# Integrating Ontology and LLMs for Diagnosis and Repair of Concrete Surface Defects

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**Abstract –**

**This paper explores the integration of a novel Ontology for Concrete Surface Defects (OCSD) with a Large Language Model (LLM), specifically GPT-4o (omni), to enhance defect diagnosis and repair strategies in concrete structures. While LLMs independently offer significant reasoning and natural language capabilities, this study demonstrates the value of combining their interpretative power with the structured knowledge representation provided by OCSD. By enabling adaptive reasoning, where the LLM relies on the ontology's domain-specific relationships and thresholds, and updates its conclusions for specific defect types, the system flexibly adjusts its decision-making based on context. This integration improves diagnosis accuracy, reasoning transparency, and decision-making efficiency. The proposed method is validated through a case study, highlighting the synergy of OCSD and GPT-4o in addressing challenges in defects diagnosis and repair.**

**Keywords –**

**Large Language Models (LLMs), GPT-4o, AI-based Reasoning, Concrete surface defects, Ontology**

## 1 Introduction

The durability and safety of concrete structures depend on accurate and timely diagnosis of defects such as cracks, spalling, and delamination. These defects compromise the structural integrity and pose significant maintenance and financial challenges. While traditional methods for defect diagnosis rely heavily on manual inspection and expert judgment, advancements in artificial intelligence (AI) have introduced powerful tools for enhancing this process. On the other hand, ontologies formalize domain knowledge into structured representations, enabling systematic diagnosis and informed decision-making [1–4]. Ontology for Concrete Surface Defects (OCSD), developed in our previous work [5], provides a comprehensive framework for modeling knowledge about inspection, diagnosis, and 3R (Repair, Rehabilitation, and Replacement) processes for concrete defects. However, ontologies, by their static nature, may fall short when applied to context-specific scenarios. Recent advancements have demonstrated that integrating domain-specific ontologies with AI models enhances interpretative accuracy and contextual reasoning [6, 7]. Large Language Models (LLMs), such as GPT-4o (omni), have emerged as transformative AI systems capable of interpreting complex, unstructured data and providing natural language insights [8–11]. LLMs possess exceptional ability in analyzing textual data, which triggered the opportunity of using ontologies alongside such systems. On the other hand, ontologies provide a robust foundation for mitigating challenges like hallucinations in LLM reasoning, ensuring alignment with domain-specific standards [10].

This study presents an integrated framework for diagnosis and repair of concrete surface defects by combining OCSD [5] with the interpretative capabilities of LLMs. By leveraging the ontology's explicit semantic relationships, this integration ensures logical consistency, alignment with domain standards, and a systematic approach to defect classification, causal analysis, and repair recommendations. This synergy enhances both diagnosis accuracy and reasoning transparency, effectively addressing challenges in defect analysis through ontology-driven reasoning and advanced LLM-based interpretative capabilities. The objectives of this study are: (1) to demonstrate how integrating ontology knowledge enhances the LLM reasoning for concrete defect diagnosis and repair; and (2) to showcase the contributions of this synergy in improving response clarity and actionable recommendations. Through a detailed case study focusing on spalling defects, this research highlights the transformative potential of combining ontological frameworks with advanced LLMs, addressing critical challenges in structural inspection and repair. By bridging the gap between structured knowledge representation and adaptive reasoning, this approach provides a robust solution for structural diagnosis.

The paper is structured as follows. Section 2 reviews related works. Section 3 explains the proposed method.

Section 4 presents the implementation. Section 5 presents the testing and evaluation. The last section provides the conclusions and outlines potential areas for future research.

## 2 Literature Review

Tupayachi et al. [1] introduced AI-powered ontology construction to enhance urban decision-support systems, demonstrating how integrating structured ontologies with LLMs improves reasoning over complex data. Saeedizade and Blomqvist [2] highlighted how semantic frameworks, including ontologies, enhance LLM reasoning layers by formalizing domain-specific requirements. Similarly, Momcilovic et al. [3] illustrated that formal ontologies guide AI reasoning processes, ensuring logical consistency. Existing studies on LLM and ontology integration can be grouped into three primary categories: **(1) LLMs and ontologies in engineering and analytics:** Several works have focused on the integration of LLMs and ontologies in engineering and analytics. For instance, Allemang and Sequeda [12] used ontology-based query checks to improve LLM accuracy in question answering, addressing hallucinations, while Song and Yoon [13] employed ontology-guided LLMs in building performance simulation. Additionally, Wang et al. [7] integrated ontological reasoning into LLM workflows for predictive maintenance and demonstrated how ontologies enhance LLM contextual understanding. Nakajima and Miura [14] incorporated ontological reasoning into LLM workflows for robotic tasks and showcased their ability to improve precision in robotic reasoning. Furthermore, Babaei Giglou et al. [15] investigated LLM-driven ontology learning and evaluated LLMs in extracting structured knowledge. Baldazzi et al. [16] explored domain-specific LLM fine-tuning and emphasized ontological reasoning as a foundation for fine-tuning LLMs in financial tasks. Additionally, Margineda Mangues [17] utilized LLMs with ontologies for procedural content generation, Doumanas [18] applied iterative ontology-driven learning in engineering analytics, and Liu et al. [19] combined domain-specific ontologies with LLM reasoning for dynamic fault diagnosis. **(2) LLMs and ontologies in conversational AI:** Some studies have demonstrated the role of ontologies in enhancing conversational AI through the integration with Large Language Models (LLMs). For instance, Zhang et al. [4] employed knowledge graphs to improve conversational workflows with LLMs, while Palagin et al. [9] used ontology-driven structured prompts to enhance chatbot adaptability. These works illustrate the utility of ontologies in providing context and reducing ambiguity. **(3) LLM for ontology quality assurance:** Research has also explored the application of LLMs in ontology quality assurance. For example, Meyer et al. [8] utilized LLMs for engineering tasks within knowledge graphs, and Tsaneva et al. [20] verified ontology restrictions to address quality issues. Both studies highlight the importance of ontologies in structuring knowledge and ensuring the integrity and accuracy of AI-driven systems.

These studies emphasize that combining domain-specific ontologies with advanced LLM models can provide structured guidance, improving reasoning accuracy, domain alignment, and context-aware decisions. They highlight the value of ontologies as a stable backbone that ensures consistent semantics and prevents hallucination. Our approach distinctively employs specific ontology thresholds to enable flexible reasoning using LLM tailored to structural defect diagnosis and repair scenarios.

## 3 Proposed Method

LLMs like GPT-4o utilize both their pre-trained knowledge and domain-specific inputs to generate contextually relevant outputs. In this approach, the ontology serves as a structured repository of domain-specific knowledge, providing explicit relationships and predefined thresholds for classification, causal analysis, and repair recommendations. These thresholds standardize defect analysis, ensuring consistency and domain relevance. When interacting with the ontology, the LLM uses its language understanding capabilities to interpret relationships, contextualize attributes, and fill gaps where the ontology lacks explicit details. For example, the LLM complements the ontology by interpreting preventive measures not explicitly defined as a class, leveraging its understanding of related concepts like the 3R approaches. This combination ensures that the LLM's outputs are both guided by the ontology and enriched by its generalized knowledge, improving accuracy, relevance, and interpretability.

The method has the following main modules: **(1) Ontology-driven reasoning module:** Leveraging the OCSD ontology [5], this module maps defect attributes to semantic relationships for classification, causal analysis, and severity assessment; and **(2) Defect analysis and recommendation module:** Integrating the semantic attributes and ontology reasoning with GPT-4o, this module generates actionable insights, including specific repair strategies using the 3R processes. Adaptive reasoning is the ability of an AI system, like an LLM, to flexibly adjust its decision-making based on context and evolving inputs. In this framework, when a user specifies a defect type, the ontology filters and provides the most relevant triplets (i.e., subject–predicate–object relationships), guiding the LLM's reasoning with authoritative standards. The LLM then interprets these insights, filling any gaps with its pre-trained knowledge and updating results as new data or feedback emerge. Through this context-aware interaction, the system demonstrates true adaptive reasoning, ensuring accurate and tailored guidance for complex, real-world scenarios.

## 3.1 Ontology-driven Reasoning Module

The OCSD ontology provides a semantic framework for mapping defect attributes to structured classes and relationships. By defining explicit thresholds and categorizing defects into severity levels (e.g., *Light Spalling*, *Medium Spalling*, *Severe Spalling*), the ontology guides logical classification, causal analysis, and context-specific recommendations. Leveraging these ontology-derived relationships ensures that each defect is analyzed consistently and aligned with authoritative domain standards.

A key aspect of this process is the use of dynamically inserted variables, which are generated by querying the ontology for the most relevant defect-specific information. Rather than relying solely on user inputs, the ontology-driven reasoning module filters and selects the appropriate triplets related to the specified defect type. These ontology-derived details, such as severity thresholds, corresponding causes, or recommended repair pathways, are then programmatically inserted into the reasoning prompt at runtime. For example, if the user specifies a spalling defect, the ontology returns the relationships that define the severity classifications, potential root causes, and applicable 3R strategies leveraging the OCSD for structured and domain-specific analysis. These ontology-derived variables (i.e., *{ontology_info}*) appear as placeholders in the prompt and are replaced by the actual, contextually relevant data before the LLM is called. By doing so, the LLM's outputs reflect the most up-to-date, domain-specific information, enhancing the accuracy, relevance, and credibility of the resulting recommendations. The details of the model prompts are provided in Table 1. This table compares the baseline model and the OCSD-enhanced model prompts. The prompt of the baseline model relies only on defects attributes. The OCSD-enhanced model uses the same prompt as the baseline model but adds the provided ontology relationships.

Iterative reasoning further refines the analysis by allowing the system to repeatedly engage with the ontology and LLM as new data or feedback emerge. If the initial recommendations need adjustment, due to changes in defect attributes, updated inspection results, or evolving maintenance strategies, the ontology-driven reasoning module retrieves the related relationships and thresholds. The LLM then reinterprets this ontology-derived information, ensuring that guidance remains current and context aware. In addition to textual outputs, the approach incorporates interactive visualization to depict the relationships and semantic pathways underlying each recommendation. By visually representing ontology-derived nodes (e.g., defect classes) and relationships, the user gains a clearer understanding of how the ontology informs LLM outputs. This graphical representation makes the reasoning process more transparent and intuitive, helping the user rapidly understand why certain causes are inferred or why specific repair actions are proposed.

## 3.2 Defect Analysis and Recommendation Module

Building on the ontology-driven reasoning described in Section 3.1, this module employs GPT-4o to produce scenario-specific recommendations. By processing the severity classification and ontology-derived details, the model confirms the defect's classification, identifies underlying causes, and suggests actions aligned with authoritative standards. The defined 3R interventions guides the selection of repair strategies, ensuring that each recommendation is contextually relevant and rooted in established domain knowledge.

In this module, the structured prompt integrates the previously retrieved ontology relationships, severity classifications, and any available defect attributes. This

Table 1. Comparison of prompts of baseline model and OCSD-enhanced model

| Baseline model prompt | Enhanced model with OCSD prompt |
|---|---|
| You are a structural engineer specializing in concrete defects. You have been provided with the following information:<br>Defect Description:<br>- Type: '{defect_description}'<br>Defect Attributes:<br>{attributes_info}<br>Using the provided defect attributes, please perform the following tasks:<br>1. Severity classification<br>2. Diagnosis of potential causes.<br>3. Recommendation of remedial actions.<br>4. Preventative measures<br>Please ensure that your analysis is thorough and that you logically integrate the defect attributes to support your conclusions. Present your response in a clear and structured manner. | You are a structural engineer specializing in concrete defects. You have been provided with the following information:<br>Defect Description:<br>- Type: '{defect_description}'<br>Defect Attributes:<br>{attributes_info}<br>**Relevant Ontology Relationships.**<br>**{ontology_info}**<br>Using the provided **ontology relationships** and defect attributes, please perform the following tasks:<br>1. Severity classification<br>2. Diagnosis of potential causes.<br>3. Recommendation of remedial actions.<br>4. Preventative measures<br>Please ensure that your analysis is thorough and that you logically integrate the **ontology information** and defect attributes to support your conclusions. Present your response in a clear and structured manner. |

combined input enables GPT-4o to generate logically consistent outputs tailored to the defect's unique characteristics. The resulting analysis provides clear justifications for proposed repair actions, linking them directly to the identified causes and ensuring a transparent, actionable reasoning process.

## 4 Implementation

This section details the practical implementation of a prototype system based on the proposed method developed using Python. The application integrates various libraries and tools to process input data and interact with the ontology and LLM. It uses *rdflib* to parse and query the ontology, *networkx* and *pyvis* for building and displaying interactive relationship graphs, and *OpenAi* for calling the GPT-4o model's API. The developed prototype system based on the method supports automated data ingestion, dynamic ontology querying, and adaptive reasoning calls to GPT-4o, ensuring an integrated and reproducible environment for experimentation and analysis. Figure 1 shows the developed user interface.

In this implementation, supplementary image analysis was conducted using GPT-4o API for extracting defect attributes. The image of a concrete surface with dimensions of $1m \times 2m$ was uploaded into the developed application for analysis. The GPT-4o model was accessed through the OpenAI API and tasked with identifying the major defect type, classifying individual defects, and extracting their attributes considering the surface dimensions. Figure 1(a) shows an example of an image that was fed to the system. Five spalls have been detected, and their attributes have been extracted automatically. Figure 1(b) shows the extracted defects attributes from the image analysis. For instance, Defect 4 has the width of about 20 cm, height of about 2 cm, and depth of about 2 cm, with features including being the widest defect, and having uneven erosion and discoloration. The defect attributes are used as input for the prompt as explained in Section 3.1. These attributes could also be derived from point cloud semantic segmentation results, as demonstrated in prior work [21], or obtained through on-site inspections and entered to the system by the user as shown in Figure 1(c). As the type of the detected defect is spalls, Figure 1(d), enlarged in Figure 2, shows only 38 classes and 9 instances for the threshold's related to spalls, which were automatically extracted from the complete ontology which has a total of 335 classes.

## 5 Testing and Evaluation

Table 2 provides two example comparing responses from the baseline and enhanced models for two defects (Defects 1 and 4). Condition assessment utilizes predefined severity thresholds encoded in the OCSD, which are compared with the defect dimensions, ensuring consistency in defect evaluation. Furthermore, by leveraging the OCSD ontological relationships, our reasoning module identified plausible cause-and-effect relationships between specific defect characteristics and

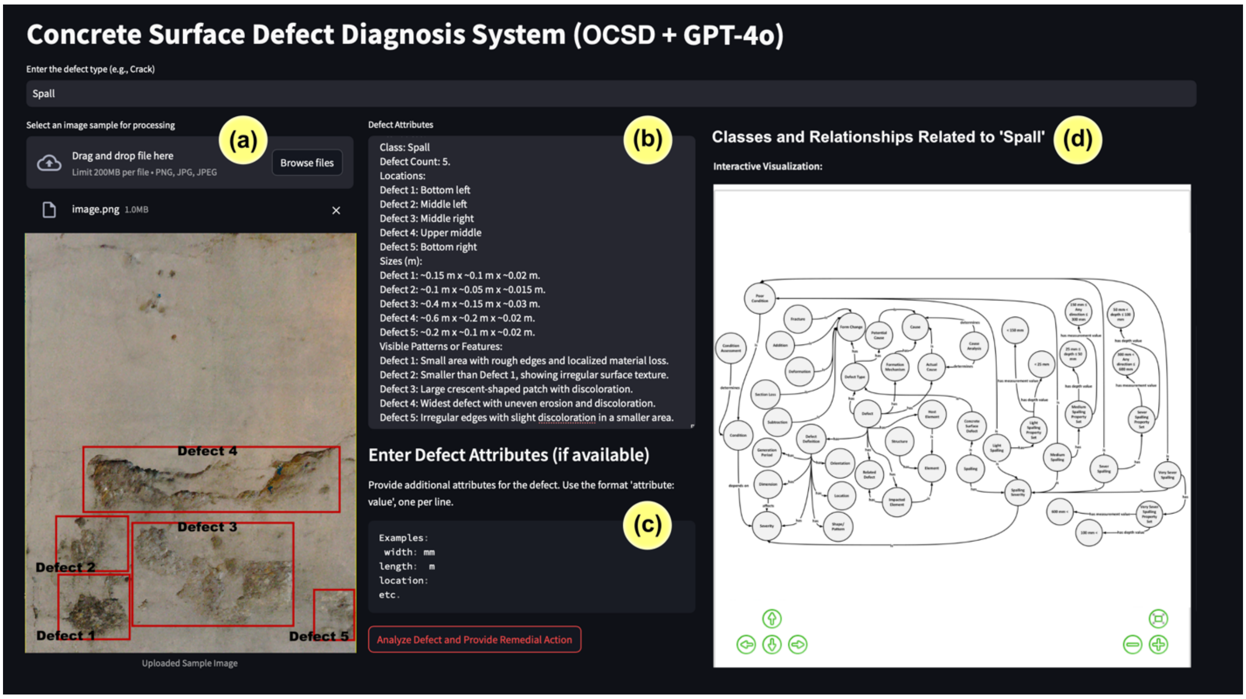


Figure 1. User interface of the prototype system

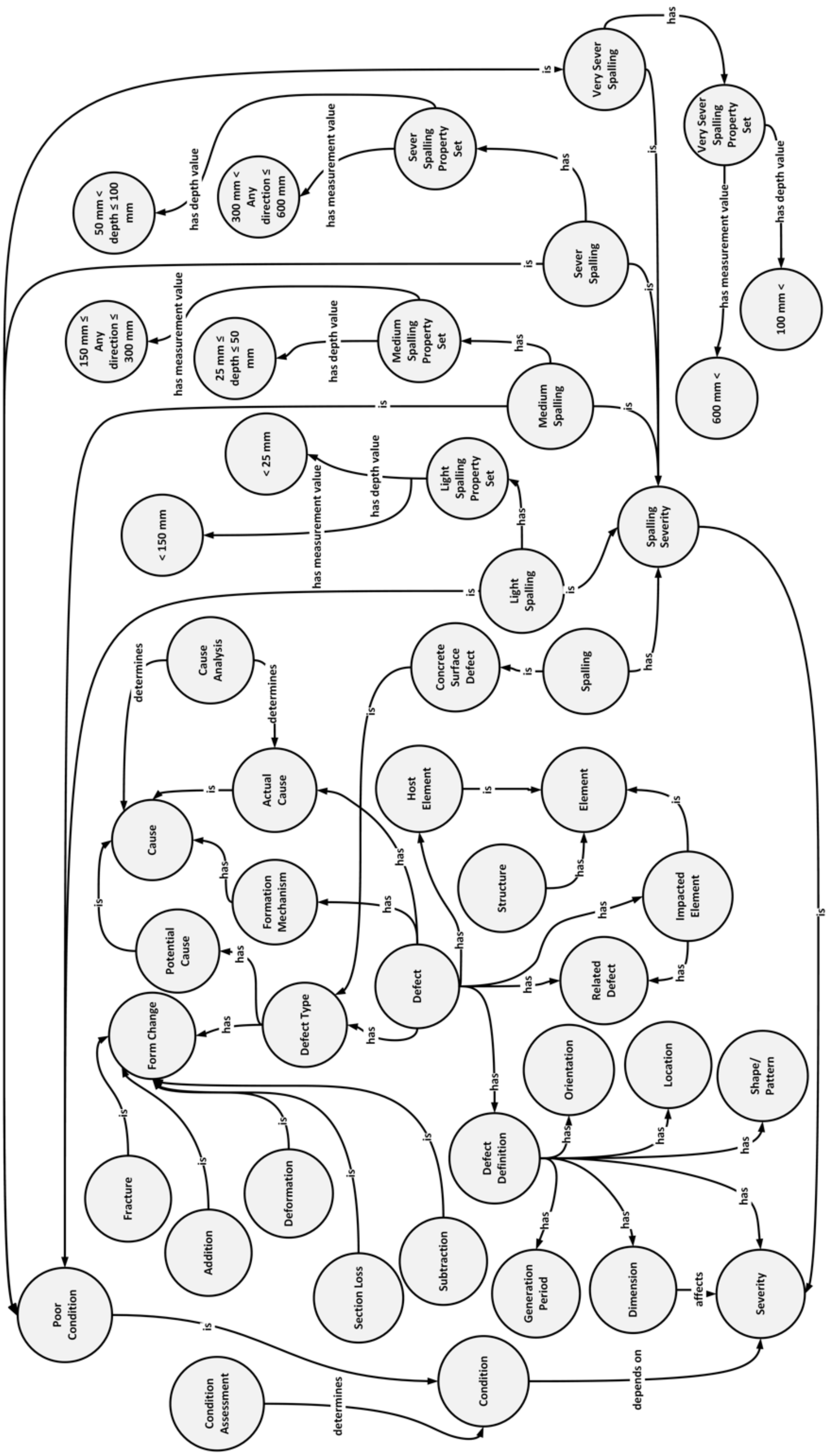


Figure 2. An example of interactive visualization of OCSD-derived thresholds for condition assessment of spalling

their underlying factors. For Defect 1, the baseline model classified Defect 1 as low severity due to its irregular texture and smaller size, attributing it primarily to minor surface erosion. However, the OCSD-enhanced model identified it as *medium spalling*, emphasizing moisture ingress and chemical exposure as contributing factors. By leveraging ontology-driven thresholds, the enhanced model provided a more refined diagnosis, recommending surface treatments aligned with spalling severity classifications. This result, representative of the model's performance across five spalling defects, illustrates how incorporating authoritative knowledge sources leads to more contextually accurate and actionable guidance. The enhanced model, informed by ontology-derived insights, provided a precise classification for Defect 4 (*severe spalling*) rather than a generic label, identified clearly documented causes, and recommended standards-based repair and preventative measures. For example, severe spalling in Defect 4 indicated more advanced chemical degradation, potentially from de-icing agents, and the impacts of freeze-thaw cycles. Informed by the ontology-derived severity classifications and guided by the 3R interventions, GPT-4o provided well-structured repair strategies for each identified defect. For Defect 4, characterized by severe spalling, the system advised partial or complete replacement, reflecting the severity of material loss and structural compromise. Preventative strategies here focused on advanced sealants and thorough, regular inspections to forestall recurrence. Across all defect cases, GPT-4o's recommendations demonstrated logical consistency with the severity levels, causal insights, and the repair and preventative strategies defined by the ontology.

The effectiveness of integrating the ontology-based framework with LLMs in diagnosing and repairing spalling defects is evaluated focusing on four key metrics: severity classification, cause identification, remedial actions, and preventative measures. Partial matches were counted to accommodate natural variations in phrasing, ensuring a comprehensive assessment. These metrics and their associated terms are drawn from recognized standards and guidelines, as defined in *Concrete Structures Protection, Repair and Rehabilitation* [23] and the *Ontario Structure Inspection Manual (OSIM)*

Table 2. Comparison of responses of baseline model and OCSD-enhanced model for Defects 1 and 4

| Baseline model response | Enhanced model with OCSD response |
|---|---|
| **Defect 1** - Location (Bottom-left), Smaller Area with Rough Edges<br>*1. Severity Classification:* Low Severity: The defect has irregular surface texture, indicating initial material surface degradation.<br>*2. Potential Causes:* Surface Erosion: Possibly due to weather exposure or inadequate curing.<br>Concrete Quality: Inadequate surface finishing leading to early wear.<br>Reasoning: Smaller size with irregular texture suggests less severe environmental action, likely a surface treatment issue<br>*3. Remedial Actions:*<br>Surface Sealing: Apply a protective surface sealant to prevent moisture ingress and further surface degradation.<br>Rationale: Sealing restores the integrity and protects against environmental exposure.<br>*4. Long-term Preventative Measures:*<br>Proper Curing: Ensure adequate curing times to enhance surface strength and durability.<br>Surface Coatings: Use protective coatings to shield surfaces from weather and chemical attacks. | **Defect 1:** Location: (Bottom-left)<br>Size: Medium size with irregular surface texture and discoloration.<br>*1. Severity Classification: MediumSpalling*<br>Justification: Medium defect size and discoloration indicate a severity higher than LightSpalling. OCSD's MediumSpalling class involves more notable material loss and visual deterioration.<br>*2. Potential Causes Inherited from OCSD:* (a) Moisture ingress with discoloration: Medium-severe discoloration effects. (b) Chemical exposure: Such as chloride ingress from de-icing agents.<br>*3. Remedial Actions (3R Approach):*<br>Surface treatments or coatings: Justification: Mitigation needed for discoloration and moderate material loss. OCSD guidelines suggest comprehensive surface treatment for medium spalling.<br>*4. Long-term Preventative Measures:* (a) Improved concrete mixes: Utilize mixtures that resist spalling agents. (b) Surface cleaning protocols: Avoid accumulation of harmful substances.<br>*5. Summary:* Medium spalling needs enhanced materials addressing both aesthetic and structural perspectives, guided by OCSD, while providing clarity on moderate deterioration and avoiding overly extensive solutions. |
| **Defect 4** - Location (Upper-middle), Widest, Uneven Erosion, Discoloration<br>*1. Severity Classification:* High Severity: With uneven erosion and discoloration, it heavily impacts the structural performance.<br>*2. Potential Causes:* (a) Severe Moisture Exposure: Possible long-term exposure to water and chemical agents. (b) Aggregate Reaction: Alkali-silica reaction could cause both erosion and discoloration.<br>Reasoning: The extent and characteristics suggest significant chemical and physical reactions over time.<br>*3. Remedial Actions:* (a) Comprehensive Repair: Extensive removal, including damaged rebar sections, repair or replacement of rebar, and concrete restoration. (b) Rationale: Ensures safety by restoring both external and internal structural components.<br>*4. Long-term Preventative Measures:* (a) Enhanced Concrete Mixes: Use mixes resistant to alkali-silica reactions and high moisture environments. (b) Improved Design Drainage: Ensure design includes proper drainage systems to minimize water retention on the surface. | **Defect 4**: Location: (Upper-middle)<br>Size: Widest defect with uneven erosion and discoloration.<br>*1. Severity Classification:* Severe Spalling<br>Justification: The largest area with significant erosion matches OCSD's Severe Spalling definitions due to extensive material loss and discoloration.<br>*2. Potential Causes inherited from OCSD:* (a) Aggressive chemical attack: May be from industrial exposure or pollutants leading to severe erosion. (b) Freeze-thaw cycles: Intensifies with large and deep spalling areas.<br>*3. Remedial Actions (3R Approach):*<br>Partial or complete replacement: Justification: Severe Spalling defects compromise integrity, necessitating comprehensive intervention. Aligns with OCSD suggesting replacement for severe cases.<br>*4. Long-term Preventative Measures:*<br>Advanced sealants and coatings: Prevent further degeneration.<br>Regular, in-depth inspections: Address early signs of similar severe deterioration.<br>*5. Summary:* Severe defects need major structural interventions guided by OCSD, providing well-planned steps for long-term effectiveness over ad-hoc methods. |

[24]. By using widely accepted terminology drawn from these references, the evaluation ensures that the chosen terms reflect common engineering practice, rather than proprietary ontology constructs. Specifically, for severity classification, the terms *Light Spalling*, *Medium Spalling*, and *Severe Spalling* were applied. To represent common underlying causes, *moisture penetration*, *freeze-thaw cycles*, *chemical attack*, and *reinforcement corrosion* were selected. For remedial actions, *patch repair*, *surface coating*, and *corrosion inhibitors* were used, while *waterproofing*, *high-performance concrete mixes*, and *regular inspections* served as preventative measures.

Figure 3 shows a bar chart summarizes how frequently each model correctly employs the established key terms. Along the horizontal axis are the four metrics, and the vertical axis indicates the count of recognized terms. The enhanced model's higher bars in categories like severity classification and remedial actions emphasise its stronger alignment with domain standards.

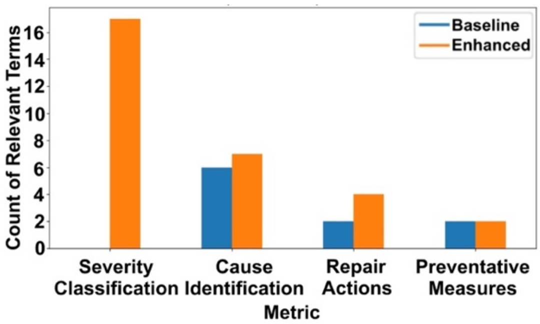


Figure 3. Frequency of correctly identified terms across the four defined metrics

The radar plot shown in Figure 4 provides a holistic view by plotting each metric on a different axis, forming a polygon for each model. The enhanced model's polygon extends further along all axes, especially severity classification, indicating a more balanced and comprehensive understanding of the key concepts.

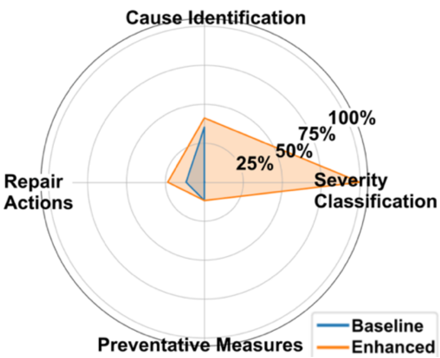


Figure 4. Normalized visual comparison of the models across the four defined metrics

Overall, by grounding the evaluation in accepted industry references [17] and OSIM, and using figures that clearly illustrate comparative performance, the analysis demonstrates that ontology integration significantly enhances the LLM's ability to produce structured, accurate, and actionable responses for spalling defect diagnosis and repair.

## 6 Conclusions and Future Work

This paper introduced an integrated framework for diagnosing and analyzing concrete surface defects by combining ontology-driven reasoning with the advanced interpretative capabilities of an LLM, GPT-4o. The proposed method is implemented in a prototype system integrating OCSD with GPT-4o API. By leveraging GPT-4o for ontology-based reasoning, the system provided a comprehensive and context-aware workflow for defect classification, causal analysis, and repair planning. A case study involving spalling defects demonstrated the efficacy of this approach. The proposed framework offers several advantages over traditional methods: (1) The use of OCSD ensures that diagnosis outputs are grounded in structured domain knowledge, enhancing the reliability of the results; and (2) The integration of defect attributes and ontology relationships enables specific and context-aware repair strategies. The evaluation results indicate that integrating domain-specific ontologies, such as the OCSD, significantly enhances the depth, accuracy, and actionability of LLM-generated outputs for defect diagnosis and repair.

Despite the promising results, the following limitations were identified: (1) While the OCSD provides a structured framework for defect classification, it may not comprehensively cover all defect types, causes, and repair strategies. (2) The quality of the LLM's outputs depends on prompt clarity and data specificity, making it susceptible to errors if attribute extraction is incomplete or ambiguous. (3) Reliance on the OpenAI API for GPT-4o introduces computational costs, and scaling up the system for broader deployments could increase these expenses, posing challenges in resource allocation. To address these limitations, future research can expand the OCSD by incorporating additional classes and relationships, thereby improving coverage and versatility. Fine-tuning domain-specific LLMs and integrating advanced 3D semantic segmentation techniques can enhance the precision of attribute extraction and severity assessment. Moreover, exploring strategies to optimize computational costs, such as deploying more efficient models or refining interaction protocols, would support sustainable, large-scale implementation.

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