts

LLM: GPT4o - GPT4.1

Prompt 1 write a summary that explains the uploaded diagram to a non-technical audience

Prompt 2 (chain-of-prompts) detect UML classes and return a table listing:

- NAME
- **DESCRIPTION** (20–30 words, non-technical, explaining role and interactions)
- TYPE (digital / actor-organisation / natural resource / other)
- POSITION (X, Y, width, height)

Evaluation criteria

Criteria 1-4 inspired by prior work [Ferrari et al., 2024]

- 1. Completeness: the text covers the content of all the (main) entities with a sufficient degree of detail to explain the content of the model to potential stakeholders.
- 2. Correctness: the text describes a system structure that is coherent and consistent with the diagram.
- 3. **Degree of understandability**: the text is sufficiently clear, given the complexity of the diagram, and does not contain redundancies.
- 4. Terminological alignment: the terminology used in the generated text aligns with the one used in the diagram.

Additional criteria

5. **Acceptability**: the extent to which the positions of the tooltips in the generated interactive layer align with their correct placement as defined in the UML source model.

Likert scale 5: "1– Not fulfilled at all; 2– Fulfilled to a minimal extent; 3– Partially fulfilled; 4– Mainly fulfilled; 5– Completely fulfilled" + comments

2 evaluators, evaluations averaged

2. A. Ferrari, S. Abualhaija, and C. Arora, "Model generation with Ilms: From requirements to uml sequence diagrams," in 2024 IEEE REW.

Execution and results / 1

PROMPT 1 - diagram summary

- 18 summaries, av. 220 words (range 176-260)
- GPT-4.1 longer outputs: av. 239 words; GPT-4o, av. 202 words

Criteria: Completeness, Correctness, Degree of understandability, Terminological alignment

• The average output quality is high (between 4 and 5)

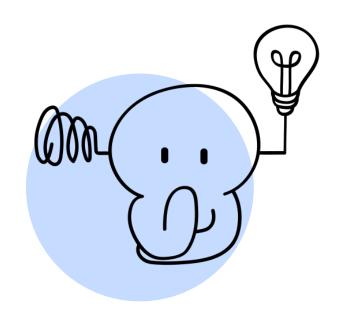
Comments from evaluators: extra content not present in the original data; commentary and interpretative statements; a few instances of hallucination (unmentioned operations), omissions

Execution and results / 2

PROMPT 2 - tooltip table

STEP	CRITERIA	APPROACH	KEY RESULTS
Class extraction	Completeness	Precision: TP (nodes correctly detected) / TP + FP (nodes incorrectly identified) Recall: TP / FN (nodes missed)	 GPT-4.1 perfect score GPT-4o: variability (low on case 1)
I LOOITIN ASSCRIPTION	Completeness, Correctness, Degree of understandability	Completeness: accuracy (no. edges mentioned/no. edges) Other: 5-point Likert scale + comments	 Variability (medium-high results) Notes: aggregation not recognised; missing info; content additions
Classification	Correctness	Boolean + comment	 Error rate: 0% GPT-4.1; 18% GPT-4o Weather station and moisture sensor classified as natural resources
Positioning	Acceptability	Likert scale + comment	 High variability (low-medium results) GPT-4.1 higher score

Takeaway lessons



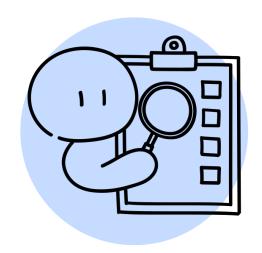
Although based on preliminary findings, results highlight the **technical feasibility of an LLM-generated layer** to support users in diagram reading and validation, across most features overall, and **encourage further experimentation**.



Limitations: both models struggle with contextual understanding, fine-grained details, and risk introducing hallucinated content.

Possible solution: alert users when content is AI-generated and allow them to choose between models.

Future works



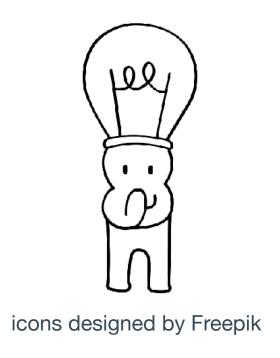
User validation: Test the interactive LLM-generated layer with real users



Extend technical exploration: Experiment with additional models (GPT-5, recently released), LLMs (DeepSeek, LLama, Gemini, and others), increase the input data even with more complex diagrams, or diagrams containing errors or inconsistencies, focus on specific evaluation criteria, test advanced prompting strategies

Thanks for the attention

Your feedback is much appreciated



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