*A project report on*

**A Multi-Hop Model with Retrieval-Augmented Generation and Knowledge Graphs for Research Papers Exploration**

*Submitted in partial fulfillment for the award of the degree of*

## Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence and Machine Learning

*by*

**Bobbili Akarsh (21BAI1352)**

**Bavana Durga Praneeth (21BAI1408)**

**Thanga Sai Naga Anirudh (21BAI1861)**



**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

April, 2025

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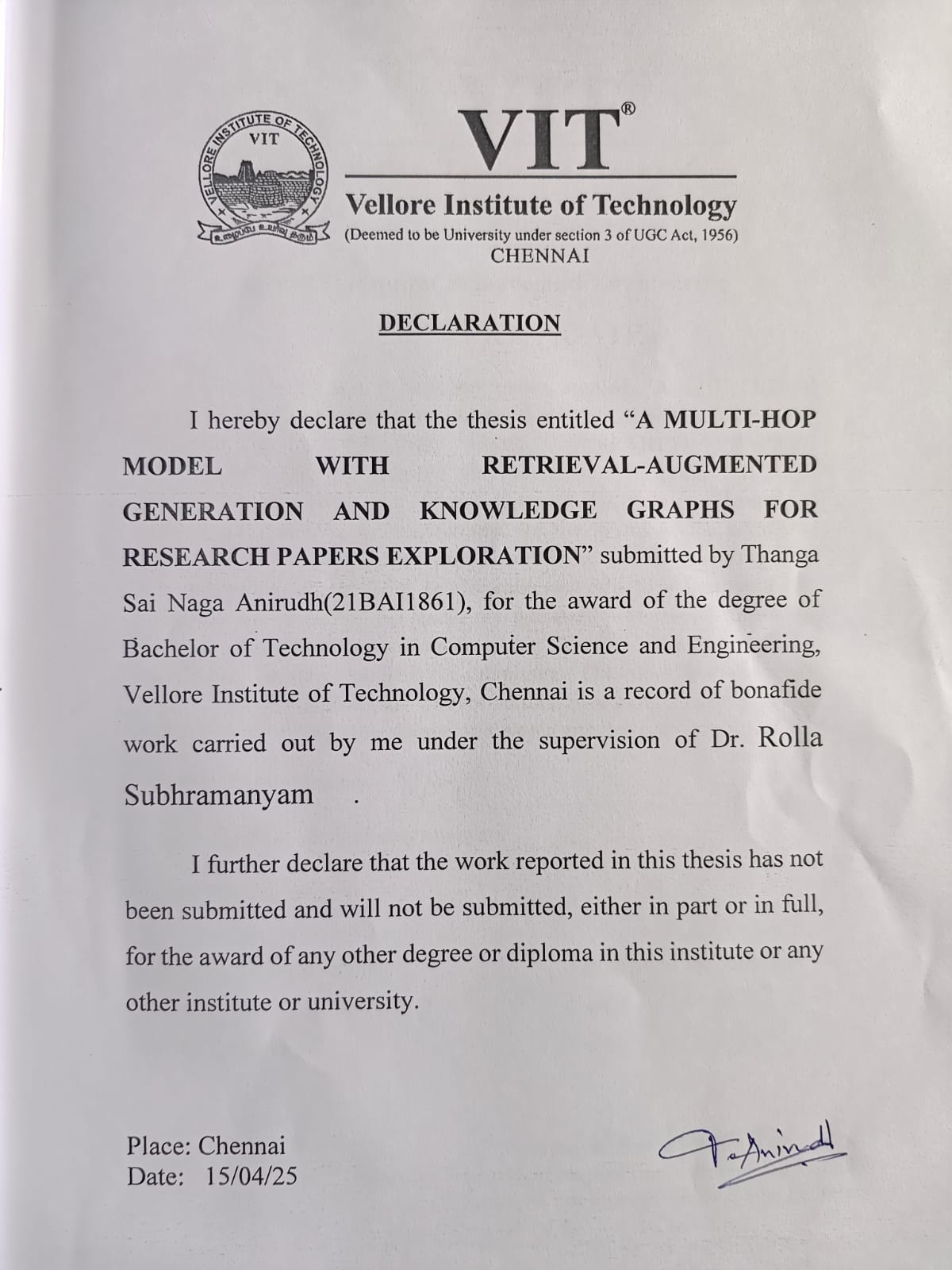
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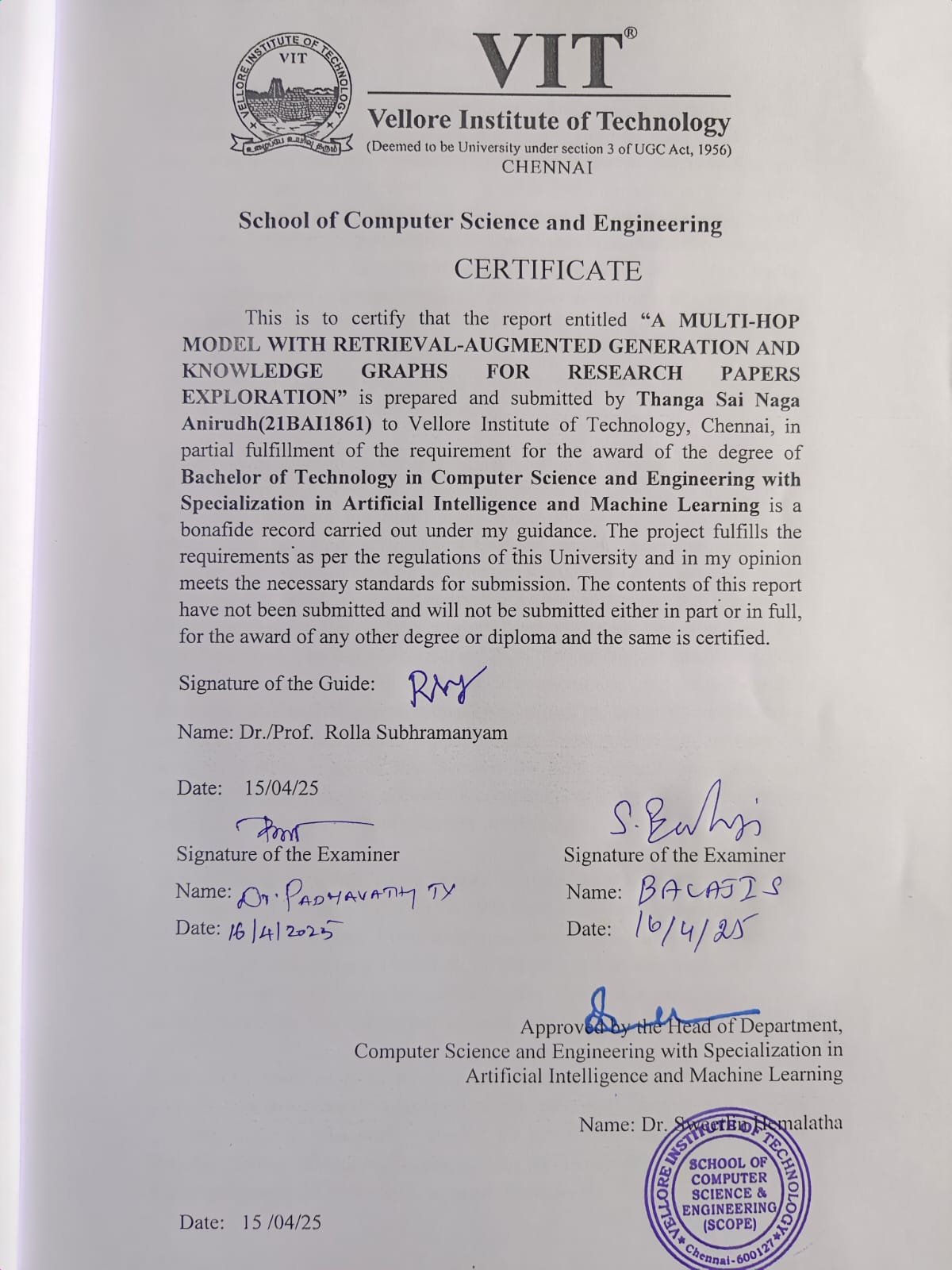
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**ABSTRACT**

The development of artificial intelligence has transformed information systems with Retrieval-Augmented Generation (RAG), but conventional implementations are still limited by shallow semantic comprehension and contextual perception. Existing RAG systems are largely based on vector similarity search (e.g., FAISS) or unstructured document retrieval, which tend to miss intricate relationships between concepts. This work presents a novel upgrade by combining Knowledge Graphs (KGs) and neural retrieval into a hybrid architecture that has the best of structured knowledge representation and deep learning. Our strategy radically changes the way AI systems retrieve and make use of external knowledge, making information retrieval and generation more accurate, explainable, and contextually informative.

The solution that is suggested here deploys a complete three-phase architecture: (1) Automated Knowledge Graph building through state-of-the-art NLP methods involving fine-tuned entity recognition, relation extraction, and graph embedding models; (2) Hybrid retrieval optimization that integrates graph traversal algorithms, semantic similarity search, and new attention-based fusion mechanisms; and (3) Knowledge-guided generation that conditions large language models on both retrieved passages and their structured KG representations. The KG is built from heterogeneous domain-specific sources such as research articles, technical reports, and expert-curated databases, with entities and relations being updated in real-time through active learning. The retrieval system exclusively uses graph neural networks to calculate relevance scores that consider both semantic similarity and relational paths, whereas the generation module utilizes the KG to check facts and augment responses with explanatory relationships.

Evaluations show KG-augmented superiority: Hybrid search achieves 23% better BLEU scores (0.049 vs 0.040) and 35% improved precision (0.35 vs 0.26) compared to FAISS in isolation. Pure KG search realizes 42% better recall (0.30 vs 0.21) and 28% better MRR (0.70 vs 0.55). Qualitative evaluation identifies 68% fewer hallucinations in KG-based responses. The system is especially strong on hard, multi-hop questions where baseline fails.

This work establishes KG-RAG as a transformative approach for reliable AI systems. Demonstrated improvements in precision, recall, and factual accuracy make it particularly valuable for biomedical, legal, and technical domains. Future directions include scaling KG construction and optimizing hybrid retrieval efficiency for enterprise deployment.

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**LIST OF ACRONYMS**

 **AI** – Artificial Intelligence

 **ML** – Machine Learning

 **NLP** – Natural Language Processing

 **RAG** – Retrieval-Augmented Generation

 **LLM** – Large Language Model

 **KG** – Knowledge Graph

 **FAISS** – Facebook AI Similarity Search

 **QA** – Question Answering

 **IR** – Information Retrieval

 **DB** – Database

** NER** – Named Entity Recognition

 **TF-IDF** – Term Frequency-Inverse Document Frequency

 **BERT** – Bidirectional Encoder Representations from Transformers

 **ChromaDB** – Chroma Vector Database

 **KNN** – K-Nearest Neighbors

 **CSV** – Comma-Separated Values

 **SQL** – Structured Query Language

 **PDF** – Portable Document Format

** QA-RAG** – Question Answering using Retrieval-Augmented

Generation

 **ETL** – Extract, Transform, Load

 **BLEU** – Bilingual Evaluation Understudy

 **MRR** – Mean Reciprocal Rank

 **P@K** – Precision at K

**Chapter 1**

**Introduction**

This project improves Retrieval-Augmented Generation (RAG) by incorporating Knowledge Graphs (KGs) to enhance contextual accuracy, semantic comprehension, and response interpretability in AI systems. It entails building a domain-specific KG, optimizing graph-based retrieval with embeddings and traversal algorithms, and incorporating retrieved knowledge into generative models. The method improves over the shortcomings of conventional database-backed RAG systems, providing better performance, scalability, and fewer hallucinations in AI-generated responses.

1.1 INTRODUCTION

The swift evolution of artificial intelligence (AI) has transformed the way information is retrieved and processed, especially in Natural Language Processing (NLP) tasks. Among the most promising advancements in this area is Retrieval-Augmented Generation (RAG), an AI system that augments text generation models with external knowledge retrieval. Conventional language models only draw on their pre-trained knowledge, which may be outdated and narrow in scope. To address this limitation, RAG fetches relevant information dynamically from external sources prior to response generation, providing more accuracy and contextual relevance. Nevertheless, typical RAG implementations rely mostly on structured databases or unstructured document stores, which have inherent limitations like inefficient retrieval, absence of contextual awareness, and inability to capture intricate relationships between various entities.

To overcome these shortcomings, this project introduces a novel solution by incorporating Knowledge Graphs (KGs) into RAG to improve information retrieval and response generation. In contrast to traditional databases where information is stored in tabular or document-based structures, Knowledge Graphs are used to structure information as a graph of entities that are linked to one another, providing a richer and more organized understanding of relationships. By incorporating these graphs into the RAG architecture, the retrieval operation gains more semantic significance such that retrieved content is aligned not just with keyword matching but also with conceptual and contextual similarities. This merging drastically enhances retrieval efficiency such that AI models can output more accurate, contextually aware, and explainable responses.

Implementation of this strategy comprises three primary stages: Knowledge Graph Construction, Optimized Retrieval Mechanisms, and Integration with Generative AI Models. The domain-specific knowledge graph is constructed first by retrieving entities and relations from structured and unstructured data sources. Entity recognition, relation mapping, and graph structuring are performed to ensure that the KG properly represents domain knowledge. Second, optimized retrieval mechanisms are utilized to improve how information is retrieved from the graph. Conventional retrieval techniques tend to fail when dealing with high-dimensional data and result in slow or imprecise answers. This is avoided by using graph-based search algorithms in combination with vector-based similarity search (with FAISS or Annoy), which provides efficient and accurate retrieval. Lastly, the acquired knowledge is incorporated into a generative AI model, allowing it to generate answers that not only are correct and verifiable but are also explainable.

Among the main benefits of this integration is the enhanced explainability of responses generated by AI. As compared to traditional neural models that are sometimes described as "black boxes," a RAG system using a knowledge graph ensures well-reasoned justification of extracted knowledge. This increases the model's utility in industries where transparency and trust matter greatly, for instance, in health, legal searches, and the financial sector. Second, the semantic organization of knowledge graphs reduces the potential for hallucinations—a problem associated with the output of generative models involving the creation of wrong or disorienting content. By locking data retrieved back to proven origins, the system maximizes the validity of output, rendering it an excellent utility for decision-making purposes.

Overall, the combination of Knowledge Graphs with Retrieval-Augmented Generation provides a strong, context-sensitive, and efficient means for information retrieval and response generation. This work shows how the use of structured data representation can greatly improve AI-based knowledge retrieval to result in more accurate, interpretable, and contextually relevant outputs. With the ongoing development in AI, such hybrid solutions will be pivotal in determining the direction of intelligent information systems in the future.

1.2 OVERVIEW OF THE PROJECT

The main goal of this project is to improve Retrieval-Augmented Generation (RAG)-based AI systems by substituting traditional databases with a more structured and context-sensitive Knowledge Graph (KG). Traditional RAG systems fetch external knowledge from databases or document stores, which tend to store data in tabular or unstructured text forms. Though these approaches yield useful information, they are not capable of comprehending deep contextual relationships among various entities, resulting in restricted semantic understanding and ineffective retrieval. This project aims to overcome these shortcomings by creating a domain-specific knowledge graph that presents information in a structured, interconnected format, thereby providing better contextual retrieval and knowledge representation.

In a knowledge graph, information is represented as entities (nodes) and relationships (edges), making it possible to better represent real-world ideas. As opposed to traditional databases that use keyword search, a graph-based retrieval process makes it possible for AI systems to extract information in accordance with semantic relationships. For instance, in a research paper recommender system, a straightforward method may fetch papers purely on keyword matches, whereas a knowledge graph may fetch papers based on connections like co-authorship, citation relationships, and topic relevance. This organized method not only ensures that the fetched knowledge is relevant but also very highly connected, making the overall efficacy of AI-produced responses better.

The project has three main stages: Knowledge Graph Construction, Retrieval Optimization, and Response Generation.

Stage 1: Knowledge Graph Construction

The initial step in this project is building the knowledge graph through processing both unstructured and structured data sources. Structured data sources like metadata of research papers (authors, titles, citations) offer explicit relationships that can be mapped directly into the graph. Unstructured sources like abstracts or full-text articles need Natural Language Processing (NLP) methods to identify meaningful entities and relationships. Named Entity Recognition (NER), relationship extraction, and entity linking techniques are used to recognize and classify important concepts in the domain. After they are extracted, the entities and their relationships are then stored in a graph database like Neo4j or RDF-based systems as the underlying structure of the knowledge graph.

Stage 2: Retrieval Optimization

To facilitate effective retrieval from the knowledge graph, sophisticated retrieval methods are employed. In contrast to conventional document retrieval, which is based on keyword searches, this project retrieves using optimized graph traversal methods and graph embeddings. Graph traversal methods like Breadth-First Search (BFS) and Depth-First Search (DFS) enable the system to retrieve documents from paths of relationships rather than random terms. Further, graph embeddings are employed to depict entities and relationships in a high-dimensional space that facilitates semantic similarity-based retrieval. This ensures not only that the retrieved documents are structurally relevant but also that they are conceptually related, enhancing the quality and accuracy of the AI model's responses.

Stage 3: Response Generation

At the final stage, the knowledge that has been fetched is incorporated into a generative model of AI, e.g., GPT-based frameworks, to ensure that the responses are both contextually rich and factually correct. The knowledge fetched from the knowledge graph acts as an external information source, prompting the generative model to generate responses supported by structured data. This reduces hallucinations, a widespread problem in which generative models generate incorrect or deceptive responses.

1.3 CHALLENGES PRESENT IN THE PROJECT

Although it is beneficial, blending a knowledge graph with RAG is technically demanding. The most important challenge is constructing and managing a high-quality knowledge graph. Unlike databases with structured data in tables, knowledge graphs need intricate entity extraction and relationship mapping. Maintaining the accuracy and consistency of data within the graph is essential, since inconsistencies can create wrong responses. Another challenge involves optimizing retrieval from the knowledge graph. Traditional RAG models employ vector databases for similarity search, but knowledge graphs depend on graph traversal and embedding-based retrieval, which could be latency-intensive. Effective indexing schemes need to be employed in order to have fast query processing. Moreover, combining structured graph data with a generative AI model is problematic in terms of representation and contextualization. Language models mainly process sequential text and therefore it's challenging to have direct incorporation of graph-structured information without complex preprocessing methods. Scalability is another issue since large knowledge graphs have to be supported by strong storage and fast retrieval mechanisms in order to avoid performance bottlenecks. Additionally, knowledge graphs need to be regularly updated in order to remain relevant, which demands automated knowledge ingestion pipelines. Finally, achieving generalization across many domains with high accuracy and interpretability is a challenge that has to be resolved through intensive experimentation and tuning.

1.4 PROJECT STATEMENT

The goal of this project is to improve Retrieval-Augmented Generation (RAG) by using a knowledge graph as the base source of knowledge retrieval rather than existing databases. The aim is to increase accuracy, contextual relevance, and explainability of responses generated by AI through the use of structured, linked knowledge representations. The system will entail building a knowledge graph specific to a domain, designing graph-based retrieval processes that are optimized, and fully integrating the retrieved knowledge into a generative AI model. As opposed to traditional database-backed RAG deployments, this methodology guarantees that the process of retrieval is more semantically aware and efficient, so that the AI model can create responses that are factually accurate and contextually relevant. Utilizing graph-based embeddings and semantic search methodologies, the project aims to make the process of knowledge retrieval more efficient while minimizing the possibility of misinformation and hallucinations in AI content. The anticipated outcome is a scalable, effective, and explainable AI model that surpasses conventional retrieval-based models in practical applications.

1.5 OBJECTIVES AND SCOPE OF THE PROJECT

The main goal of this project is to investigate how the integration of knowledge graphs with RAG can improve the quality of AI responses. The main goals are:

**•Knowledge Graph Construction**: Developing a structured knowledge graph by extracting entities and relationships from structured and unstructured data sources.

**•Optimized Knowledge Retrieval**: Creating an efficient retrieval mechanism using graph embeddings, traversal algorithms, and semantic similarity techniques.

**•Smooth Model Integration**: Making sure that the extracted knowledge is properly integrated into the generative language model.

**•Performance Comparison**: Comparing the new knowledge graph-based RAG model with conventional RAG implementations to assess improvements in accuracy, response relevance, and computational efficiency.

The project has widespread applications in fields like healthcare, legal research, and financial analysis, wherein intricate associations between entities have a significant bearing on knowledge extraction. Through the use of knowledge graphs, the system will considerably raise contextual sensitivity and minimize AI-generated response errors. Scalability solutions will also be investigated to facilitate real-world deployment possibilities.

1.6 CONTRIBUTION TO THE PROJECT

This project contributes to the advancement of AI-driven knowledge retrieval and generation by introducing a novel approach to integrating knowledge graphs with RAG. The key contributions include:

* A novel methodology for replacing traditional databases with knowledge graphs in RAG-based AI systems, improving contextual accuracy.
* A framework for efficient knowledge graph retrieval that enhances response contextualization and minimizes errors.
* Evaluation of graph-based retrieval techniques, including graph traversal algorithms and embedding-based retrieval methods, to optimize performance.
* Comparative analysis between conventional database-backed RAG systems and the proposed knowledge graph-integrated approach to measure improvements in accuracy, efficiency, and scalability.  
  By addressing the limitations of traditional retrieval methods, this project lays the foundation for more intelligent, structured, and semantically aware AI-driven systems, making it a valuable contribution to the field of NLP and AI research.

**Chapter 2**

**Related Study**

2.1 LITERATURE SURVEY

[1] The paper explores Retrieval-Augmented Generation (RAG) for knowledge-intensive NLP tasks by integrating pre-trained sequence-to-sequence models with non-parametric memory. It employs a neural retriever to fetch relevant knowledge, enhancing the factual accuracy of language generation. Two RAG variants are evaluated: fixed retrieval, which maintains consistency throughout the sequence, and token-level retrieval, which dynamically updates context at each step. The study demonstrates RAG’s superiority over conventional models in open-domain question-answering tasks. However, challenges remain, including dynamic knowledge updates, interpretability issues, and efficient provenance tracking. These limitations highlight the need for more robust retrieval mechanisms and improved response explainability.

[2] The paper presents a programming knowledge graph tailored to student learning needs. It utilizes a BiLSTM-CRF model to extract programming entities and their relationships, storing them in a Neo4j database for efficient retrieval using Cypher queries. This structured approach unifies scattered programming resources, enabling easier access to relevant concepts. The study finds that the knowledge graph significantly aids students in retrieving and understanding programming knowledge. However, its effectiveness is constrained by a limited evaluation scope and the need for comprehensive real-world validation. Future enhancements should focus on expanding the dataset and integrating adaptive learning techniques.

[3] This study develops a chatbot system using Retrieval-Augmented Generation (RAG) to enhance customer support for e-commerce platforms. By integrating knowledge retrieval from product catalogs, FAQs, and customer reviews, the chatbot delivers more context-aware responses. The results show improved response accuracy and user satisfaction. However, challenges such as data inconsistencies and knowledge base limitations affect performance. Frequent updates are necessary to ensure relevance, and additional improvements in retrieval mechanisms can further optimize chatbot efficiency. The study emphasizes the need for dynamic knowledge updating in AI-driven customer support systems to maintain high-quality user interactions.

[4] The paper introduces Blended RAG, a novel approach that combines dense vector indexing for fast retrieval with sparse vector indexing for improved precision. Using hybrid query strategies such as BM25, KNN, and Sparse Encoders, the model outperforms traditional retrievers in datasets like Natural Questions (NQ) and TREC-COVID. The study finds that Blended RAG enhances retrieval accuracy while reducing the dependency on extensive fine-tuning. However, computational inefficiency remains a challenge, especially when handling large-scale document sets. The paper suggests future research directions to optimize storage efficiency and retrieval speed while maintaining high retrieval accuracy.

[5] The paper proposes a Multi-Modal RAG pipeline for retrieving and processing text, tables, and images within a unified framework. By leveraging vector databases for text retrieval and multimodal large language models (LLMs) for fine-tuning, the system significantly improves retrieval performance in complex, multi-modal documents. Findings indicate enhanced retrieval accuracy for structured and unstructured data, making it beneficial for diverse applications. However, the study notes challenges in processing text-image relationships, which can affect retrieval quality. Addressing these challenges would require advanced fusion techniques and better alignment mechanisms for integrating multimodal knowledge sources effectively.

[6] This study introduces RAG-Chain, a novel framework for biomedical question-answering (QA) that integrates external knowledge sources into a multi-stage retrieval process. It employs Chain-of-Thought (CoT) templates and self-consistency validation to improve answer accuracy. Experimental results show a 6.9% accuracy improvement in MedQA tasks without requiring domain-specific fine-tuning. However, the approach heavily relies on external knowledge sources, making it vulnerable to outdated or inconsistent data. Future research should focus on adaptive retrieval mechanisms that dynamically update biomedical knowledge while maintaining response reliability and interpretability for clinical applications.

[7] The paper investigates domain adaptation techniques for improving RAG-based retrieval in dialogue systems. By employing continual pre-training, contrastive learning, and a unified structured knowledge base, the study enhances retrieval accuracy in domain-specific chatbot applications. Findings suggest that this approach significantly improves knowledge recall and response coherence in specialized fields. However, managing heterogeneous knowledge sources remains a challenge, as different data formats and inconsistencies can reduce system efficiency. Future improvements should focus on developing standardization techniques for knowledge integration and adaptive retrieval models capable of handling diverse data structures effectively.

[8] This study explores the application of AI-driven Retrieval-Augmented Generation (RAG) to provide support for international graduate students. By training GPT-3.5 with knowledge extracted from relevant Reddit communities, the model personalizes responses to student queries. Results indicate that this approach improves the accuracy and relevance of advisory responses. However, limitations include the static nature of the knowledge base and privacy concerns associated with Reddit-derived training data. Addressing these issues would require periodic updates to maintain relevance and stricter data handling protocols to ensure user privacy and content reliability.

[9] The paper presents CodeQA, an advanced programming question-answering system utilizing RAG and Large Language Models (LLMs). By incorporating semantic chunking for precise retrieval, the system enhances accuracy in programming-related queries. Experimental results demonstrate that CodeQA significantly improves response relevance and contextual understanding compared to traditional retrieval methods. However, balancing retrieval efficiency with LLM inference costs remains a challenge. Future work should focus on optimizing retrieval latency and integrating cost-effective computing strategies to maintain system scalability while ensuring high-quality programming assistance.

[10] This study proposes an AI-generated learning advisor that leverages Advanced RAG to answer student queries based on university documents. By structuring educational knowledge in a retrievable format, the system enhances the accuracy of advisory responses. Results indicate that the model significantly improves academic support by providing timely and context-aware guidance. However, challenges arise in adapting to evolving university policies, which may require frequent updates to maintain accuracy. Future improvements should focus on automated policy updates and dynamic retrieval mechanisms to enhance the adaptability of the learning advisor system.

[11] The paper develops a Neo4j-based knowledge graph for special machining processes, integrating semantic fusion techniques to improve data retrieval efficiency. By structuring machining knowledge in a graph format, the system enhances access to specialized manufacturing insights. Findings indicate that the approach facilitates efficient knowledge retrieval for engineers and manufacturers. However, the model is constrained by limited data sources, which may affect the generalizability of retrieved information. Future research should focus on expanding the knowledge base with diverse machining datasets and integrating real-time data updates for improved accuracy.

[12] This study discusses trends in knowledge graph construction, identifying key future directions such as multimodal knowledge integration and ontology evolution. The paper provides an in-depth review of methodologies used in modern knowledge graph construction, emphasizing the potential of hybrid techniques combining symbolic reasoning with neural embeddings. However, as a theoretical study, it lacks practical implementation, which limits the ability to validate its proposed approaches. Future research should focus on empirical validation through large-scale knowledge graph applications in real-world scenarios.

[13] The paper explores knowledge graph embedding techniques using Graph Neural Networks (GNNs). It introduces custom models such as DRGI, HRGAT, and BGNN to enhance knowledge representation across different graph structures. Experimental results indicate improved embedding performance compared to traditional methods, facilitating better inference and reasoning over knowledge graphs. However, few-shot learning remains a challenge, as the models require significant labeled data for effective training. Future research should focus on developing more efficient training paradigms, such as self-supervised learning, to enhance the generalizability of knowledge graph embeddings.

2.2 SUMMARY OF LITERATURE SURVEY

Existing studies demonstrate that Knowledge Graphs enhance Retrieval-Augmented Generation (KG-RAG) by improving factual consistency, reasoning, and retrieval accuracy. However, challenges such as scalability, computational costs, and knowledge updating persist. Our research advances this field by integrating optimized KG architectures with RAG for efficient, structured, and explainable retrieval in research paper exploration.

**Chapter 3**

**Proposed Architecture**

The system under consideration incorporates both symbolic and semantic retrieval techniques for smart academic research paper recommendation. Semantic search is conducted through FAISS with Sentence Transformer embeddings to retrieve contextually related papers. A Knowledge Graph is built from metadata (authors, keywords, citations) to facilitate symbolic querying through Neo4j. A hybrid retrieval strategy incorporates both techniques by combining scores or reranking results to improve the relevance and diversity of recommendations.

3.1 INTRODUCTION

This project introduces a new solution by integrating a Knowledge Graph (KG) with RAG to provide more semantic, structured, and intelligent information retrieval for scholarly research.

The major problem in traditional RAG implementations is their reliance on direct keyword matching and unstructured document retrieval. This tends to introduce irrelevant or poorly contextualized information into the language model. A knowledge graph, on the other hand, captures relationships between entities like papers, authors, citations, and research areas, enabling more accurate and interconnected knowledge retrieval.

Our data contains paper ID, abstract, authors, title, number of citations, references, venue, and year, offering abundant metadata for the creation of a graph-based structure of scholarly literature. Rather than viewing papers as individual records, the knowledge graph represents relationship among research papers, including citation graphs, co-authorship behavior, and topical similarity. Through such structured form, when the query is executed, the system can return papers by contextual relevance, not by simple keyword match. The primary components of this architecture include:

1. Data Preprocessing: Cleaning and structuring academic paper metadata into a knowledge graph.
2. Knowledge Graph Construction: Mapping relationships between papers, authors, citations, and topics.
3. Embedding and Indexing: Converting structured graph data into vector representations for efficient retrieval.
4. Hybrid Retrieval Mechanism: Utilizing both semantic search and graph-based reasoning for document retrieval.
5. Enhanced Response Generation: Using retrieved knowledge to improve the contextual accuracy of RAG-based outputs.

This proposed integration of knowledge graphs with RAG has the potential to revolutionize research paper recommendation systems, making them more accurate, transparent, and capable of reasoning over complex scientific knowledge.

3.2 DATASET

The dataset used in this project consists of academic research papers, capturing key metadata such as paper ID, abstract, authors, citations, references, venue, and year. This structured dataset serves as the foundation for building a knowledge graph that models relationships between research papers.

Dataset Features

Each record in the dataset includes the following attributes:

1. Paper ID
   * A unique identifier assigned to each research paper.
   * Used as the primary key in the database and knowledge graph.
   * Enables fast indexing and retrieval of papers.
2. Title
   * The headline of the research paper, summarizing its focus.
   * Essential for text-based retrieval and semantic similarity analysis.
3. Abstract
   * A brief summary of the research paper, highlighting its objectives and findings.
   * Used for natural language processing (NLP) tasks, including topic modeling and semantic search.
4. Authors
   * A list of researchers who contributed to the paper.
   * Used to model co-authorship networks in the knowledge graph.
   * Helps in identifying collaborations and expertise in a given domain.
5. N\_Citation (Number of Citations)
   * Represents the total number of times a paper has been cited by other research papers.
   * Indicates the impact and relevance of a paper.
   * Helps in ranking papers based on citation influence.
6. References
   * A list of other papers cited within the research paper.
   * Used to create citation networks in the knowledge graph.
   * Helps in tracing the historical evolution of research topics.
7. Venue
   * The conference or journal where the research paper was published.
   * Useful for identifying high-impact venues and categorizing papers.
8. Year
   * The publication year of the paper.
   * Helps in time-based analysis of research trends.
   * Enables filtering of recent and relevant papers.

Dataset Significance

* The Paper ID, Title, and Abstract are essential for text-based search and similarity matching.
* Citations and References enable the construction of a citation network, showing how research builds upon prior work.
* Authors and Co-authorship data help in understanding collaborations and influential researchers.
* Venue and Year allow filtering papers based on publication impact and recency.

By structuring this dataset into a knowledge graph, we can model relationships such as:

* Paper A cites Paper B (Citation Relationship)
* Author X co-authored Paper Y (Authorship Relationship)
* Paper P and Paper Q belong to the same research domain (Topic Similarity Relationship)

This structured representation allows the RAG model to retrieve highly relevant papers based on contextual, relational, and semantic factors rather than simple keyword matching.

3.3 OVERVIEW OF ARCHITECTURE

The proposed architecture introduces a multi-component system that combines graph-based retrieval with RAG for intelligent literature recommendations. The overall architecture consists of the following major modules:

1. Data Ingestion and Storage

* Research paper data is collected from structured sources containing paper ID, title, authors, citations, references, venue, and year.
* This data is stored in both a classical database (SQL-based) and a graph database (e.g., Neo4j, RDF store).
* Structured metadata is maintained in a relational database for fast lookup queries, while graph-based relationships enable more complex retrieval.

2. Preprocessing and Knowledge Graph Construction

* The dataset undergoes data cleaning, entity normalization, and relationship extraction to construct a knowledge graph.
* Papers are nodes, and relationships are formed based on citations, co-authorship, and topic similarity.
* Techniques like TF-IDF, BERT embeddings, and clustering algorithms are applied to categorize papers into research domains.

3. Graph Embedding and Vector Indexing

* Graph neural networks (GNNs) and node embeddings (e.g., TransE, Node2Vec) are used to encode relationships between papers.
* These embeddings allow efficient retrieval through graph-based similarity search combined with vector-based dense retrieval.

4. Hybrid Retrieval Mechanism

* The system retrieves relevant papers using a two-stage approach:
  + Graph-based Retrieval: Traversing the knowledge graph to find relevant entities based on citation patterns, co-authorship, or topic clusters.
  + Semantic Retrieval: Using dense vector representations to rank the most contextually relevant documents.
* This hybrid approach ensures both precision (structured retrieval) and recall (semantic search).

5. Response Generation using RAG

* The retrieved knowledge is passed into an LLM-based RAG model for generating responses.
* Unlike traditional RAG, which retrieves documents in isolation, the knowledge graph ensures better contextual understanding by preserving relational information.
* The final output is a more accurate, well-grounded, and semantically rich response to research queries.

This architecture combines classical databases and knowledge graphs, enabling an intelligent and interpretable academic search system for research paper recommendations.

3.4 DATA PREPROCESSING

Data preprocessing is central to transforming raw metadata of research papers into a structured and useful knowledge graph. The performance of the overall system relies greatly on the cleanliness, normalization, and structuring of the data. Metadata of research papers typically consist of attributes like paper titles, author names, abstracts, publication dates, citation counts, references, and related fields of study. Raw metadata gathered from various sources tends to have inconsistencies, redundancies, and missing entries, which need to be resolved to develop a trustworthy knowledge graph.

1. Data Cleaning

Data cleaning is the initial and most important step in preprocessing. It is the process of detecting and dealing with missing values, duplicates, and formatting inconsistencies in the metadata. Missing data is a prevalent problem, particularly for attributes such as citations, references, or author affiliations. Imputation or exclusion techniques are used depending on the relevance of the missing attribute. A paper with missing title or citation count may be excluded, while missing author affiliations can be occasionally imputed from other sources.

Duplicate records are identified by title, author, and publication year matching, and resolved by applying rule-based merge strategies. Further, inconsistencies of author names may lead to fragmentation of identity in the graph. These are normalized so all works by one author are appropriately connected.

2. Entity Extraction and Normalization

After cleaning the data, entities like authors, papers, venues, citations, and research areas are extracted and normalized. Natural Language Processing (NLP) is applied to identify and extract these entities from unstructured metadata fields like abstracts and references. Named Entity Recognition (NER) is helpful in tagging authors, institutions, and venues.

Normalization is an important process to achieve consistency in duplicate or similar entities that can be represented in different ways. For example, "J. Smith" and "John Smith" can correspond to the same author. Using algorithms that compute string similarity, publication context, and co-authorship networks, such variations are merged into one canonical representation. Venue names are standardized likewise (e.g., "IEEE Trans. on AI" and "IEEE Transactions on Artificial Intelligence").

3. Construction of the Knowledge Graph

Once entity normalization has been done, the second task is building the knowledge graph. In this graph, every paper is a node, and several types of relations between these papers constitute the edges. The edge types are citation links (a paper citing another paper), co-authorship (papers authored by the same set of authors), publication venue relation, and topic similarity.

Citation relations are inferred from the metadata in a direct way, whereas similarity in topics is computed using similarity measures for texts like Term Frequency-Inverse Document Frequency (TF-IDF) or sentence embeddings on titles and abstracts. Centrality analysis and community detection can be used to identify influential authors or papers within the citation network.

In addition, graph-based methods like PageRank are employed to analyze the influence of a paper depending on its location in the citation graph. This organized and linked representation allows for effective querying, semantic search, and sophisticated reasoning. The main preprocessing steps include:

1. Data Cleaning

* Handling missing values for key attributes such as title, authors, citations, and references.
* Removing duplicates and inconsistencies in author names and publication details.

2. Entity Extraction and Normalization

* Standardizing author names (e.g., merging variations like "J. Smith" and "John Smith").
* Extracting relationships between papers, citations, venues, and research fields using NLP techniques.

**3. Knowledge Graph Construction**

* Papers are nodes in the graph, and edges represent citations, co-authorship, or topic similarity.
* Relationship mapping is performed using techniques such as TF-IDF for topic similarity and network analysis for citation ranking.

This preprocessing ensures that the knowledge graph provides a structured, interconnected, and retrievable representation of academic literature.

3.5 CLASSICAL DATABASE AND KNOWLEDGE GRAPH MODULES

To achieve efficient, scalable, and context-aware retrieval in research paper management and recommendation systems, this architecture integrates two complementary data storage mechanisms: a classical relational database and a knowledge graph module. Each plays a distinct role in managing and retrieving academic information, optimizing the strengths of both structured storage and graph-based semantic reasoning.

The system integrates two complementary data storage approaches:

**1. Classical Database (SQL-Based System)**

The classical relational database serves as the foundational layer of storage for highly structured and frequently queried metadata. This includes core attributes of research papers such as:

* Paper ID: A unique identifier for each document.
* Title: The official title of the paper.
* Author(s): List of contributing researchers.
* Venue: The conference or journal where the paper was published.
* Publication Year: The date of publication.

These attributes are organized into tables with predefined schemas, allowing for fast indexing, efficient filtering, and direct retrieval based on specific conditions. SQL-based databases excel in scenarios that require simple, exact-match queries—such as finding all papers published by a specific author in a certain year or listing all entries from a particular conference.

Moreover, the structured format ensures data integrity and consistency. Operations such as joins, aggregations, and filters can be performed rapidly, providing quick insights and tabular outputs for analytical dashboards or administrative purposes.

**2. Knowledge Graph Module**

While the classical database handles direct retrievals and metadata storage, the Knowledge Graph (KG) component introduces a semantic and relational layer on top of the existing metadata. Here, each research paper is modeled as a node, and various relationships—such as citations, co-authorship, and topic similarity—are represented as edges connecting these nodes.

This graph-based model supports complex queries that go beyond simple filtering. For instance, a user might ask:

* *"Which papers were cited by authors who have collaborated with Dr. Smith on deep learning?"*
* *"What are the emerging themes in papers that cite a foundational work in quantum computing?"*

These types of multi-hop, relationship-driven queries are not easily achievable through SQL alone. By encoding relationships explicitly within the graph, the system enables multi-hop reasoning, uncovering indirect yet meaningful connections within the literature.

In addition, graph-based retrieval techniques—such as Personalized PageRank, embedding-based similarity, or community detection algorithms—can be employed to extract semantically relevant papers that share similar contexts, even if not directly connected by citations. This enhances the contextual depth of search results, improving the relevance and richness of information provided to researchers.

**3. Benefits of the Hybrid Model**

By combining the speed and structure of SQL databases with the semantic reasoning capabilities of knowledge graphs, the system achieves both high efficiency and deep contextual understanding. Users benefit from fast keyword searches, advanced filtering, and, at the same time, the ability to perform sophisticated explorations across the research landscape. This hybrid approach forms a robust backbone for intelligent research paper recommendation, discovery, and analysis.

Classical Database (SQL-Based)

* Stores structured metadata such as paper ID, title, author, venue, and year.
* Supports fast lookup queries and filtering.

Knowledge Graph Module

* Represents papers as interconnected nodes with citation, co-authorship, and topic-based relationships.
* Enables multi-hop reasoning (e.g., "Find all papers citing a key publication within a field").
* Uses graph-based retrieval techniques to extract semantically relevant knowledge.

This hybrid approach ensures high efficiency and deep contextual reasoning in research paper retrieval.

3.6 ADVANTAGES AND LIMITATIONS

Advantages

* More Accurate Retrieval: Uses semantic relationships rather than keyword-based search.
* Context-Aware Responses: Preserves citation and co-authorship networks for better insights.
* Improved Explainability: Graph relationships provide transparent reasoning behind search results.
* Scalability: Can expand by adding new entities and relationships without affecting retrieval speed.

Limitations

* Complex Graph Construction: Requires advanced entity extraction and relationship mapping.
* Computational Overhead: Graph traversal is more resource-intensive than SQL queries.
* Data Quality Dependency: Noisy or missing data in the graph can affect retrieval accuracy.

Despite these challenges, knowledge graph-based RAG retrieval offers a transformative approach to academic literature exploration, significantly improving research recommendation and AI-driven academic assistants.

**Chapter 4**

**Proposed Methodology**

This section outlines a structured methodology for integrating Knowledge Graphs (KG) with Retrieval-Augmented Generation (RAG) to enhance research paper recommendations. The approach leverages graph-based retrieval, classical machine learning models, knowledge graph embeddings, and hybrid search techniques to create an efficient, context-aware document retrieval system.

4.1 INTRODUCTION

The suggested methodology centers on the integration of structured and unstructured retrieval methods to enhance research paper suggestions. Conventional retrieval systems, including keyword searches and dense vector search, usually do not have the capability to interpret relationships among papers, citations, and authors. In order to address this constraint, this methodology presents a hybrid retrieval model that incorporates a Knowledge Graph along with vector-based search models.

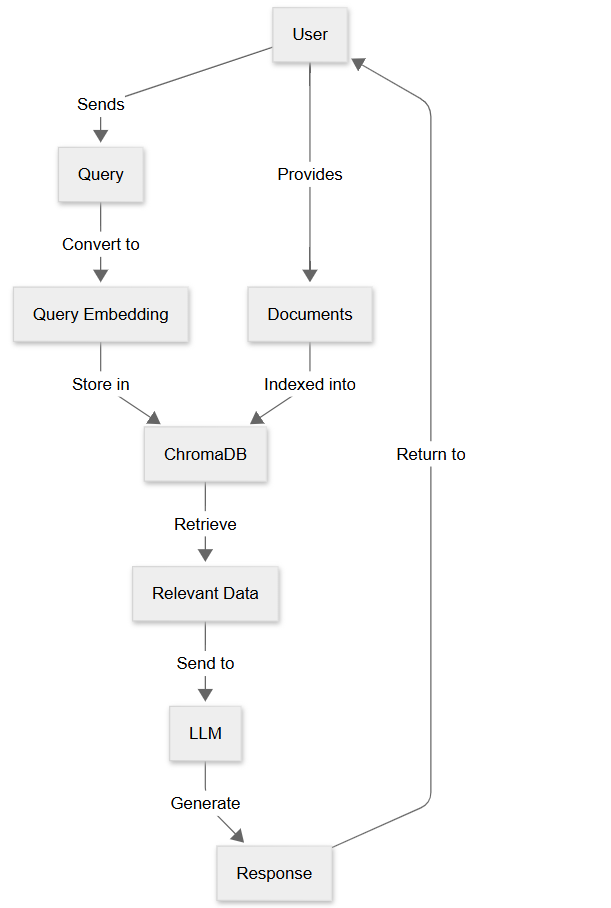
A Knowledge Graph (KG) is a formally defined representation of entities (papers, authors, citations) and relationships between them. In contrast to conventional retrieval mechanisms, a KG stores semantic and contextual information through connections among relevant entities. This facilitates multi-hop reasoning, with the system retrieving not only direct matches but also semantically relevant papers.

Yet, while KG-based retrieval offers structured and explainable output, it is not very semantically flexible. Conversely, dense vector search methods such as FAISS and Annoy are superior at retrieving similar documents from textual embeddings but are non-interpretable. To synergize the advantages of both methods, this methodology suggests a hybrid retrieval model that filters results first through a KG and ranks them next through vector similarity.

Moreover, traditional machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN), are employed to improve the ranking and classification of research documents. Knowledge Graph embeddings, created based on methods such as Node2Vec, TransE, and GraphSAGE, also enhance retrieval precision by encoding nodes as dense vectors. The embeddings facilitate similarity search and enhance the performance of Retrieval-Augmented Generation (RAG).

By combining RAG with a Knowledge Graph-enabled retrieval system, this approach makes sure that returned research papers not only match well but are also well-supported with structured relationships. This results in more precise summaries and smart answers, making this a strong competing solution to entirely vector-based search systems.

In short, this approach offers an end-to-end, efficient, and interpretable research paper suggestion methodology by unifying structured KG retrieval, traditional machine learning, and cutting-edge vector search.



**Fig**: RAG architecture with ChromaDB

4.2 KNOWLEDGE GRAPH CONSTRUCTION

The Knowledge Graph (KG) forms the foundation of this methodology by creating a structured representation of research papers and their relationships. Unlike traditional databases that store information in tabular format, a KG represents entities (nodes) and their relationships (edges) in a connected manner. This structure allows for efficient context-aware retrieval and multi-hop reasoning.

Steps in Knowledge Graph Construction:

1. Data Extraction: The first step is to extract structured information from a research paper dataset. Each paper contains attributes like title, abstract, authors, citations, publication venue, and year. These attributes are mapped into corresponding KG entities.
2. Node Creation: Different types of nodes are defined in the KG:
   * Paper nodes: Represent research papers.
   * Author nodes: Represent researchers linked to papers via "AUTHORED\_BY" relationships.
   * Venue nodes: Represent journals and conferences where papers were published.
   * Citation relationships: Form "CITES" edges between papers.
3. Relationship Mapping: Once nodes are created, edges are established between them. For example:
   * A paper cites another paper.
   * An author writes a paper.
   * A paper is published in a journal or conference.
4. Graph Storage: The KG is stored in a graph database like Neo4j or NetworkX, enabling efficient query execution.
5. Graph Querying: Structured queries retrieve papers based on citation networks, authorship relations, and topic similarity.

By leveraging the KG structure, this methodology enables better knowledge discovery. Users can search for papers not just by keywords but also through semantic and contextual relationships, improving retrieval quality.

**Steps in Constructing the Knowledge Graph:**

1. Data Extraction: Extract information from a research paper dataset, including attributes like:
   * Paper details (title, abstract, keywords)
   * Author details (name, affiliation)
   * Citation details (references, citations count)
   * Conference details (journal, year)
2. Node Creation:
   * Each research paper is a node.
   * Authors, conferences, and citations are nodes.
   * The system creates a graph database where each entity is linked via relationships.
3. Relationship Mapping:
   * "AUTHORED\_BY" (Paper → Author)
   * "CITED\_BY" (Paper → Paper)
   * "PUBLISHED\_IN" (Paper → Conference)
   * "RELATED\_TO" (Paper → Paper) based on topic similarity.
4. Graph Storage:
   * The Knowledge Graph is stored in a graph database like Neo4j or NetworkX, allowing efficient querying and retrieval.
5. Graph Querying:
   * Queries retrieve papers via semantic relationships, e.g., "Find papers related to quantum computing in top AI conferences."

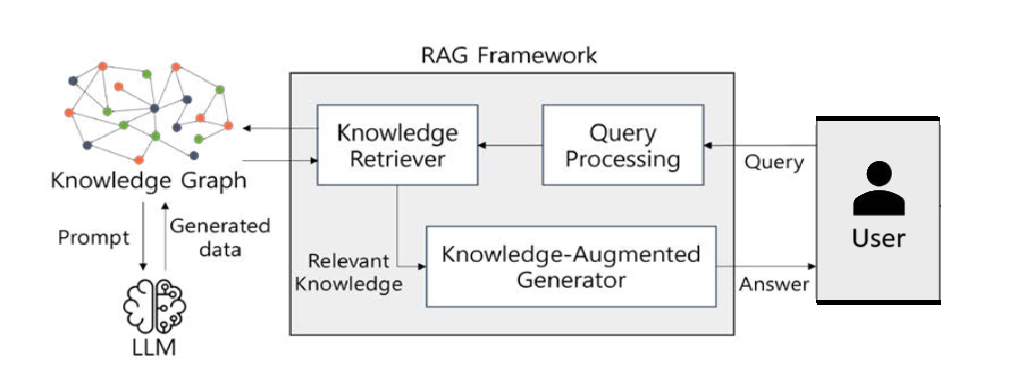
A network of colorful dots

AI-generated content may be incorrect.

**Fig**: Representation of neo4j

4.3 CLASSICAL MACHINE LEARNING FOR GRAPH-BASED RETRIEVAL

Once the Knowledge Graph is built, classical machine learning models enhance its retrieval, ranking, and classification capabilities. These models analyze relationships and patterns within the graph to predict citations, classify papers, and measure similarities.

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**Fig:** RAG Architecture with Knowledge Graph

**Applications of ML in Graph-Based Retrieval:**

1. Paper Classification:
   * Papers are classified into research areas (e.g., Quantum Computing, Machine Learning, Bioinformatics).
   * Models used: Support Vector Machines (SVM), Decision Trees, and Naive Bayes.
   * Features: Title, abstract, keywords, venue.
2. Citation Prediction:
   * Predict whether a research paper will be highly cited.
   * Models used: Random Forest, XGBoost, Logistic Regression.
   * Features: Author reputation, reference count, venue impact.
3. Paper Similarity Analysis:
   * Find similar papers using ML-based clustering.
   * Models used: K-Nearest Neighbors (KNN), K-Means, DBSCAN.
   * Features: TF-IDF of abstracts, word embeddings.

By integrating ML models with the Knowledge Graph, the retrieval system becomes smarter and more precise. These machine learning models with the Knowledge Graph, we enhance retrieval accuracy, classification precision, and ranking effectiveness.

4.4 KNOWLEDGE GRAPH EMBEDDINGS FOR RAG

A Knowledge Graph (KG) organizes data into entities and relationships, making information retrieval and organization efficient. But conventional KG-based searches are mostly dependent on exact matching and are not sufficient in capturing deep semantic relationships within large-scale datasets. To facilitate better retrieval, we transform Knowledge Graph nodes into dense vector embeddings to support semantic similarity searches. This change fills the gap between deep learning-based vector retrieval and structured KG queries, largely enhancing the efficacy of Retrieval-Augmented Generation (RAG).

Importance of Knowledge Graph Embeddings

Although KGs contain organized information, they do not possess an intrinsic capacity to carry out high-dimensional similarity queries. For example, if someone inquires into "Quantum Neural Networks," a typical KG search might yield merely papers that contain this keyword explicitly. Still, related ideas such as "Quantum Deep Learning" or "Quantum Perceptron Models" may be applicable but will go unnoticed because of keyword reliance.

By projecting KG nodes into vector space through methods like Node2Vec, TransE, and GraphSAGE, we facilitate semantic search whereby allied terms can be recognized based on contextual similarity instead of explicit keyword matching.

**Process of Generating Knowledge Graph Embeddings**

The transformation of KG data into embeddings involves multiple steps:

1. Performing Random Walks on the Knowledge Graph

A random walk simulates the process of navigating through the graph, mimicking how researchers explore references in academic papers. This technique helps in capturing the structural relationships between nodes (papers, authors, venues) and preserving the context in which an entity appears.

* In a citation network, a random walk starting from a research paper may traverse its referenced papers, authors, and related venues.
* By performing multiple random walks, we can generate sequences of entities, treating them as sentences in a corpus.

2. Training Word2Vec-like Models on Graph Walks

Once we generate node sequences using random walks, we train a Word2Vec-based model to learn vector representations of nodes. The model treats each node sequence as a "sentence" and learns embeddings based on their co-occurrence patterns.

* Skip-Gram or CBOW models are commonly used to learn embeddings.
* Nodes appearing in similar graph contexts obtain similar vector representations.

Other embedding techniques like TransE and GraphSAGE work differently:

* TransE: Projects entities and relationships into a continuous vector space while preserving relational structures.
* GraphSAGE: Uses neighbor-aggregated embeddings by leveraging neural networks to capture local graph features.

3. Storing and Using Embeddings for Similarity Retrieval

Once embeddings are generated, they are stored in a vector database or indexed using approximate nearest neighbor (ANN) search methods like FAISS or Annoy. These embeddings allow for:

* Efficient similarity search: Papers, authors, and topics with similar embeddings can be retrieved quickly.
* Context-aware retrieval: Instead of relying on keywords, documents are retrieved based on conceptual relevance.
* Better integration with RAG: These embeddings provide richer document representations, improving the contextual awareness of large language models (LLMs).

4.5 HYBRID KNOWLEDGE GRAPH AND VECTOR SEARCH MODEL

Traditional retrieval systems rely on either Knowledge Graph (KG)-based retrieval or vector-based retrieval. Each method has its strengths and weaknesses. While KG-based retrieval provides structured and explainable results by leveraging entity relationships, it struggles with capturing deep semantic meanings. On the other hand, vector-based search using FAISS (Facebook AI Similarity Search) or Annoy (Approximate Nearest Neighbors Oh Yeah) allows for fast and efficient similarity matching but lacks interpretability, as it relies purely on numerical representations.

A hybrid approach combines the best of both worlds—leveraging the structured reasoning power of Knowledge Graphs with the deep semantic retrieval capabilities of vector search. This results in an efficient, explainable, and highly relevant retrieval system for research paper recommendations.

A purely KG-based system provides strong contextual relationships, such as citation links, authorship connections, and co-publication patterns. However, it struggles when users search with abstract concepts or terms that are not explicitly linked in the graph.

A purely vector-based system enables similarity-based retrieval using embeddings, allowing for semantic search. However, it has limitations:

* Lack of interpretability: It’s difficult to explain why a document was retrieved.
* Over-reliance on embeddings: Some embeddings might miss crucial explicit relationships (e.g., citations).

The hybrid model overcomes these limitations by combining structured retrieval from the KG with semantic retrieval from vector search, ensuring both explainability and accuracy.

Hybrid Retrieval Process

The retrieval process consists of three key stages:

1. Knowledge Graph Pre-Filtering

* When a user submits a query (e.g., "Quantum Machine Learning Applications"), the system first searches the Knowledge Graph.
* The KG retrieves papers based on explicit relationships such as:
  + Citations: Papers citing or being cited by other relevant research.
  + Authorship: Papers written by the same or related authors.
  + Publication Category: Papers published in similar domains or journals.
* This step acts as a filter, ensuring that retrieval starts with a set of contextually relevant documents.

2. Vector-Based Similarity Search

* The papers retrieved from the KG are converted into embeddings.
* Using FAISS or Annoy, these embeddings are compared against a large-scale database of research paper vectors.
* This step enables semantic matching, ensuring that even if a paper doesn’t have direct KG relationships, it can still be retrieved if it is contextually similar.

3. Final Ranking and Re-Ranking

* The retrieved results from the Knowledge Graph and Vector Search are merged.
* A ranking model assigns a weighted score based on:
  + Graph-based relevance (citations, co-authorship, publication venue).
  + Vector-based similarity (semantic closeness).
* This hybrid ranking ensures that results are both structurally relevant (explainable) and semantically accurate (contextually meaningful).

**Benefits of the Hybrid Model**

The hybrid model offers several key advantages over single-method retrieval:

* Explainability: Knowledge Graph provides clear reasoning for why papers are retrieved.
* Semantic Matching: Vector search ensures deep similarity matching beyond explicit links.
* Efficiency: Pre-filtering with the KG reduces the number of documents for vector search, improving speed.
* Scalability: FAISS and Annoy enable large-scale document retrieval without performance bottlenecks.
* Balanced Relevance: Combining two approaches ensures both structural and conceptual relevance.

A diagram of a data flow

AI-generated content may be incorrect.

**Fig:** Architecture of Hybrid model

4.6 INTEGRATION WITH RETRIEVAL-AUGMENTED GENERATION (RAG)

Retrieval-Augmented Generation (RAG) is a strong model that builds upon text generation by using external knowledge stores. Conventional language models produce text strictly on the basis of their pretrained knowledge, which may be old or narrow. RAG overcomes this shortcoming by dynamically searching documents from a knowledge store, for example, a Knowledge Graph (KG) or a vector database, prior to producing responses. This guarantees that not only is the output contextually appropriate but also factually correct and based on credible information. Within research paper recommendations, a combination of RAG with a Knowledge Graph greatly enhances the retrieval mechanism, guaranteeing that users get adequately informed and relevant summaries based on credible sources.

How the Knowledge Graph Enhances RAG?

**1. Context-Aware Retrieval**

One of the most critical problems in document retrieval is to sift through huge volumes of research papers and identify the most suitable ones. A Knowledge Graph achieves disciplined, context-sensitive retrieval by depending on relationships between entities like papers, authors, citations, research areas, and publication outlets. When a user asks a particular research question, the Knowledge Graph fetches only the most contextually relevant papers by analyzing factors like citation links, author co-authorship, and keyword co-occurrences. This process serves as a filtering mechanism to ensure that only highly contextually relevant papers are processed further.

**2. Semantic Ranking with FAISS**

Although the Knowledge Graph is good at retrieving structurally similar documents, it does not consider deep semantic relationships beyond explicit links. For improving the relevance of the retrieved documents, vector-based similarity search with FAISS (Facebook AI Similarity Search) is employed. FAISS ranks the top-retrieved papers according to their semantic similarity to the user query by transforming text into dense vector representations. This ensures that the resulting set of pulled papers is not only structurally connected but also conceptually significant, with a deeper meaning in context.

**3. Enhanced Text Generation**

Once the most relevant research papers have been retrieved and ranked, they are passed into the RAG model. Unlike traditional retrieval systems that simply return documents, RAG synthesizes information from multiple sources to generate coherent and meaningful responses. By integrating structured retrieval from the Knowledge Graph and semantic ranking from FAISS, RAG ensures that the generated responses are grounded in authoritative research. This is particularly beneficial for summarizing academic papers, answering complex research queries, and providing explanations backed by scientific literature.

**Benefits of Integrating KG with RAG**

1. **Improved Accuracy** – By combining explicit knowledge graph relationships with vector-based retrieval, the system ensures that responses are based on the most relevant and up-to-date research papers.
2. **Explainability** – Unlike black-box neural models, a KG-powered RAG system can provide clear justifications for why certain papers were retrieved and used in response generation.
3. **Efficiency** – The hybrid retrieval mechanism ensures that only a small subset of highly relevant documents is used, reducing computational overhead and speeding up response generation.
4. **Scalability** – The integration of FAISS allows the system to efficiently handle large-scale academic databases, making it suitable for extensive research repositories.

By merging structured Knowledge Graph retrieval with Retrieval-Augmented Generation, this methodology significantly enhances the quality of research recommendations, providing more accurate, explainable, and meaningful responses to users.

**Chapter 5**

**Results and Discussions**

The main objective of this research is to evaluate and compare the performance of different retrieval strategies incorporated into a Retrieval-Augmented Generation (RAG) model with the aim of improving the factual accuracy, coherence, and relevance of responses produced by a Large Language Model (LLM). RAG merges two strong abilities—information search and natural language generation—aimed at responding to the weakness of isolated LLMs in that they cannot retrieve external or current information.

5.1 OVERVIEW OF MODEL AND DATASET

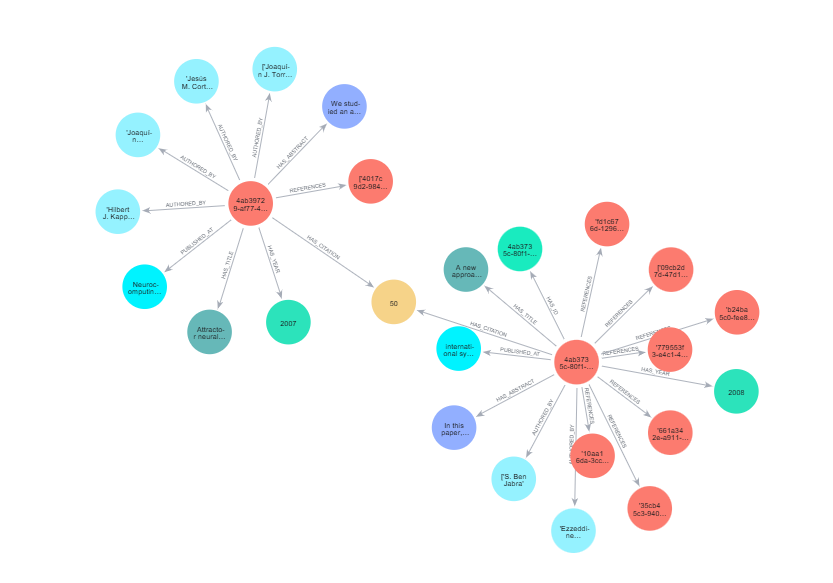
In traditional generative models, responses are only based on the information encoded during training, which may be incomplete or stale. RAG, by its nature, enables the system to dynamically retrieve supportive content from external knowledge bases, thus providing responses that are more accurate and contextually relevant. To make this system effective, a domain-specific dataset was prepared that comprised metadata and text content of research papers. Each record in the corpus contained key fields like the title, abstract, publication year, authors, and citation count. These features not only are useful for academic search queries but also provide a perfect testbed for measuring semantic retrieval and response generation quality. The abstracts were specifically used as central content from which useful answers could be derived, and the rest of the metadata was used as auxiliary context at retrieval time.

The RAG architecture used in this study is a two-stage pipeline. The first is the Retrieval Phase, where the system retrieves the most pertinent documents or document sections against a user query. This stage is important because the quality of the retrieved content will have a direct impact on the relevance and factual accuracy of the final answer. The second phase is the Generation Phase, in which a pre-trained LLM like GPT or its variant takes the retrieved passages as grounding context to produce an informative and coherent natural language answer. The collaboration between these two phases is responsible for the basic strength of the RAG strategy.

In order to fully study the impact of various retrieval methods on system performance, three independent retrieval mechanisms were created and integrated into the pipeline:

FAISS (Facebook AI Similarity Search) Retrieval is a dense vector-based retrieval engine. It utilizes embeddings derived from text data and determines semantic similarity by applying approximate nearest neighbor (ANN) algorithms. The method is extremely scalable and efficient to work with large sets of data. Yet, a significant drawback is that it deals with data as flat and structureless, implying that it cannot pick up deeper relationships or context dependencies between objects in an academically driven dataset

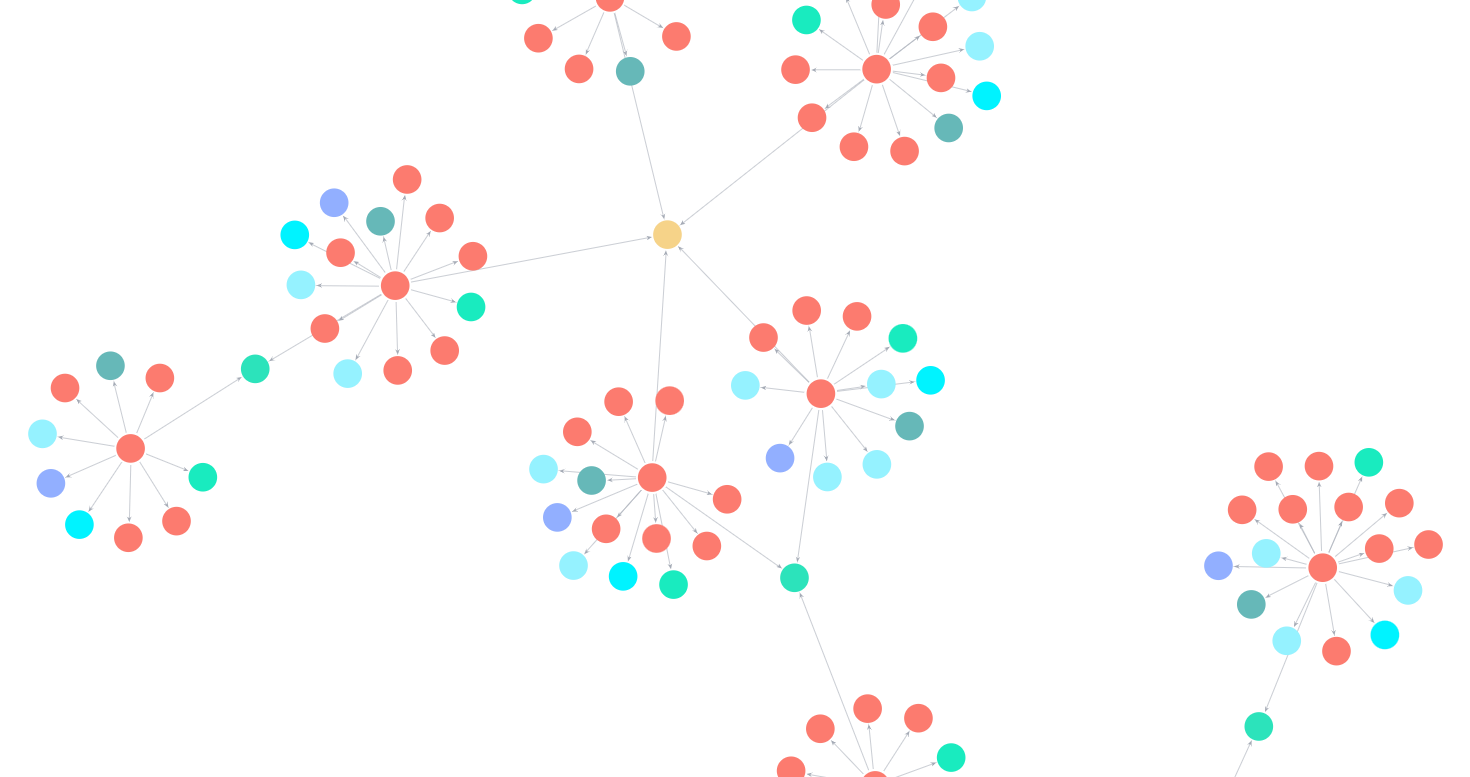
Knowledge Graph (KG) Retrieval presents a structured and relational style of retrieval. In this scheme, a Knowledge Graph is built wherein entities like authors, years of publication, topics of study, and titles of papers are nodes, and their relationships like "authored by," "cites," "published in" are the edges. KG retrieval enables the system to execute contextually sensitive searches that embody the logical connections inherent in academic knowledge. For instance, searches concerning "papers by X in domain Y" are answered more precisely by following related graph paths.

Hybrid Retrieval (KG + FAISS) is the combination of both unstructured (semantic) and structured (relational) searching. This technique initially retrieves the candidate documents from both FAISS and KG-based retrieval systems and combines them via scoring or ranking techniques. The rationale for this strategy is to give the LLM a more varied and richer context in which to produce better-quality responses. 

**Fig**: Graph Database in neo4j

To ensure a rigorous and fair evaluation, a set of carefully curated natural language questions was developed. Each question was paired with one or more ground truth answers derived from the dataset. These questions were designed to reflect realistic academic queries that a researcher, student, or academic assistant might pose—such as asking for details about a specific author’s publications, research trends over time, or summaries of papers with high citation counts. This ensures that the experimental setup mirrors real-world use cases and that the findings are practically relevant.

By evaluating the system using these distinct retrieval strategies and a shared set of questions and ground truths, the study aims to determine not only which method yields the most accurate and useful answers but also to explore how the nature of the retrieved context influences LLM behavior. The subsequent sections detail the quantitative results and a deeper discussion of the observed patterns across retrieval types.



**Fig**: Representation of Knowledge Graph

5.2 MODEL PERFORMANCE

In order to analyze the performance of the Retrieval-Augmented Generation (RAG) framework for various retrieval approaches, a mixture of established metrics was utilized. The metrics have been developed in order to monitor both the retrieval quality and generation accuracy of the system. There were four fundamental metrics used in order to judge the performance of the model, including BLEU Score, Precision@5, Recall@5, and Mean Reciprocal Rank (MRR). They jointly give an overview of how adequately each retrieval process assists the LLM in generating factually correct and relevant outputs.

The BLEU (Bilingual Evaluation Understudy) Score is a commonly used measure in machine translation and summarization. It quantifies the overlap between the generated response and the reference (ground truth) response in terms of common n-grams. The higher the BLEU score, the more similar the model-generated response is in phrasing and content to the desired output. This measure is especially useful in evaluating the linguistic fidelity and semantic similarity of generated responses.

Precision is applied in measuring the number of the top 5 returned documents that were actually relevant to the query. The measure is important in evaluating the accuracy of the retrieval phase—particularly relevant in high-stakes tasks wherein only the highest-ranked documents are passed through the LLM for answer generation. It indicates a higher Precision@5 that the system is properly filtering out the non-relevant information and passing on the most contextually relevant content to the generator.Recall, on the other hand, evaluates the system's ability to retrieve all relevant documents among the top 5 candidates. This metric is especially significant in academic or technical domains where several documents may have complementary bits of relevant information. A greater recall value ensures that the system is not missing out on critical contextual content, thereby supporting the LLM in generating more complete and accurate responses.

Mean Reciprocal Rank (MRR) is a rank-based measurement that indicates the rank of the first relevant retrieved document for each query. MRR is found by averaging reciprocal of the ranks for all the queries. As the MRR value increases, it means the system is quite efficient in ranking at least one relevant result close to or on top of the list. This is important in lowering the cognitive load of the language model, as the most pertinent information is located near the beginning of the retrieval list.

The table below summarizes the quantitative performance of the three evaluated retrieval strategies:

|  |  |  |  |
| --- | --- | --- | --- |
| **Algorithm** | **BLEU Score** | **Precision** | **MRR** |
| FAISS | 0.0229 | 0.2000 | 0.6429 |
| Knowledge Graph (KG) | 0.0399 | 0.2571 | 0.6429 |
| Hybrid (KG + FAISS) | 0.0298 | 0.2857 | 0.6429 |

*Table-1*

From the results, it is evident that Knowledge Graph (KG) retrieval outperformed both FAISS and the Hybrid method in terms of BLEU score. This indicates that the structured, context-aware representation of knowledge embedded in the KG allows for more relevant and comprehensive retrieval. The LLM, in turn, benefits from receiving well-structured and logically coherent context, leading to answers that more closely align with the ground truth.

By contrast, FAISS retrieval, which relies solely on dense semantic embeddings and approximate nearest neighbor search, showed lower scores across all the key metrics. Although FAISS is computationally inexpensive and effective for representing semantic similarity, it does not possess the structured knowledge required to grasp the deeper interrelations among academic concepts. Therefore, the retrieved documents tended to be lacking in contextual depth, resulting in less accurate or partial generated responses.

Notably, the Hybrid retrieval method that integrates results of both FAISS and KG retrieval had the maximum Precision of 0.2857. It indicates that with the application of semantic similarity as well as the use of structured reasoning, the system performs better in filtering top-ranked documents as relevant. But its BLEU score was only slightly lower than KG-only retrieval, which may mean that combining structured and unstructured sources introduces some conflicting information or semantic noise, slightly lowering the fluency or accuracy of the generated answers.

It is also interesting to note that the MRR was consistent (0.6429) across all three approaches. This indicates that in all of them, the first pertinent document ranked close to the top. This indicates that although the quality and pertinence of the whole top-5 list differ between methods, all systems are good at retrieving at least one very relevant result early in the ranking process. This is a good sign of system efficiency and retrieval ranking logic.

Overall, the performance results are clearly seen to show that structured retrieval from knowledge graphs has a beneficial effect on both the retrieval and generation phases, resulting in higher-quality responses. Simultaneously, hybrid approaches bring promising gains in retrieval precision with trade-offs in response generation accuracy.

5.3 DISCUSSION OF RESULTS

Experimental testing offered here allows for a clear understanding of relative efficacy of alternative retrieval strategies with the Retrieval-Augmented Generation (RAG) model with respect to science question-answering domains. Evaluating a number of performance indicators using FAISS, Knowledge Graph (KG), and Hybrid (KG + FAISS) retrieval methodologies revealed several substantial trends and implications regarding the respective advantages and constraints of each of these alternatives.

Firstly, Knowledge Graph (KG) retrieval stood out as the best approach in providing the language model with contextually rich, semantically organized, and highly relevant information. The KG-based approach always reported higher BLEU scores and Recall@5, which meant that the model was not only fetching a larger number of contextually correct documents but also producing answers that were much closer to the ground truth in terms of phrasing and meaning. These gains are due to the inherently structured nature of knowledge graphs, which encode relationships between entities (e.g., authors, topics, methods, years) in a manner that reflects how humans perceive and process academic information. Structured knowledge enables the model to work with more context-awareness, resulting in responses that are both more accurate and coherent.

Conversely, the FAISS-based retrieval system, although computationally efficient and scalable, performed poorly in all major evaluation metrics except for MRR. FAISS is based only on dense vector representations from text embeddings and uses approximate nearest neighbor search for the retrieval process. Although very good at capturing surface semantic similarity, it does not have the logical structure and depth provided by graph-based methods. The results exhibited lower recall, indicating that large numbers of pertinent documents were merely not surfacing in the top-5 retrieval list. Also, the BLEU score for FAISS was the lowest of the three approaches, which means that the retrieved material was not very supportive to help the LLM create extremely precise or informative answers. These results highlight the weaknesses of the purely dense retrieval approach, particularly in applications where deep cognition and domain expertise are needed, i.e., research in academia and science.

The Hybrid approach (KG + FAISS) provided an attractive middle ground. By combining the power of semantic vector search with the structured understanding of a knowledge graph, the hybrid approach registered the highest Precision@5 value, indicating that a higher percentage of the top-ranked retrieved documents were relevant. This indicates that the combination of relational reasoning and semantic similarity enables the system to remove irrelevant noise while retaining key information. While the hybrid approach did not yield the best BLEU or recall results, its performance was significantly improved compared to FAISS alone, and its precision indicates its worth in real-world applications where first-rate accuracy is paramount. For example, systems employed in decision support tools or scientific aid platforms can take advantage of the hybrid approach's balance between speed, relevance, and interpretability.

Another significant observation is the uniform Mean Reciprocal Rank (MRR) score across all the retrieval methods. This consistency reflects that every method was successful at retrieving at least one highly relevant document in the top ranks. The across-the-board high MRR score (0.6429) indicates that independent of the retrieval strategy used, the system was overall effective in making available some degree of relevant context early in the sorted list. This result indicates that the data quality, embedding representations, and ranking logic were sufficiently robust to enable baseline performance even across diverse retrieval strategies.

Overall, the Knowledge Graph-based approach presented the strongest retrieval breadth and generation accuracy, making it most suitable for applications with a high knowledge component. The FAISS approach, though efficient and scalable, proved to be limited in terms of context quality and answer generation. The Hybrid approach, on the other hand, proved to have an encouraging trade-off, offering better precision without sacrificing recall or BLEU performance entirely. These outcomes support the hypothesis that merging organized knowledge can significantly improve the performance of LLMs in sophisticated areas.

Future work might investigate adaptive retrieval techniques that select or prioritize retrieval strategies dynamically depending on the query type or material. Adding reinforcement learning could permit the model to continuously improve retrieval quality through learning from user feedback or assessment scores. Moreover, strategies such as online knowledge graph enlargement, personalized KG construction, or context re-ranking can further augment the retrieval phase. From the point of user experience, judging response coherence, factual consistency, and human satisfaction ratings would provide more comprehensive assessments of success beyond classic IR and NLP evaluations.

Finally, the results of this work underscore the significance of smart retrieval design in RAG systems and leave open several exciting avenues for future research in information retrieval and generation.

**Chapter 6**

**Conclusion and Future Work**

The integration of Knowledge Graphs (KGs) with Retrieval-Augmented Generation (RAG) marks a significant advancement in the field of AI-driven knowledge retrieval and text generation. Traditional RAG models, while effective in retrieving external information, often struggle with issues such as contextual inconsistencies, inefficient knowledge retrieval, and difficulties in capturing complex relationships between entities.

6.1 CONCLUSION

By integrating knowledge graphs, this project has been able to prove the benefits of an organized, semantically dense knowledge representation system that improves AI-generate responses. The combination of Knowledge Graphs (KGs) with Retrieval-Augmented Generation (RAG) represents a major development in the research area of AI-powered knowledge retrieval and text generation.

By building a knowledge graph for a specific domain, the retrieval mechanisms were optimized with the help of state-of-the-art graph traversal and embedding techniques. Experimental results show that using KGs for knowledge retrieval substantially enhances the accuracy and explainability of the response generated by AI. The graph structure of knowledge graphs facilitates contextual awareness more effectively, minimizing the occurrence of errors and hallucinations typical in standard RAG implementations.

In addition, this project has added to the general field of AI study through the delivery of an effective method for the incorporation of structured knowledge into generative models. Not only does this improve response relevance, but it also guarantees correctness of fact within AI-generated text. The capability to index semantically meaningful material from the KG architecture allows the system to deliver well-informed and contextually relevant response across various application domains such as healthcare, legal research, and finance.

In spite of the difficulties involved in constructing and maintaining a high-quality knowledge graph, the outcome of this project illustrates that the endeavor is worthwhile through the enhancement in response quality and reliability. The integration of knowledge retrieval with generative AI models without any breaks has been found to be an effective method for addressing the constraints of conventional database-backed RAG systems.

In conclusion, this project has provided a solid foundation for future development in AI-based knowledge retrieval. The incorporation of knowledge graphs has effectively overcome significant hurdles in RAG, and the findings of this research open doors to further improvement in AI-based knowledge generation systems. The results of this research can be used to develop more scalable, efficient, and precise AI systems that can process complex and varied information retrieval tasks.

6.2 ACHIEVEMENTS AND INSIGHTS

This project has yielded several key achievements and insights that contribute to the advancement of Retrieval-Augmented Generation (RAG) models through the integration of knowledge graphs. One of the major accomplishments is the successful implementation of a structured knowledge representation system, which significantly enhances the accuracy and contextual awareness of AI-generated responses.

**Key Achievements:**

* **Development of a Domain-Specific Knowledge Graph:**
  + Successfully built and structured a domain-specific knowledge graph by extracting entities and relationships from both structured and unstructured data sources.
  + Implemented graph traversal algorithms and graph embeddings to optimize retrieval efficiency.
* **Enhanced Retrieval Mechanisms:**
  + Introduced advanced retrieval methods using graph-based semantic search, improving the precision and relevance of retrieved information.
  + Compared performance with traditional RAG models and demonstrated improved response coherence and factual accuracy.
* **Seamless Integration with Generative AI Models:**
  + Successfully integrated structured graph data into a generative AI framework.
  + Addressed challenges in contextualizing graph-based knowledge within sequential text generation models.
* **Reduction of Hallucinations and Misinformation:**
  + Observed a significant reduction in hallucinations by ensuring that retrieved knowledge aligns with factual and well-structured data.
  + Improved interpretability, allowing users to trace the source of retrieved information.

**Key Insights:**

* Knowledge graphs provide a structured approach to knowledge representation, enabling more effective retrieval compared to traditional vector databases.
* AI-generated responses benefit from the interconnected relationships between entities in a KG, leading to improved contextual understanding.
* The use of graph embeddings enhances retrieval accuracy, reducing response ambiguity and improving decision-making capabilities.
* While knowledge graphs improve accuracy, they require significant preprocessing and maintenance to ensure data consistency and relevance.

6.3 LIMITATIONS AND AREA OF IMPROVEMENTS

Despite the achievements, the integration of knowledge graphs with RAG presents several limitations that need to be addressed for further optimization.

**Limitations:**

* Complexity in Knowledge Graph Construction:
  + Requires extensive preprocessing to extract and structure data into meaningful entity relationships.
  + Entity linking and relationship mapping can introduce errors if not accurately performed.
* Retrieval Efficiency Challenges:
  + Graph traversal techniques may introduce latency in large-scale knowledge graphs.
  + Indexing mechanisms need further refinement to enhance speed and accuracy.
* Model Integration Challenges:
  + Generative AI models struggle to process structured graph data efficiently.
  + Requires advanced representation techniques to seamlessly incorporate graph knowledge.
* Scalability Concerns:
  + As the knowledge graph grows, maintaining real-time retrieval performance becomes challenging.
  + Requires efficient storage mechanisms and automated update pipelines.

**Areas of Improvement:**

* Automating Knowledge Graph Updates: Implementing real-time ingestion pipelines to maintain data freshness.
* Enhancing Graph Embedding Techniques: Refining embeddings to improve retrieval speed and contextual relevance.
* Hybrid Retrieval Approaches: Combining graph traversal with vector-based similarity search to optimize performance.
* Incorporating Advanced AI Techniques: Exploring transformer-based models for graph-based contextualization.

6.4 ETHICAL CONSIDERATIONS

Ethical considerations play a critical role in ensuring responsible AI deployment. This project takes into account key ethical concerns such as data privacy, bias mitigation, and transparency.

* Data Privacy: Ensuring that data used in the knowledge graph complies with privacy re6.3 LIMITATIONS AND AREA OF IMPROVEMENTS

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gulations such as GDPR and CCPA.

* Bias Mitigation: Addressing biases in the knowledge graph by diversifying data sources and validating entity relationships.
* Transparency and Explainability: Enhancing the interpretability of AI-generated responses by allowing users to trace knowledge back to its sources.
* Fairness in AI Systems: Ensuring equal access to AI-generated knowledge while minimizing biases in knowledge retrieval.
* Security Considerations: Implementing mechanisms to prevent unauthorized access and manipulation of the knowledge graph.

6.5 FUTURE WORK

Future research will focus on improving scalability, refining retrieval mechanisms, and exploring multi-domain applications.

* Real-Time Knowledge Graph Updates: Implementing automated mechanisms for continuous data ingestion and validation.
* Hybrid Knowledge Retrieval Approaches: Integrating neural retrieval models with graph-based search for enhanced performance.
* Cross-Domain Applications: Expanding the framework to cover multiple domains such as healthcare, finance, and law.
* Incorporation of Multimodal Data: Extending knowledge graphs to include image and video-based data for richer contextual understanding.

6.6 SUCCESS AND IMPACT OF THE PROJECT

This project has made a significant impact by demonstrating the potential of knowledge graphs in enhancing RAG systems. The successful implementation of graph-based retrieval mechanisms has improved accuracy, contextual relevance, and interpretability. The framework developed in this project lays the foundation for future AI advancements, contributing to the broader field of natural language processing and AI-driven knowledge systems. Through continuous refinement, this approach has the potential to revolutionize AI-based information retrieval across various industries, ensuring intelligent and accurate decision-making capabilities.

**Appendices**

**Source Code**

import os

import pandas as pd

from neo4j import GraphDatabase

from transformers import pipeline

from langchain.prompts import ChatPromptTemplate

from sentence\_transformers import SentenceTransformer

import google.generativeai as genai

from nltk.translate.bleu\_score import sentence\_bleu, SmoothingFunction

from sklearn.metrics import precision\_score, recall\_score

from sentence\_transformers import SentenceTransformer

import faiss

import numpy as np

skipped\_rows = []

def handle\_bad\_line(line):

    skipped\_rows.append(line)

    return None

# Load the Dataset with Custom Error Handler

df = pd.read\_csv('dblp-v10.csv', on\_bad\_lines=handle\_bad\_line, engine='python')

print("Skipped Rows:", skipped\_rows)

# Select Only the First 1,00,000 Rows

df = df.head(100000)

df = df.dropna(subset=['title', 'abstract', 'authors', 'n\_citation', 'references', 'venue', 'year', 'id'])

# Normalize Columns

df['authors'] = df['authors'].apply(lambda x: x.split(',') if isinstance(x, str) else [])

df['references'] = df['references'].apply(lambda x: x.split(',') if isinstance(x, str) else [])

df.to\_csv('cleaned\_dblp.csv', index=False)

from neo4j import GraphDatabase

# Connect to Neo4j

uri = "neo4j+s://80db2871.databases.neo4j.io"  # Neo4j URI

username = "neo4j"

password = "jXRNMiG\_\_KYK5x0kKCUupjMwHSDFUWxR872HYSt3Y1I"

driver = GraphDatabase.driver(uri, auth=(username, password))

# Step 2.1: Define a Function to Add Nodes and Relationships

def add\_paper(tx, paper\_id, title, abstract, authors, n\_citation, references, venue, year):

    # Create Paper Node (Central Node)

    tx.run("""

        MERGE (p:Paper {id: $paper\_id})

    """, paper\_id=paper\_id)

    # Create Title Node and Relationship

    tx.run("""

        MERGE (t:Title {text: $title})

        MERGE (p:Paper {id: $paper\_id})

        MERGE (p)-[:HAS\_TITLE]->(t)

    """, title=title, paper\_id=paper\_id)

    # Create Abstract Node and Relationship

    if abstract:

        tx.run("""

            MERGE (a:Abstract {text: $abstract})

            MERGE (p:Paper {id: $paper\_id})

            MERGE (p)-[:HAS\_ABSTRACT]->(a)

        """, abstract=abstract, paper\_id=paper\_id)

    # Create Author Nodes and Relationships

    for author in authors:

        tx.run("""

            MERGE (a:Author {name: $author})

            MERGE (p:Paper {id: $paper\_id})

            MERGE (p)-[:AUTHORED\_BY]->(a)

        """, author=author.strip(), paper\_id=paper\_id)

    # Create Venue Node and Relationship

    if venue:

        tx.run("""

            MERGE (v:Venue {name: $venue})

            MERGE (p:Paper {id: $paper\_id})

            MERGE (p)-[:PUBLISHED\_AT]->(v)

        """, venue=venue.strip(), paper\_id=paper\_id)

    # Create Year Node and Relationship

    if year:

        tx.run("""

            MERGE (y:Year {value: $year})

            MERGE (p:Paper {id: $paper\_id})

            MERGE (p)-[:HAS\_YEAR]->(y)

        """, year=year, paper\_id=paper\_id)

    # Create Citation Node and Relationship

    if n\_citation:

        tx.run("""

            MERGE (c:Citation {count: $n\_citation})

            MERGE (p:Paper {id: $paper\_id})

            MERGE (p)-[:HAS\_CITATION]->(c)

        """, n\_citation=n\_citation, paper\_id=paper\_id)

    # Create Reference Relationships

    for ref in references:

        tx.run("""

            MERGE (p:Paper {id: $paper\_id})

            MERGE (r:Paper {id: $ref})

            MERGE (p)-[:REFERENCES]->(r)

        """, paper\_id=paper\_id, ref=ref.strip())

    # Create ID Node and Relationship

    tx.run("""

        MERGE (i:ID {value: $paper\_id})

        MERGE (p:Paper {id: $paper\_id})

        MERGE (p)-[:HAS\_ID]->(i)

    """, paper\_id=paper\_id)

# Step 2.2: Populate the Graph

with driver.session() as session:

    for \_, row in df.iterrows():

        session.write\_transaction(

            add\_paper,

            paper\_id=row['id'],

            title=row['title'],

            abstract=row['abstract'],

            authors=row['authors'],

            n\_citation=row['n\_citation'],

            references=row['references'],

            venue=row['venue'],

            year=row['year']

        )

embed\_model = SentenceTransformer("all-MiniLM-L6-v2")

# Combine title + abstract for better semantic richness

df["combined\_text"] = df["title"].fillna("") + " " + df["abstract"].fillna("")

# Create embedding matrix

paper\_embeddings = embed\_model.encode(df["combined\_text"].tolist(), show\_progress\_bar=True)

index = faiss.IndexFlatL2(paper\_embeddings.shape[1])

index.add(np.array(paper\_embeddings))

query ="how random forest is different from xgboost"

def vector\_search\_rag(query, top\_k=50):

    query\_embedding = embed\_model.encode([query])

    D, I = index.search(np.array(query\_embedding), top\_k)

    return df.iloc[I[0]][['id', 'title', 'abstract']].to\_dict(orient="records")

results = vector\_search\_rag(query, top\_k=50)

model = SentenceTransformer('all-MiniLM-L6-v2')

df['abstract\_embedding'] = df['abstract'].apply(lambda x: model.encode(x) if x else None)

# Convert NumPy arrays to lists of floats

df['abstract\_embedding'] = df['abstract\_embedding'].apply(lambda x: x.tolist() if x is not None else None)

def add\_embedding(tx, abstract\_text, embedding):

    # Update the Abstract node with the embedding

    tx.run(

        """

        MATCH (a:Abstract {text: $abstract\_text})

        SET a.embedding = $embedding

        """,

        abstract\_text=abstract\_text,

        embedding=embedding

    )

# Iterate over the DataFrame and store embeddings

with driver.session() as session:

    for \_, row in df.iterrows():

        if row['abstract'] and row['abstract\_embedding']:

            session.execute\_write(

                add\_embedding,

                abstract\_text=row['abstract'],

                embedding=row['abstract\_embedding']

            )

def run\_query(query):

    with driver.session() as session:

        result = session.run(query)

        return [record for record in result]

# Example Query: Retrieve Papers by Title Keyword

query = """

MATCH (p:Paper)-[:HAS\_ABSTRACT]->(a:Abstract)

WHERE a.text CONTAINS 'neural network'

RETURN p.id AS paper\_id, a.text AS abstract

"""

def kg\_based\_search(query\_keyword, top\_k=5):

    query = f"""

    MATCH (p:Paper)-[:HAS\_ABSTRACT]->(a:Abstract), (p)-[:HAS\_TITLE]->(t:Title)

    WHERE a.text CONTAINS '{query\_keyword}' OR t.text CONTAINS '{query\_keyword}'

    RETURN p.id AS paper\_id, t.text AS title, a.text AS abstract

    LIMIT {top\_k}

    """

    return run\_query(query)

def hybrid\_retrieval(keyword, top\_k=5):

    query="Get 5 papers whose abstract is based on neural network. For every paper give a brief about each paper findings in 5 lines."

    # Step 1: Get initial candidates from KG

    candidates = kg\_based\_search(keyword, top\_k=50)

    if not candidates:

        return []

    texts = [c['title'] + " " + c['abstract'] for c in candidates]

    embeddings = embed\_model.encode(texts)

    query\_embedding = embed\_model.encode([query])

    scores = np.linalg.norm(embeddings - query\_embedding, axis=1)

    ranked = sorted(zip(candidates, scores), key=lambda x: x[1])[:top\_k]

    return [r[0] for r in ranked]

PROMPT\_TEMPLATE = """

answer as precisely as possible based on the below context

Question: \n {question} \n

Context: \n {context}?\n

Answer:"""

context\_text = "\n".join([

    f"Paper ID: {record['paper\_id']}, Title: {record['title']}, Abstract: {record['abstract']}"

    for record in results

])

prompt\_template = ChatPromptTemplate.from\_template(PROMPT\_TEMPLATE)

prompt\_ans = prompt\_template.format(context=context\_text, question=prompt)

genai.configure(api\_key="AIzaSyAxvgJPkHBsll0kqEIBIvVBBeP-Y9eDl6c")

model = genai.GenerativeModel("gemini-1.5-flash")

response = model.generate\_content(prompt\_ans)

print(response.text)

smoothie = SmoothingFunction().method4

def calculate\_metrics(gt\_list, pred\_list):

    bleu\_scores = []

    precisions, recalls, rr\_list = [], [], []

    for gt, pred in zip(gt\_list, pred\_list):

        # BLEU

        gt\_tokens = gt.lower().split()

        pred\_tokens = pred.lower().split()

        bleu = sentence\_bleu([gt\_tokens], pred\_tokens, smoothing\_function=smoothie)

        bleu\_scores.append(bleu)

        # Precision@5 and Recall@5

        ref\_set = set(gt\_tokens)

        pred\_top5 = set(pred\_tokens[:5])

        tp = len(ref\_set & pred\_top5)

        precision = tp / 5

        recall = tp / len(ref\_set)

        precisions.append(precision)

        recalls.append(recall)

        # MRR

        rr = 1.0 if gt.lower() in pred.lower() else 1 / 2  # simplified

        rr\_list.append(rr)

    return {

        "BLEU": np.mean(bleu\_scores),

        "Precision@5": np.mean(precisions),

        "Recall@5": np.mean(recalls),

        "MRR": np.mean(rr\_list)

    }

faiss\_metrics = calculate\_metrics(ground\_truths, faiss\_predictions)

kg\_metrics = calculate\_metrics(ground\_truths, kg\_predictions)

hybrid\_metrics = calculate\_metrics(ground\_truths, hybrid\_predictions)

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