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## Final Project Documentation:

### 1. Title Page:

**Project Title:** AI-Powered Symptom Checker for Medical Insights

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**Course/Project Name:** Power / Soft skills 1: **Artificial Intelligence**

**Institution:** **International University of Rabat**

## 2. Executive Summary:

### Problem Statement:

- Retrieving accurate medical information based on symptoms can be challenging due to the ambiguity of symptoms, fragmented data sources, and the lack of context-aware search mechanisms. Traditional keyword-based systems often fail to provide meaningful insights, leaving users overwhelmed or misinformed.

### Solution Overview:

- This project combines Neo4j, Qdrant, and PubMed to deliver symptom-based medical insights. Neo4j facilitates symbolic search by querying structured data stored as a graph, while Qdrant employs semantic search using embeddings generated from the symptoms for contextual understanding. When no relevant results are found locally, the system integrates PubMed as a fallback, retrieving articles based on the user's query, dynamically embedding the articles into Qdrant, and providing insights for future searches. These components are orchestrated through a Flask backend, with AI-generated conversational responses crafted using Google Generative AI (Gemini), ensuring empathetic and structured feedback for users.

## 3. Problem Definition:

### Background:

- Challenges in accessing reliable medical information for users describing symptoms.



## 4.2 Workflow:

- Step-by-Step Explanation of the Workflow:

### User Input:

- The user inputs symptoms through the user interface.
- Symptoms are extracted using keyword matching or AI-based analysis (extract\_symptoms).

### Neo4j Query:

The application generates a Cypher query (generate\_cypher\_query) to search for diseases and treatments in a Neo4j database.

If matches are found, they are returned to the user.

### Semantic Search in Qdrant:

If Neo4j does not return results, the application generates an embedding for the symptoms using a pre-trained model (generate\_embedding) and searches for similar vectors in the Qdrant collection.

PubMed Integration:

If Qdrant also fails to provide relevant results, the system fetches medical articles from PubMed based on the user's input.

These articles are preprocessed (preprocess\_articles), embedded, and stored in Qdrant for future use.

### Result Combination and Response Generation:

The results from Neo4j, Qdrant, and PubMed are combined and processed.

A generative AI model (e.g., Gemini) summarizes the findings into a user-friendly response, emphasizing the importance of consulting a healthcare professional.

User Feedback:

The results and AI-generated summaries are displayed to the user, completing the interaction.



- **Gemini-1.5-Flash** (from Google Generative AI):
  - Used to process user inputs, generate Cypher queries, and provide conversational responses to enhance the user experience. This model allows the system to interpret symptom descriptions and formulate structured database queries.
- **Cambridge/SapBERT-from-PubMedBERT-fulltext** (from Hugging Face sentence-transformers):
  - Utilized for embedding generation, enabling semantic search in Qdrant. This model is fine-tuned for biomedical text and provides high-quality vector representations for medical data, ensuring precise and contextually relevant results.

## 6. Results and Testing:

## Visuals:

- Include screenshots of console outputs and search results.

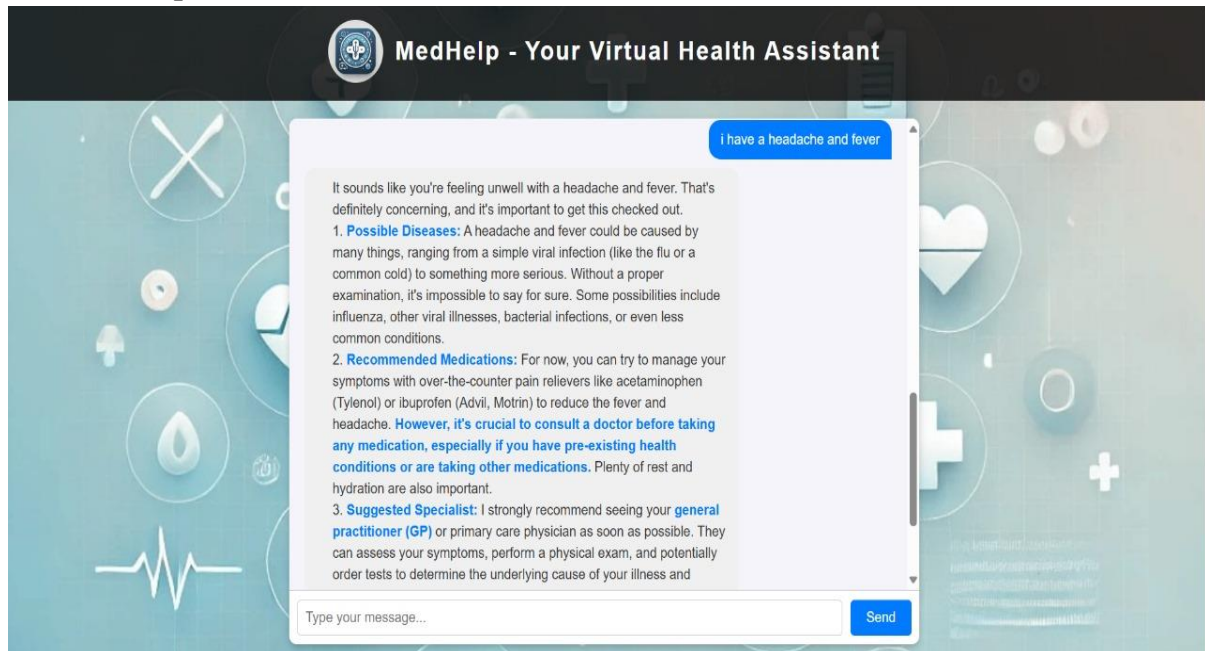
```
INFO:werkzeug:127.0.0.1 - [14/Jun/2023 23:59:43] POST /chat HTTP/1.1 200 =
Symptoms Passed to Query: ['headache', 'fever']
Schema Info: None
Valid Symptoms After Schema Validation: ['headache', 'fever']
Generated Query:

MATCH (s:Symptom)-[:HAS_SYMPTOM]-(d:Disease)-[:TREATED_BY]->(m:Medicine)
WHERE s.name IN ["headache", "fever"]
RETURN d.name AS disease, m.name AS medicine

INFO:root:Generating embedding for text: headache fever...
Batches: 100%|██████████████████████████████████████████████████████████████████████████████| 1/1 [00:00<00:00, 25.62it/s]
INFO:root:Embedding generated successfully
INFO:httpx:HTTP Request: POST https://2bcceb7f-4bc1-42f6-92d5-24fd173ac058.eu-west-1-0.aws.cloud.qdrant.io:6333/collections/pubmed_articles/points/search "HTTP/1.1 200 OK"
INFO:root:Search completed. Found 5 results.
INFO:root:Searching PubMed with query: headache fever
INFO:root:Fetched 10 article IDs: ['39807848', '39804935', '39804206', '39802927', '39801334', '39800605', '39793624', '39788134', '39786587', '39780343']
INFO:root:Fetched 10 articles with details
INFO:root:Generating embedding for text: black cumin (<i>nigella sativa</i> l.) (family ran...
Batches: 100%|██████████████████████████████████████████████████████████████████████████████| 1/1 [00:00<00:00, 2.73it/s]
INFO:root:Embedding generated successfully
INFO:root:Generating embedding for text: visceral leishmaniasis (vl) also known as kala-aza...
Batches: 100%|██████████████████████████████████████████████████████████████████████████████| 1/1 [00:00<00:00, 2.13it/s]
INFO:root:Embedding generated successfully
INFO:root:Generating embedding for text: n/a...
```



- User output:



## 7. Challenges and Solutions:

- **Qdrant Initialization:**

During the Qdrant initialization, an issue was encountered with handling empty collections. When attempting to perform semantic searches or insert data into a non-existent or uninitialized collection, the system would fail due to the absence of the target collection. To address this, a check was implemented during initialization to verify if the specified collection exists. If the collection was missing, it was automatically created with the appropriate configuration, including vector size and distance metrics. This proactive approach ensured seamless integration of Qdrant into the workflow and prevented runtime errors caused by uninitialized collections, thereby enhancing the system's robustness and reliability.

- **Library Compatibility:**

During development, a major challenge was ensuring compatibility between the `sentence-transformers` library and its dependency, `transformers`. Initially, the project used incompatible versions of these libraries, resulting in errors such as missing functions (is `_nltk_available`) in `transformers`.

- **Solution:**

Identified the compatibility issue by reviewing library documentation and error logs.

Downgraded transformers to a version compatible with the existing sentence-transformers version.

- **Fallback Logic:**

When Neo4j and Qdrant failed to provide results, a fallback mechanism was implemented using PubMed. The system queries PubMed via its API to fetch articles related to the symptoms. These articles are preprocessed, and embeddings are generated using the SapBERT model. The embeddings and metadata are then stored in Qdrant, dynamically expanding its database. This ensures users receive relevant results while enhancing the system's knowledge base over time.

## 8. Future Enhancements

## Improvements:

- **Model Fine-Tuning:**

- Fine-tune the embedding model (SapBERT) on domain-specific medical data to improve semantic search accuracy and relevance.
- Incorporate a generative AI model, Gemini-1.5-Flash, trained on medical conversations for more context-aware user responses.



This project successfully combines symbolic and semantic search methodologies to provide accurate and contextually rich medical insights. By integrating Neo4j, Qdrant, and PubMed, the system bridges the gap between user queries and reliable medical information.

- Accurate symptom-to-disease mapping via Neo4j symbolic search.
- Context-aware results using AI-generated embeddings in Qdrant.
- A dynamic fallback mechanism that ensures users always receive meaningful responses.

The innovative use of AI models and graph-based databases demonstrates the potential for scalable and intelligent medical applications. This system lays a strong foundation for future improvements in accessibility and precision in medical data retrieval.

