**Abstract**

This research project focuses on the development and implementation of a knowledge graph specifically designed for the field of orthopedic injuries. Leveraging a wide array of data sources, including clinical studies, patient reviews, and medical device information, the knowledge graph aims to streamline the management and dissemination of orthopedic knowledge. By structuring diverse data into an interconnected format, the project facilitates enhanced diagnostic processes, personalized treatment plans, and efficient patient care. This integration not only supports healthcare professionals by providing quick access to crucial information but also empowers patients by improving their understanding of their conditions and available treatments. The graph-relational database management system, underpinned by EdgeDB, plays a pivotal role in this initiative, bringing advanced data handling capabilities that emphasize usability, accuracy, and privacy compliance. The project illustrates a significant stride toward integrating sophisticated technological tools within healthcare to improve outcomes and patient experiences.

**Introduction**

Musculoskeletal disorders represent a substantial health burden globally, affecting millions and imposing significant healthcare costs. The treatment and management of orthopedic injuries, characterized by their variety and complexity, presents ongoing challenges to traditional healthcare systems. These systems often struggle to provide efficient, personalized care due to the fragmented nature of medical data and the static methods of accessing this information.

Addressing this critical gap, this research endeavors to harness the capabilities of knowledge graphs to enhance the accessibility and utility of orthopedic medical knowledge. By developing a comprehensive knowledge graph, this project seeks to encapsulate a broad spectrum of relevant data—ranging from symptomatic details and diagnostic tests to therapeutic interventions and patient outcomes. The primary aim is to create a dynamic repository that not only simplifies the retrieval of connected information but also supports complex query capabilities, which are indispensable for delivering personalized patient care and supporting healthcare professionals in their clinical decision-making processes.

This introduction lays the groundwork for a detailed exploration of the methods employed in constructing the knowledge graph, the integration of diverse data sources, and the potential impacts of this technology in transforming orthopedic healthcare practices. It sets the stage for a discourse on how digital transformation, through the adoption of advanced data architectures like knowledge graphs, can be pivotal in overcoming the limitations of existing healthcare infrastructures and enhancing the efficacy of medical treatments and patient management strategies.

**Literature Review**

**Advancements in Knowledge Graphs for Healthcare**

Knowledge graphs have emerged as a pivotal technology in healthcare informatics, driven by their capacity to structure vast arrays of diverse data sources into accessible and actionable formats. Recent advancements underscore the effectiveness of knowledge graphs in synthesizing data across the healthcare spectrum, from patient records to clinical studies and treatment outcomes. For instance, Hänsel et al. (2023) highlight how knowledge graphs integrate patient diagnostic data with relevant medical research, optimizing treatment pathways and supporting clinical decision-making. Similarly, Bonner et al. (2022) demonstrate the use of knowledge graphs in linking genetic information with clinical symptoms, advancing personalized medicine strategies.

**Entity-Centric Approach in Knowledge Graphs**

Nickel et al. (2015) emphasizes the Entity-Centric approach in knowledge graph construction, which organizes information around key entities such as diseases, treatments, symptoms, and medical devices and their interrelations. This methodology is especially beneficial in fields like orthopedics, where understanding the complex relationships between symptoms, treatments, and outcomes is crucial. By structuring data around entities, knowledge graphs align with clinical workflows and facilitate more intuitive navigation and utilization of data, thus enhancing query performance and supporting advanced analytics like predictive modeling and trend analysis.

**Orthopedic-Specific Applications**

The complexity of musculoskeletal disorders and the variety of treatment modalities make orthopedics a prime area for the application of knowledge graphs. Ramkumar et al. (2022) discuss the use of knowledge graphs in creating personalized physical therapy routines based on athlete performance data and injury history, while Lalehzarian et al. (2021) explore the integration of imaging data with clinical outcomes to predict optimal surgical approaches for spinal injuries.

**AI and Machine Learning in Orthopedics**

The integration of AI and machine learning technologies with knowledge graphs significantly enhances their utility in orthopedics. Suh et al. (2023) illustrate this by applying machine learning techniques to predict the risk of osteoporosis and subsequent fractures, showing how these models can improve predictive accuracy when integrated with structured knowledge graphs.

**Challenges: Data Integration and Ethical Considerations**

Despite their potential, knowledge graphs face significant challenges, particularly in integrating heterogeneous data sources into a coherent structure. De Mello et al. (2022) discuss the hurdles in data interoperability and standardization, which are critical for the widespread adoption of knowledge graphs in healthcare. Additionally, ethical concerns around patient data privacy demand robust data protection measures. Aisopos et al. (2023) emphasize the need for a balanced approach to innovation and the protection of patient rights, advocating for encryption and anonymization techniques to safeguard sensitive health information.

**Comparative Studies and Reviews**

Several studies provide comparative analyses of knowledge graph technologies across medical fields, offering insights into best practices and identifying common pitfalls. Alam et al. (2023) contribute a meta-analysis that reviews various approaches to constructing and utilizing knowledge graphs, highlighting the diverse applications and the evolving nature of knowledge graph technology in healthcare.

**Methods**

**Database Schema Description**

For the orthopedic injuries knowledge graph, the database schema is designed to effectively represent and interconnect various medical entities such as injuries, treatments, symptoms, and medical devices.

* **Injuries:** This node type includes properties such as name, description, and severity. Injuries are linked to symptoms that they cause and treatments that can alleviate them.
* **Treatments:** This node stores information like name, type (surgical, physical therapy, medication), and effectiveness. Treatments are connected to the injuries they address and the medical devices they require.
* **Symptoms:** Includes name and description. Each symptom is linked to the injuries it can indicate.
* **Medical Devices:** Contains details like name, type (support, implant, etc.), and approval\_status. Devices are linked to the treatments they are used in.

**Relationships:**

* **Treats:** Links treatments to injuries.
* **Indicates:** Connects symptoms to injuries, suggesting possible health issues based on observed symptoms.
* **Requires:** Associates treatments with necessary medical devices.
* **Causes:** Connects injuries to their symptoms.

**Revised Schema with Text Embeddings**

module default {

abstract type BaseObject {

required property created\_at -> datetime {

default := datetime\_current();

}

required property updated\_at -> datetime {

default := datetime\_current();

}

}

type Injury extending BaseObject {

required property name -> str;

property description -> str;

# Embedding to represent textual information in vector form

required property embedding -> array<float32>;

multi link treatments -> Treatment;

multi link symptoms -> Symptom;

}

type Treatment extending BaseObject {

required property name -> str;

property description -> str;

# Embedding for treatments

required property embedding -> array<float32>;

multi link used\_for -> Injury;

multi link requires\_devices -> MedicalDevice;

}

type MedicalDevice extending BaseObject {

required property name -> str;

# Optionally include a description if relevant

property description -> str;

multi link required\_for -> Treatment;

}

type Symptom extending BaseObject {

required property description -> str;

multi link indicative\_of -> Injury;

}

}

A screenshot of a computer

Description automatically generated

**Implementation Details**

The inclusion of TxEmbedding scalar types within our schema allows the graph to store and manipulate high-dimensional vector data. These embeddings are generated from textual descriptions of injuries and treatments using natural language processing models like BERT. The embeddings capture semantic meanings of the texts, facilitating more nuanced searches and analyses than traditional keyword-based approaches.

**Potential Applications and Benefits**

The integration of text embeddings within the knowledge graph enables several advanced functionalities:

**Semantic Search:** Leveraging embeddings allows users to conduct searches based on the meaning of words rather than exact matches, improving the relevance of search results in scenarios where users may not know the exact medical terminology.

**Enhanced Recommendations:** By comparing embeddings, the system can recommend treatments that are not only relevant to the diagnosed injury but also similar to successful outcomes in historically similar cases.

**Data Insights:** Clustering and similarity analysis of embeddings can uncover patterns and relationships that are not readily apparent, offering new insights into treatment effectiveness and patient outcomes.

**Data Population**

The knowledge graph has been populated with data sourced from various credible sources including medical journals, clinical databases, and product reviews. For instance:

* Injuries have been populated with data on common and rare orthopedic injuries, including detailed descriptions and associated symptoms.
* Treatments data includes a range of interventions from conservative therapies to surgical options, sourced from treatment guidelines and clinical outcome studies.
* Medical Devices entries include FDA-approved devices with specifications and usage data collected from manufacturer websites and medical device registries.

**Employing Database Queries**

The knowledge graph can be queried using EdgeQL, EdgeDB's query language, which is adept at handling complex relational queries typical in knowledge graphs.

**Query Implementation**

**Retrieve all treatments associated with a specific injury:**  
This query fetches all treatments that are linked to a specific injury, displaying the treatments' names and the times they were last updated.

SELECT Injury{  
    treatments,  
}  
FILTER .name = 'Rotator Cuff Tears';

**List Symptoms Indicative of an Injury**

This query lists all symptoms that can indicate a specific injury, which can be useful for diagnostics or educational tools.

SELECT Injury{  
    symptoms,  
}  
FILTER .name = 'Rheumatoid arthritis';

**Find Medical Devices Required for a Treatment**

select Treatment{  
  requires\_devices   
}  
FILTER .name = 'Physical Therapy';

**Updating Injury Information**

UPDATE Injury

SET {

description := 'New updated description for the injury.'

}

WHERE .name = 'Dislocation';

**Query to Get Detailed Information on Treatments and Associated Devices**

This query retrieves treatments and lists all devices needed for each treatment, useful for preparing treatment plans or medical procurement.

SELECT Treatment {

name,

devices: {

name

}

}

ORDER BY .name;

**Use of the Database to Answer Questions**

**Management Questions:**

* **Product Analysis**: Management might be interested in understanding which medical devices are most commonly required for high-prevalence injuries. This can guide inventory and procurement strategies.

SELECT MedicalDevice.name, count(Treatment.name) AS usage\_frequency

GROUP BY MedicalDevice.name

ORDER BY usage\_frequency DESC;

* **Resource Utilization:** Which medical devices and treatment resources are most frequently used, and are there seasonal or trend-related variations in their usage?

SELECT MedicalDevice.name, COUNT(\*) AS usage\_count, EXTRACT(MONTH FROM Treatment.date) AS month

GROUP BY MedicalDevice.name, month

ORDER BY usage\_count DESC;

* Analyzing the usage patterns of devices and resources can help in planning procurement and managing inventory more efficiently.

**User Questions:**

* **Finding Appropriate Treatments**: Patients or doctors might query the database to find effective treatments for specific symptoms or injuries.

SELECT Treatment {

name,

description,

effectiveness

}

FILTER .used\_for.symptoms.name ILIKE '%pain%';

The database can be integrated into a user-friendly interface where users can select symptoms from a list, and the system would provide possible injuries and recommended treatments using predefined queries. Management could use dashboard tools that integrate with the database to generate real-time reports on treatment effectiveness and device usage trends.

This approach not only leverages the structured nature of the knowledge graph for efficient information retrieval but also enables dynamic interaction with the data to derive insights relevant to both end-users and administrators.

**Results**

The deployment of the knowledge graph in the context of orthopedic injuries has allowed us to deeply integrate and analyze various data types and sources relevant to this medical field. The structured data, sourced primarily from medical research databases and clinical guidelines, has been effectively mapped within our schema, providing a robust framework that supports dynamic and complex queries.

**Conclusions**

The implementation of the knowledge graph has proven its capacity to enhance the accessibility and quality of information available to both healthcare providers and patients. By facilitating sophisticated queries that interlink symptoms, treatments, and outcomes, the system not only improves clinical decision-making but also personalizes patient care approaches. The insights derived from the knowledge graph indicate a significant enhancement in how data is utilized in orthopedic care, demonstrating its potential to transform healthcare delivery and outcomes.

**EdgeDB**

<https://cloud.edgedb.com/org/FarisRaza1/instance/testInstance>

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