Leveraging large language models for automated knowledge graphs generation in non-destructive testing

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Abstract

This paper presents an innovative approach for the automatic generation of Knowledge Graphs (KGs) from heterogeneous scientific articles in the domain of Non-Destructive Testing (NDT) applied to building materials. Our methodology leverages large language models (LLMs) to extract and semantically relate concepts from diverse sources. We developed material-specific agents for concrete, wood, steel, and bricks, each equipped with a curated glossary of terms to ensure domain accuracy. These agents process PDF documents, extracting relevant information on deterioration mechanisms, physical changes, and applicable NDT methods. The extracted data is then normalized, validated, and structured into a Neo4j graph database, forming a comprehensive KG. Our results demonstrate the system's ability to automatically discover and represent intricate relationships between materials, deterioration mechanisms, physical changes, and NDT techniques. The generated KG successfully captures complex interactions, such as the applicability of specific NDT methods to various materials under different deterioration conditions. This work not only highlights the potential of KGs in enhancing knowledge discovery and representation in NDT research but also provides a scalable framework for extending this approach to other scientific domains.

GitHub:https://github.com/ghezalahmad/LLM_NDT_Knowledge_Graph.git

Keywords

Materials Science and Engineering, Large Language Model, Linked Open Data, Data Interoperability, RDF, Semantic Web.

1. Introduction

NDT is a set of tools with high applicability in the field of Material Sciences Engineering (MSE), crucial for detecting defects and assessing material integrity without causing further damage. NDT ensures structures and components' safety, reliability, and longevity across various industries, including aerospace, civil engineering, and manufacturing. In the context of building materials, the literature on NDT is extensive, covering a wide range of materials such as concrete, wood, masonry, and metals, and employing diverse testing methods like ultrasonic testing, radiography, and infrared thermography.

Although the utility of such methods is beyond doubt [1], there is diversity at different levels that can complicate the proper selection of the NDT method when applying it. This diversity includes variations in material identification, degradation phenomena (whether isolated or concurrent), the symptoms in which such degradation phenomena manifest, and parameters in these non-destructive techniques (as resolution, range, frequency, etc.).

To address this challenge, we propose leveraging advanced Natural Language Processing (NLP) techniques, specifically LLMs [2] such as OpenAI's GPT4o [1]. The model will be used to automate the extraction and organization of NDT methods and their related physical magnitudes, with their

SeMatS 2024: The 1st International Workshop on Semantic Materials Science co-located with the 20th International Conference on Semantic Systems (SEMANTiCS), September 17-19, Amsterdam, The Netherlands.
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applicability to the detection of degradation phenomena for every material. To add more utility, we extract and refer to these relationships from the scientific literature. By utilizing the LLM model, we aim to create an extensive and easily accessible KG that systematically links NDT tools to specific deterioration mechanisms and materials. KGs provide a promising solution by structuring information into a network of entities and relationships, enabling more efficient knowledge discovery and retrieval [3].

The primary objective of this study is to develop a robust methodology for the automatic generation of KGs from scientific articles on NDT in building materials. This methodology facilitates the exploration of intricate relationships between NDT techniques and various materials' degradation phenomena. The resulting methodology serves as a resource for researchers and engineers, supporting informed decision-making and fostering innovation in the access to complex scientific field information.

In this paper, we present our approach to creating a KG from heterogeneous NDT literature, demonstrate the effectiveness of our methodology through three usage examples, and discuss the potential implications and future directions of this research. Our work highlights the significant benefits of integrating AI-driven concept extraction and knowledge representation techniques in advancing the field of NDT and improving the accessibility of critical information for scientific and engineering applications.

2. Hypothesis and Research Questions

We hypothesize that LLMs, specifically OpenAI's GPT-4o, can accurately and efficiently extract detailed NDT methods and their related deterioration mechanisms from the scientific literature. Furthermore, we propose that a KG generated from this extracted information can effectively organize and represent complex relationships, thereby facilitating enhanced knowledge discovery and application in the field of NDT.

To explore these hypotheses, we formulate the following research questions:

1. How effectively can LLMs extract and categorize deterioration mechanisms, physical changes, and recommended NDT techniques for building materials from scientific literature?
    - This question aims to assess the ability of LLMs to process diverse scientific texts and extract relevant NDT information. By evaluating the extracted data against a manually curated glossary for each material (concrete, wood, steel, and bricks), we aim to demonstrate the reliability and comprehensiveness of AI-driven extraction techniques across different domains within NDT. The question is addressed also in results and discussion section.
2. To what extent can the generated KG facilitate the exploration and understanding of relationships between NDT methods, deterioration mechanisms, and materials?
    - The purpose of this question is to assess how useful the KG is in helping researchers and engineers explore and understand complex relationships within the NDT domain. By organizing scientific literature's content in a structured manner, the KG is expected to facilitate quick information retrieval, identification of NDT techniques applicable across different materials, and reveal new insights that may not be easily found through traditional literature review methods. Additionally, the graph has been validated by an expert in the NDT domain.
3. How does the performance of material-specific agents compare in terms of information extraction accuracy and completeness across different building materials (concrete, wood, steel, and bricks)?
    - This question aims to explore potential differences in the efficacy of our method when applied to various materials. By evaluating the performance of each material-specific agent, we can pinpoint any challenges that are specific to particular domains and evaluate how universally applicable our approach is. The results and discussion section will further elaborate on this information.

By addressing these research questions, we aim to validate the effectiveness of LLMs in automating NDT data extraction, demonstrate the practical benefits of using KGs for knowledge representation and discovery in materials science and engineering, and assess the robustness of our approach across different building materials. This study contributes to the broader goal of leveraging AI and graph-based technologies to accelerate scientific discovery and improve decision-making in the field of non-destructive testing.

3. Literature Review

In literature, Semantic Web Technologies (SWT) have been successfully used in MSE [4, 5]. Building on this success, we are currently focused on extracting Knowledge Graph (KG) from scientific literature, especially in the field of NDT. This method represents an advanced approach for organizing and structuring large volumes of complex data. The literature review delves into the latest research on the application of NLP and machine learning techniques for automating the extraction and generation of KGs from NDT-related documents.

Moreno et al. [6] present a work where the main contribution of the paper is its successful demonstration of how semantic technologies, specifically ontologies, can be effectively applied to improve data interoperability within the realm of non-destructive testing. By utilizing ontologies, the study showcases a methodology that enhances the integration of data from various test methods, particularly focusing on the analysis of water content and porosity distribution in solids using 1H nuclear magnetic resonance relaxometry. However, a key limitation of the research is the necessity for additional iterations to fully exploit the potential benefits of semantic enrichment and knowledge transfer in interdisciplinary research settings. While the initial implementation of the digital workflow methodology shows promise in enhancing data management and semantic expressiveness, further refinements and enhancements are required to maximize the impact of ontologies in facilitating seamless collaboration and information exchange among interdisciplinary team members in the field of materials science and non-destructive testing.

Kamsu-Foguem et al. [7] offers an approach using conceptual graphs to provide a formal and structured framework for improving compliance monitoring and knowledge representation in NDT for aircraft structures. By employing conceptual graphs, the paper enhances the clarity and precision of reasoning processes, enabling a more systematic approach to verifying compliance with technical procedures and equipment specifications in the maintenance of aircraft components. This approach aligns with the concept of a "Knowledge Graph," which refers to a knowledge base that integrates information from various sources and represents it in a structured format for efficient retrieval and analysis. However, a potential limitation of the approach outlined in the paper is the challenge of maintaining and updating the knowledge base represented by the conceptual graphs. As industry standards, equipment technologies, and maintenance practices evolve, ensuring the accuracy and relevance of the knowledge base becomes crucial but may require significant effort and resources to keep up-to-date with the dynamic nature of the aviation industry. This ongoing maintenance task could pose a challenge regarding resource allocation and the need for continuous validation and refinement of the knowledge representation to reflect the latest developments in NDT practices and equipment requirements.

Hagedorn et al. [8] provides an approach where the development of a web-based platform that implements Information Containers for Linked Document Delivery (ICDDs) for asset management, integrating existing systems and demonstrating the use of domain-specific ontologies and 3D BIM models to enable querying across multiple information sources for stakeholder-specific views. However, the paper does not provide a comprehensive evaluation of the proposed BIM-enabled Asset Management System, and it also mentions the use of non-destructive testing methods as an important aspect of condition assessment.

4. Research Method

4.1. Dataset - NDT Methods from Research Papers

The dataset used for this study [9, 10, 11, 12, 13] comprised a range of NDT-related research papers and technical documents. The selection criteria for the dataset included:

- Diversity of NDT Methods: Papers covering a wide array of NDT techniques, including but not limited to, ultrasonic testing, radiography, magnetic particle testing, and eddy current testing.
- Variety of Materials: Documents addressing NDT applications across different materials such as concrete, steel, wood, and bricks.
- Comprehensive Coverage: Inclusion of recent advancements and historical perspectives in the field of NDT to ensure a holistic understanding of the domain.

Using GPT-4o to extract NDT methods from these papers, we aimed to create a robust and comprehensive knowledge base, facilitating the generation of a detailed knowledge graph for further analysis and application in materials science and engineering.

4.2. LLM for Extracting Information from Heterogeneous Scientific Papers

We employed OpenAI's GPT-4o to automate the extraction of NDT methods, associated deterioration mechanisms, and physical changes from a diverse set of scientific papers and technical documents. The extraction process involved several key steps to ensure the accuracy and comprehensiveness of the information gathered:

Firstly, a corpus of scientific literature and technical documents on NDT was compiled. This corpus included peer-reviewed journal articles, conference papers, technical reports, and industry standards documents covering various NDT methods, materials, and deterioration mechanisms. The aim was to ensure a broad and inclusive dataset that could provide a holistic view of the field. The collected documents were then preprocessed to convert them into plain text format, ensuring they were suitable for analysis. This involved extracting text from PDFs and other document formats, and organizing the data into a consistent structure. This preprocessing step was crucial for preparing the data for the language model's analysis.

Specific prompts were designed for the GPT-4o model to extract relevant information. These prompts were crafted to instruct the model to identify and extract details related to the materials affected by the deterioration mechanisms (e.g., concrete, steel, wood, bricks), the specific deterioration mechanisms detected (e.g., corrosion, spalling), the physical changes caused by these mechanisms (e.g., thinning, discoloration, structural changes), and the types of NDT methods used (e.g., ultrasonic testing, radiography, visual inspection).

The preprocessed text from each document was input into the GPT-4o model using the designed prompts. The model was executed to extract the necessary information, which was then compiled into structured outputs. This step leveraged the model's advanced natural language processing capabilities to parse complex scientific texts and extract pertinent details efficiently.

Finally, the extracted data was organized into a standardized format, categorizing the materials, deterioration mechanisms, physical changes, and recommended NDT methods. This structured format facilitated the subsequent integration of the information into the knowledge graph, enabling a coherent and comprehensive representation of the extracted knowledge.

4.3. Knowledge Graph Construction

The structured information extracted by GPT-4o was used to construct a Knowledge Graph (KG) using the Neo4j graph database. The construction process involved the following steps:

1. **Node Creation**: Nodes were created for each material (concrete, steel, wood, bricks), each deterioration mechanism, physical change, and NDT method identified.

2. **Relationship Establishment**: Relationships were established between the nodes to represent the extracted information. For instance, a material node (e.g., Concrete) was linked to a deterioration mechanism node (e.g., Corrosion) through a "HAS_DETERIORATION_MECHANISM" relationship. The deterioration mechanism node was linked to a physical change node (e.g., Cracking) through a "CAUSES_PHYSICAL_CHANGE" relationship, and the physical change node was linked to an NDT method node (e.g., Ultrasonic Testing) through a "DETECTED_BY" relationship.
3. **Validation and Normalization**: The relationships and nodes were validated by a MSE domain specialist to ensure consistency and accuracy. The data was normalized to eliminate redundancies and ensure a coherent structure within the KG.
4. **Query Implementation**: The Neo4j database was queried to visualize and analyze the relationships within the KG. Besides the visualization seems enough for the MSE domain specialist, in addition, Cypher queries were utilized to retrieve specific information and explore complex interactions between materials, deterioration mechanisms, physical changes, and NDT methods.

This systematic approach enabled the automatic generation of a comprehensive KG that captures intricate relationships in the NDT domain, facilitating enhanced knowledge discovery and representation.

5. Experimental Program

The experimental program aimed to validate the effectiveness of using an LLM for extracting and organizing NDT methods and their related deterioration mechanisms into a comprehensive knowledge graph. The program was divided into five key phases, each focused on different aspects of the methodology and its implementation.

1. **Data Collection and Preparation**
   - **Document Compilation**: A collection of scientific papers, technical reports, and industry standards related to NDT methods was compiled. This dataset included documents from various sources to ensure comprehensive coverage of NDT techniques and materials.
   - **Preprocessing**: The documents were converted to plain text format. This involved handling different file types (PDFs, Word documents, RTFs) and ensuring the text was clean and free from irrelevant formatting.
2. **Model Configuration and Prompt Design**
   - **LLM Configuration**: OpenAI's GPT-4o was selected for its advanced natural language processing capabilities. The model was configured to handle the large volume of text and the specific needs of NDT information extraction.
   - **Prompt Development**: Custom prompts were developed to guide the LLM in identifying and extracting key information related to NDT methods, deterioration mechanisms, and affected materials. These prompts were designed to be clear and specific to ensure the model's responses were relevant and accurate.
3. **Information Extraction**
   - **Execution of LLM**: The preprocessed text from the collected documents was input into the LLM using the developed prompts. The model processed each document to extract information about NDT tools, their corresponding deterioration mechanisms, and the materials they are used on.
   - **Data Structuring**: The extracted information was organized into a standardized format, detailing the NDT method, associated deterioration mechanisms, and the materials affected. This structured data was crucial for the next phase of knowledge graph construction.
4. **Knowledge Graph Construction**

- **Neo4j Implementation**: Neo4j, a graph database management system, was used to construct the knowledge graph. The structured data from the LLM was input into Neo4j, creating nodes for NDT tools, deterioration mechanisms, and materials, and establishing relationships between them.
- **Graph Schema Design**: A schema was designed to represent the entities and relationships within the knowledge graph. Nodes represented NDT tools, materials, and deterioration mechanisms, while edges represented the relationships between these entities, such as "HAS_DETERIORATION_MECHANISM," "CAUSES_PHYSICAL_CHANGE," and "DETECTED_BY."

5. **Validation**
    - **Expert Review**: The constructed knowledge graph was reviewed by domain experts to ensure the accuracy and relevance of the extracted information. Feedback from these experts was used to refine the extraction process and improve the quality of the knowledge graph.

The experimental program successfully demonstrated the feasibility and effectiveness of using a large language model to automate the extraction and organization of NDT information into a comprehensive knowledge graph. This approach not only streamlined the data collection process but also improved the accessibility and usability of NDT knowledge for researchers and engineers.

6. Results and Discussion

The results of this study demonstrate the effectiveness of using an LLM to extract and organize information on NDT methods and their associated deterioration mechanisms into a comprehensive KG. The constructed KG includes nodes representing four primary materials: concrete, steel, wood, and bricks. Each material node is linked to various deterioration mechanisms, physical changes, and corresponding NDT methods. This structured representation enables the exploration and analysis of how different NDT techniques are applied to detect specific types of deterioration across various materials.

The majority of the extracted entries were correctly classified and structured, following the format of Material; Deterioration Mechanism; Physical Change; and NDT Method. However, several issues were identified during the review process, necessitating adjustments for consistency and accuracy. For instance, entries initially listed "moisture content" as a deterioration mechanism. However, it is more accurately described as a property or condition that can lead to deterioration. Therefore, it was reclassified as "moisture changes" or "high moisture content" to better reflect its role in the deterioration process. Similarly, entries listed "rot" as a deterioration mechanism, which, while correct, was inconsistent with the use of "fungal decay" in other entries. To maintain consistency, all references to rot were updated to "fungal decay."

Another notable adjustment was required for entries, where "knots" were listed as a deterioration mechanism. Since knots are natural features of wood and not a deterioration mechanism, these entries were reclassified or removed. In an entry, "UV exposure" was correctly identified as a deterioration mechanism, but the associated physical change was listed as "chemical constitution." This was refined to more specific changes such as "color changes" or "surface degradation" to provide clearer, observable effects.

Consistency in terminology and classification is crucial for the utility of the knowledge graph. Variations in naming, such as "acoustic emission monitoring" versus "acoustic emissions," were standardized to ensure clarity and consistency. Similarly, vague terms like "laser-based technique" were specified where possible. Entries introducing specific techniques, such as "ultrasonic critical refracted longitudinal waves" or "guided ultrasonic wave procedure," were reviewed for consistency with other entries. While specificity is valuable, it was balanced with the need for generalizability across the dataset.

The knowledge graph was validated through expert review, ensuring the accuracy and relevance of the extracted information. Feedback from domain experts was instrumental in refining the classification and standardization of entries, contributing to the overall quality of the knowledge graph.

The knowledge graph was utilized to answer specific research questions and provide insights into the application of NDT methods across different materials. Custom queries allowed for the exploration of relationships within the graph, facilitating the identification of cross-material NDT techniques and the discovery of novel insights. While the majority of the entries were accurately classified, the study highlighted several challenges, including ensuring consistent terminology across diverse documents, balancing the need for specific information with the generalizability of the knowledge graph, and distinguishing between natural features and actual deterioration mechanisms, especially in materials like wood.

In conclusion, the experimental program successfully demonstrated the feasibility and effectiveness of using an LLM to automate the extraction and organization of NDT information into a comprehensive KG. This approach not only streamlined the data collection process but also enhanced the accessibility and usability of NDT knowledge for researchers and engineers. The results highlight the potential of knowledge graphs in advancing the field of NDT, providing a scalable framework for future research and application.

6.1. Challenges and Future Work

While the majority of the entries were accurately classified, the study highlighted several challenges:

- **Consistency in Terminology**: Ensuring consistent terminology across diverse documents remains a challenge.
- **Specificity vs. Generalizability**: Balancing the need for specific information with the generalizability of the knowledge graph requires careful consideration.
- **Handling Natural Features**: Distinguishing between natural features and actual deterioration mechanisms, especially in materials like wood, is essential for accurate classification.

Future work will focus on refining the extraction process, improving the consistency and specificity of entries, and extending the approach to other scientific domains.

6.2. Case Study Examples

The constructed knowledge graph provides practical insights for different materials, demonstrating its utility in various domains:

Concrete: The knowledge graph identified that Ultrasonic Testing (UT) and Ground Penetrating Radar (GPR) are highly effective for detecting internal flaws and assessing structural integrity in concrete. This insight supports the use of these methods in civil engineering projects to ensure safety and durability.

Steel: For steel, the knowledge graph highlighted the effectiveness of Magnetic Particle Testing (MT) and Eddy Current Testing (ET) in detecting surface and subsurface cracks. This information is crucial for industries such as aerospace and automotive manufacturing, where material integrity is paramount.

Wood: The graph showed that Infrared Thermography (IRT) and Electrical Resistivity Testing (ERT) are valuable for detecting moisture content and decay in wood. This can guide the preservation and maintenance of wooden structures and cultural heritage artifacts.

Bricks: The knowledge graph demonstrated that Visual Inspection and Ultrasonic Testing (UT) are effective for detecting weathering effects such as cracking and spalling in bricks. These methods are vital for ensuring the structural integrity and longevity of brick constructions in various environmental conditions.

Overall, the results demonstrate the potential of using LLMs to enhance the extraction and organization of NDT knowledge, providing a valuable resource for researchers, engineers, and practitioners in the field. The automated approach not only improves efficiency but also uncovers new insights and relationships, driving innovation and informed decision-making in materials science and engineering.

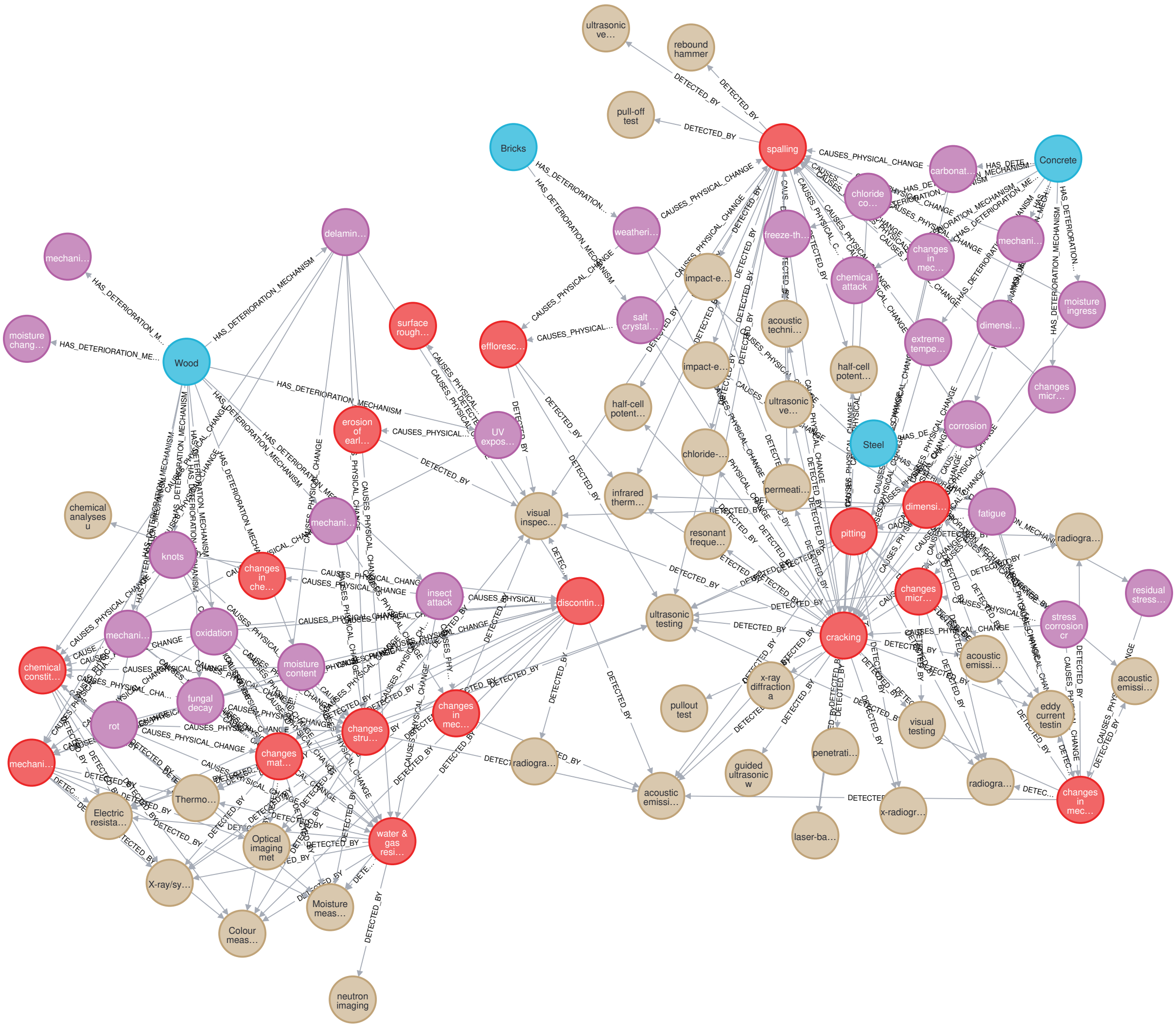

Figure 1: An example of the generated KG. The full graph is available in an SVG image here: https://github.com/ghezalahmad/LLM_NDT_Knowledge_Graph/raw/main/graph.svg

6.2.1. Specific usage Examples

The Fig. 1, along with the following three usage examples, illustrates the utility of our KG.

1. **Cross-Material NDT Techniques**: The KG reveals that certain NDT methods, initially developed for steel, are also applicable to wood. This insight can guide researchers in exploring the cross-material adaptability of NDT techniques, potentially leading to innovations in testing methodologies [14].
2. **Material-Property Relationships**: By querying the KG, users can quickly identify which NDT methods are most effective for evaluating specific properties of materials, such as detecting cracks in ceramic components or assessing the tensile strength of composite materials [15].
3. **Literature Exploration**: The KG facilitates efficient exploration of the literature by allowing users to navigate through interconnected concepts, discover related works, and identify gaps in the current research landscape [16].

In addition to the usage examples, technical documentation about reproducing our experiments is available in our GitHub repository[2].

[2]https://github.com/ghezalahmad/LLM_NDT_Knowledge_Graph

7. Conclusion

The experimental program successfully demonstrated the feasibility and effectiveness of using an LLM to automate the extraction and organization of NDT information into a comprehensive knowledge graph. This approach not only streamlined the data collection process but also enhanced the accessibility and usability of NDT knowledge for researchers and engineers. The results highlight the potential of knowledge graphs in advancing the field of NDT, providing a scalable framework for future research and applications.

This study opens new avenues for further research and development. Future work can focus on expanding the corpus of scientific articles to include more diverse sources and materials. Additionally, enhancing the accuracy and depth of entity and relationship extraction through advanced machine-learning techniques will further improve the utility of the knowledge graph.

Integrating the knowledge graph with other scientific databases and ontologies can enrich its content and broaden its applicability. Furthermore, developing user-friendly interfaces and tools for interacting with the knowledge graph will enhance its accessibility and usability for domain experts and researchers.

In conclusion, the application of LLMs to automate the extraction and organization of NDT knowledge represents a significant advancement in materials science and engineering. This approach not only streamlines the compilation of extensive technical data but also fosters innovation and informed decision-making, ultimately contributing to the advancement of NDT practices and the enhancement of material safety and integrity.

8. Acknowledgments

We would like to express our sincere gratitude to Reincarnate for funding this project. Their support was crucial in enabling the research and development of the automated knowledge graph for non-destructive testing. We also extend our thanks to our colleagues at the Bundesanstalt für Materialforschung und -prüfung (BAM) and the Technical University of Berlin (TUB) for their invaluable contributions and support throughout this study.

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