Myanmar Law Cases and Proceedings Retrieval with GraphRAG

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***Abstract*— Legal document retrieval poses various challenges due to diverse linguistic and domain-specific complexities. The GraphRAG approach represents a significant advance in retrieving and summarizing archival case documents. It deals with the difficulties of accessing relevant legal information with inherent complexities. Further, it improves the efficiency of information retrieval by using graphical representations of legal texts. It enables lawyers to navigate the complex relationships between cases, statutes, and legal principles. The framework facilitates extracting relevant information and incorporates advanced natural language processing techniques for efficient summarization. It enables users to understand key legal concepts quickly. By fostering interdisciplinary collaboration and focusing on user-centered design, GraphRAG can significantly improve access to legal information, thereby meeting the growing needs of the legal community. This paper proposes a graph-rag-based approach for multilingual legal information retrieval (ML2IR), focusing on the Burmese language. Our graph-rag-based approach addresses the hallucination problem, crucial in legal information retrieval. Additionally, our work identifies important nodes and establishes contextual relationships, leading to higher accuracy and effective information retrieval.**

Keywords—Legal Information Retrieval, Legal case retrieval, Retrieval Augmented Generation, GraphRAG

I. Introduction

In the era of data overload, information retrieval (IR) has become a vital process of extracting relevant information from large data stores based on user queries. The information explosion posed the need for systematic and technology-driven IR approaches, which laid the foundation for modern information science. Many lexical approaches are used for information retrieval. They have inherent limitations due to the need for exact word matching. With the enhancement in natural language processing (NLP), these approaches evolved to address the limitations. The performance of IR systems leaped to the next level with advanced deep learning techniques, large labeled datasets, and high computing power [1]. Overall, the performance of the retrieval model utilized techniques like query generalization, pre-training, large language model (LLM), and contrastive learning [1]. Though the generalization of IR serves the purpose, some specific applications need to be looked at differently.

Legal information retrieval (LIR) is a specialized area of information retrieval that focuses on the efficient access and retrieval of legal documents and information. The complexity of legal text is compounded by its usage of intricate language and specific terminologies. So, advanced retrieval techniques are necessary to ensure that 'legal professionals' can efficiently access relevant information. Westlaw and LexisNexis are two of the largest legal research platforms in the United States, which provide extensive databases that include a wide range of legal materials like statutes, regulations, case opinions, and court documents [2]. However, these platforms use boolean indexing, which requires users to take extensive training to navigate effectively [3]. This dependence on Boolean logic can make it more difficult for people to access legal information, especially those without formal training in legal research methodologies. Despite these limitations, the popularity of these systems emphasizes the urgent requirement for effective legal information retrieval solutions. Recent advancements in machine learning (ML) and natural language processing (NLP) have led to the development of more sophisticated retrieval models that leverage document vector embeddings and deep learning techniques, enhancing the precision and recall of legal document retrieval [3].

The presence of multiple languages in legal information retrieval presents extra complexities, particularly in jurisdictions with diverse linguistic landscapes. Multilingual information retrieval (MLIR) systems are designed to retrieve legal documents in multiple languages, allowing users to pose queries in one language while retrieving documents in another. This capability is essential in multilingual contexts, where legal practitioners may need to access documents written in various languages to ensure comprehensive legal understanding and compliance [4][5]. Integrating cross-lingual information retrieval (CLIR) techniques has become increasingly important in this regard, as it facilitates the retrieval of relevant legal information across language barriers.

Navigating the legal system in Myanmar is characterized by significant complexity due to the coexistence of English and Burmese in legal proceedings. This bilingual environment creates unique challenges for legal practitioners and individuals attempting to comprehend and engage with the legal landscape. Consequently, there is an urgent demand for effective multi-lingual legal information retrieval (MLIR) systems. Such systems are essential, as legal professionals must often access documents and resources in both languages to ensure comprehensive understanding and compliance with local laws. But nowadays bilingualism experience is terminated and legal documents are released only in the Myanmar language, providing additional impediments to retrieving information from archival documents.

This paper employs a novel approach, Graph-RAG (Retrieval-Augmented Generation), to retrieve Myanmar law cases and proceedings in the Myanmar language. Graph-RAG combines the benefits of graph structures with retrieval-augmented generation models, allowing for a more contextually enriched and relevant response to legal queries. The system can establish relational ties between legal terms, cases, and precedents by utilizing graph-based connections, providing users with more accurate and contextually aligned results.

The primary objective of this study is to assess the effectiveness of Graph-RAG in addressing Myanmar's unique legal retrieval needs. Specifically, we aim to evaluate how this approach improves the relevance, accuracy, and accessibility of legal information from law case archives. This research has broader implications, as it may pave the way for enhanced retrieval methods in other underrepresented languages and legal systems, ultimately contributing to the democratization of legal information. It allows the retrieval of a summary of archival, legal case documents using plain language without special training in information retrieval systems. In summary, our contributions are as follows:

1. We introduce the first Graph-RAG-based legal information retrieval system for the Burmese language.
2. We propose rule-based entity extraction for Burmese legal proceedings to form a context-enriching graph.
3. We conduct experimentation to support our claim of effectiveness and mitigation of hallucination.
4. We further demonstrate that the proposed method is robust and can be used in a multilingual environment.

The remainder of this paper is organized as follows: Section II reviews the literature on legal information retrieval and Graph-RAG methodologies. Section III describes our methodology, while Section IV discusses the experimental setup and results. Finally, Section V covers the implications of our findings and outlines potential future research directions.

II. Literature Review

The field of legal case retrieval has seen significant advancement due to various innovative approaches and technologies. These new methodologies aim to enhance the efficiency and accuracy of retrieving relevant legal cases.

For example, applying prompt-based input reformulation techniques can improve the alignment of legal features in case retrieval addressing the challenge of incorporating redundant information from entire case texts [6]. Researchers also proposed a legal-element-based similar case retrieval (SCR) model. They presented a new dataset called MUSER, which surpassed models like BM25, TF-IDF, and LMIR by a large margin in ranking metrics [7]. It is observed that reformulating additional queries using LLM provides detection accuracy for sparse and dense models [8]. Different researchers worked on the explainability of the legal case-matching method that utilizes inverse optimal transport to extract rationales for matching decisions [9]. Legal element-oriented modeling with multi-view contrastive learning can further improve retrieval accuracy [10]. An ontology-based semantic retrieval improved the precision of the case retrieval, enhancing its applicability in legal documents [11].

Despite the advancement in legal case retrieving, there are several limitations. While pre-trained language models (PLMs) have been widely adopted, they often fail to capture the specific legal features inherent in legal documents [12]. This inadequacy can lead to suboptimal retrieval performance because the models may not fully understand the nuances of legal language and context, which are critical for accurate case retrieval. Additionally, the reliance on large datasets for training advanced models poses a significant challenge, where substantial computational resources are often required to achieve optimal performance [13]. Thus making such techniques computationally expensive. The researchers also attributed the low performance of deep neural models to shortening the case text and missing important information, which shows the importance of relevant entity extraction [7]. Additionally, the evaluation of LIR/LCR systems continues to be a complex issue, as the effectiveness of retrieval methods can vary significantly based on the specific legal context and the nature of the queries [14].

Recent studies have highlighted the importance of integrating external knowledge sources to reduce hallucinations in LLMs. For instance, leveraging information retrieval can provide relevant background information and context that helps mitigate the generation of hallucinatory content [15]. This approach is supported by different researchers, who note that knowledge gaps within LLMs are a primary cause of hallucinations, suggesting that interaction with external knowledge bases can alleviate this issue [16]. Furthermore, retrieving substantial evidence and relevant facts in the given context is necessary to detect hallucinations effectively, indicating that retrieval methods can enhance the accuracy of LLM outputs [17].

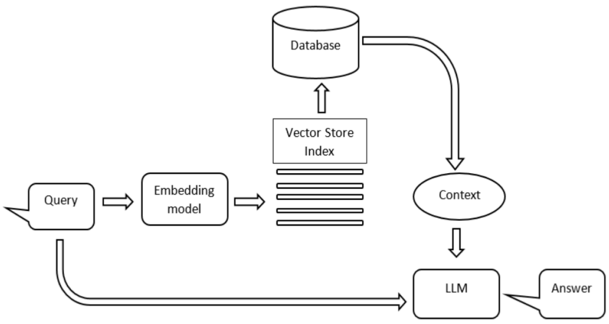

Fig. 1. Basic RAG architecture. Adapted from [20]

Large language models (LLMs) have demonstrated revolutionary capabilities in understanding and generating language while facing inherent limitations such as hallucinations and outdated internal knowledge [18]. The powerful capabilities of RAGs in providing relevant and valuable auxiliary information can be utilized to solve this problem. Thus, large language models with advanced search exploit external and authoritative knowledge bases rather than relying solely on the model's internal knowledge to improve the quality of LLM generation. Various prompt engineering (PE) methods have been proposed to overcome real-world problems, such as small-shot prompting, chain of thoughts, and retrieval augmented generation (RAG). However, RAG for legal judgment prediction (LJP) is still understudied [19]. The basic RAG architecture is shown in Fig. 1. which consists of an embedding model that transforms user queries and external sources into vectors. When the user submits a query, the architecture searches the database and finds the most relevant vectors that match the query based on a similarity function. The next step is to provide the relevant vectors to the LLM as context and instruct it to return a suitable response [20].

According to researchers, "We're Entering the Blue Links Era of RAG." In short, RAG is an evolutionary process for retrieving information using generative models. Fig. 2. shows the stages of improvement of generative artificial intelligence (AI) models. This is going to be the next stage of RAG model enhancement.

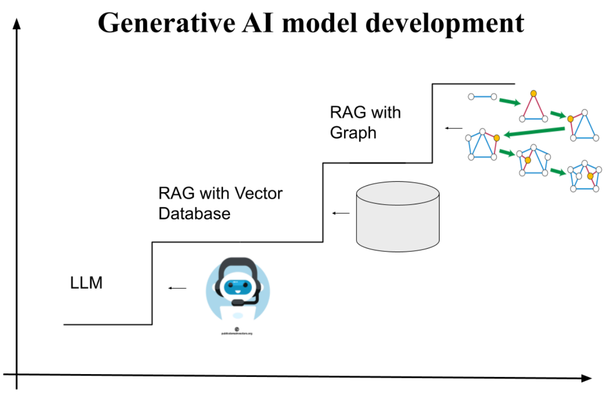

Fig. 2. Generative AI evolution model. Adapted from [21]

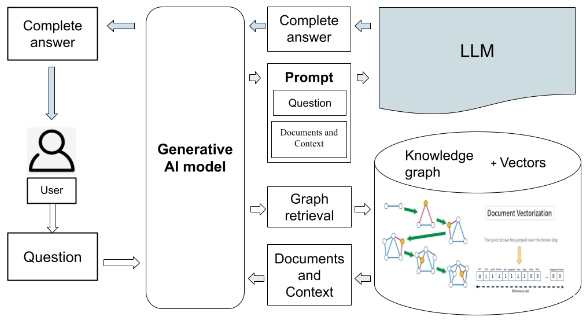

Fig. 3. GraphRAG architecture. Adapted from [21]

At its core, Graph-RAG(GraphRAG) is RAG, where the search path includes a knowledge graph [21], as shown in Fig. 3. In the case of GraphRAG, the knowledge graph enriches the searching abilities of the RAG.

Digitization has taken impetus recently, and primary language processing in Burmese has improved tremendously. However, the integration of machine learning (ML) methods into information retrieval systems for the Burmese language is still in its infancy. Although studies have shown the potential of ML approaches to improve retrieval performance, there is a lack of specialized ML models designed specifically for the linguistic features of the Burmese language. Existing models often rely on methods developed for more common languages, which may not directly apply to Burmese due to its unique grammatical and syntactic structures.

Processing the Burmese language in the context of natural language processing (NLP) and information retrieval (IR) presents several challenges. One of the most significant challenges is Word segmentation. The Burmese language does not use spaces to delimit words, complicating text processing and retrieval tasks. The lack of a standardized approach to word segmentation leads to inconsistencies in NLP applications, negatively affecting information retrieval systems' performance [22].

One of the earlier studies reported the development of a word segmentation method in Myanmar using the standard Unicode encoding [22]. Word segmentation is an important step before natural language processing in Burmese since the text in Myanmar is a character string with no obvious word boundary delimiters. The proposed method consists of two phases: syllable segmentation and syllable merging. A heuristic rule-based approach was adopted for syllable segmentation, and a statistical dictionary-based approach was adopted for syllable merging. The evaluation of the test results showed that the method was very effective for the Myanmar language.

Another critical issue is the lack of annotated datasets and parallel corpora for the Burmese language. The limited availability of high-quality training data hinders the development of effective machine-learning models for tasks such as machine translation and information retrieval [23]. This deficit impacts the performance of natural language processing systems and limits the ability of researchers to conduct comprehensive evaluations and comparisons of different methodologies.

The challenges of cross-lingual information retrieval (CLIR) are particularly pronounced in the context of the Burmese language. Some recent work highlights the importance of efficient translation engines for CLIR systems, especially in low-resource languages such as Burmese [24]. The limited availability of bilingual resources makes it difficult to implement efficient CLIR solutions.

The robustness of NLP applications is a critical factor in their real-world deployment [25]. Current systems may struggle with adversarial inputs or variations in language usage, resulting in significant performance degradation.

Research also highlights the importance of understanding cultural nuances when conducting fieldwork and interviews in Myanmar [26]. This artistic dimension is often overlooked in NLP research, yet it plays a critical role in shaping language processing tasks.

These studies highlighted the need for future research that considers the socio-cultural context of the Burmese language to develop more effective and contextually relevant NLP applications.

The following TABLE I summarizes research gaps identified in the research field of IR in the Burmese language.

TABLE I. RESEARCH GAPS IDENTIFIED

Challenges	Explanation	Source
Multilingual Legal Systems	Current models mainly focus on English legal texts.	[18]
Contextual Understanding in Low-Resource Languages	More advanced NLP tools and datasets are needed to address legal domain issues in languages such as Burmese	[18]
The Efficiency of Retrieval-Augmented Models	While RAG models show promising results, scaling them to extensive legal archives with demanding search requirements can be computationally expensive.	[19]
Bias in Legal Decision Predictions	Addressing bias in model predictions is critical, especially across legal contexts. Ensuring fairness and impartiality in case predictions	[19]
LLM Hallucinations	LLMs tend to generate plausible-sounding but incorrect results, mainly when applied to legal domains. This problem persists in both English and low-resource languages	[15] [16] [17] [19]
Lack of Burmese language processing models	Word segmentation, data scarcity, the need for tailored machine learning models, cross-language retrieval difficulties, robustness issues, and cultural considerations are key in IR.	[21] [22] [23] [24] [25] [26]

III. METHODOLOGY

In this study, we introduce our approach to reducing hallucinations in retrieving Burmese legal data. According to the nature of the data, it is best if we can retrieve the data accurately for law data when we do a Q/A task in order to maintain the original scenario of the cases. Hence, we employed the GraphRAG methodology for accurate information retrieval purposes. According to [34], GraphRAG extends the traditional Retrieval-Augmented Generation (RAG) by incorporating graph neural networks to enhance information retrieval and answer generation. The system leverages both structured knowledge represented in graphs and unstructured text data to provide more accurate and contextually relevant responses [34].

A. GraphRAG architecture in LIR

GraphRAG can be used to search and summarize archival case documents using graphical representations to improve the efficiency and accuracy of legal information retrieval. This approach is particularly relevant in the Myanmar legal system, where digitizing legal documents is becoming increasingly important. The following sections will explain how GraphRAG searches and summarizes archival case documents supported by relevant literature.
GraphRAG Engine for Legal Case Search: GraphRAG creates a graphical representation of legal documents, where nodes represent entities such as cases, statutes, and legal principles, and edges represent the relationships between these entities. This graphical structure allows for a more nuanced understanding of the relationships in legal texts, facilitating the retrieval of relevant cases based on user queries. Using graph theory techniques, GraphRAG can efficiently traverse the relationships between different legal documents, thereby identifying contextually relevant cases to a given query [27]. The retrieval process begins by converting legal documents into a graph format. Each document is analyzed to extract critical entities and relationships, which are then represented as nodes and edges in a graph. This transformation is critical because it allows the system to capture the semantic relationships inherent in legal texts, which are often complex and multifaceted [33].

B. Data Collection and Preprocessing

The study utilized a corpus of Burmese legal cases, encompassing civil and criminal proceedings, which were systematically extracted from the Myanmar Law Information System. The dataset underwent rigorous preprocessing to facilitate the construction of a knowledge graph database using rule-based methodologies, with Neo4j Aura serving as the cloud-based storage solution.

The initial extraction phase involved scraping the data from the data sources, parsing fundamental elements, including titles, and content into a structured CSV format. Subsequently, we employed the Python regex library to extract key legal entities: plaintiff and defendant identifications, case classifications, citations, temporal information, and judicial decisions.

C. Rule-based Entity Extraction

The extraction process leveraged the standardized formatting conventions prevalent in Burmese legal documentation. In this study, we have implemented and proposed the rule-based extraction rules as follows as shown in Fig. 4.:

- **Party Identification**: Plaintiff-defendant differentiation was achieved by strategically identifying the conjunction [နှင့်] within the title field, with antecedent text designated as plaintiff and subsequent text as defendant.

ဦးတိုးငွေး ပါ ၂ (Plaintiff) နှင့် ညွှန်ကြားရေးမှူးချုပ် မြို့ပြနှင့် အိမ်ရာ ဖွံ့ဖြိုးရေးဦးစီးဌာန ဆောက်လုပ်ရေးဝန်ကြီးဌာန (Defendant)

- **Case Classification**: The legal classification (civil versus criminal) was determined by analyzing the cited statutory framework.

၉၆တရားမ (CASE CATEGORY) အထွေထွေလျှောက်ထားမှုပြည်ထောင်စုတရားသူကြီးချုပ် ဦးထွန်းထွန်းဦးပြည်ထောင်စုတရားလွှတ်တော်ချုပ်တရားသူကြီးများဖြစ်ကြသောဦးစိုးညွန့်နှင့် ဦးအောင်ဇော်သိန်းတို့ရှေ့တွင်ဦးတိုးငွေး ပါ ၂နှင့်ညွှန်ကြားရေးမှူးချုပ်မြို့ပြနှင့်အိမ်ရာဖွံ့ဖြိုးရေးဦးစီးဌာနဆောက်လုပ်ရေးဝန်ကြီးဌာန(၂၀၁၅ ခုနှစ်၊ တရားမအထွေထွေလျှောက်ထားမှုအမှတ် ၁၅၀)မြေလက်ရှိဖြစ်သူအား အကြောင်းပြထုချေခွင့်မပေးဘဲ ဂရန်စာချုပ် သို့မဟုတ် အငှားစာချုပ်ကို တစ်ဖက်သတ် ပယ်ဖျက်ကြောင်း ကြေညာခဲ့ခြင်းသည် ဥပဒေနှင့်မညီခြင်း။

- **Judicial Outcomes**: Decision extraction was facilitated by identifying specific terminological markers (translated as "decision") and subsequent text capture.

ဆုံးဖြတ်ချက်။ ။ (DECISION) အမှုသည်တို့၏ အခွင့်အရေးဆက်ခံသူဆိုရာတွင် အမွေဆိုင်များ၊ သေတမ်းစာ အတည် ပြုသူများ၊ အမွေထိန်းများကဲ့သို့သော တရားဝင်ကိုယ်စားလှယ်များသာမက တရားနိုင်၏ အကျိုး ခံစားခွင့်ကို လွှဲပြောင်းရရှိသူ၊ တရားရှုံး၏ အကျိုးသက်ဆိုင်ခွင့်ကို လွှဲပြောင်းရရှိသူကဲ့သို့ အခွင့်အရေး ဆက်ခံသူတို့ လည်းပါဝင်သည်။

- **Citation and Temporal Data**: These elements were consistently enclosed in parenthetical notation within the title field, enabling systematic extraction.

ဦးတိုးငွေး ပါ ၂ နှင့် ညွှန်ကြားရေးမှူးချုပ် မြို့ပြနှင့် အိမ်ရာ ဖွံ့ဖြိုးရေးဦးစီးဌာန ဆောက်လုပ်ရေးဝန်ကြီးဌာန (၂၀၁၆၊ မတစ၊ စာ-၉၆(CITATION))[၁၃.၀၆.၂၀၁၆](TIME)

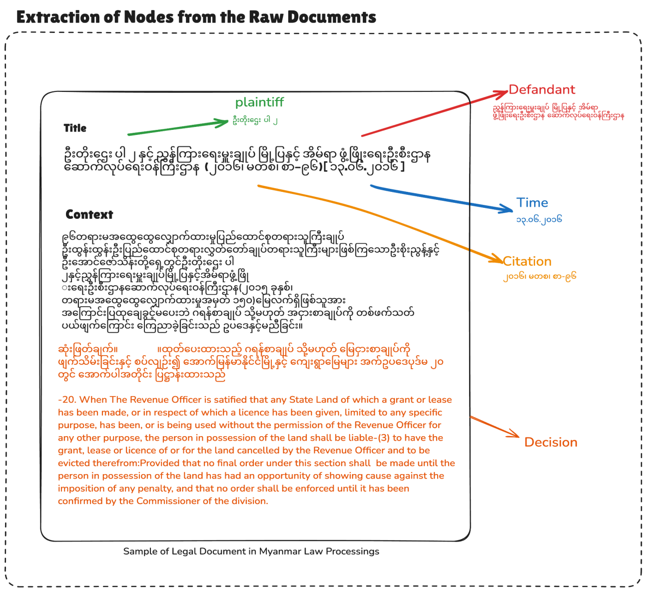

Fig. 4. Extraction of nodes from the raw documents using rule-based method

The final corpus comprises over 700 cases, with subsequent preprocessing involving null value elimination and stop word removal to enhance data quality.

D. *Query Processing*

To improve retrieval precision, we integrated a fuzzy matching algorithm to handle variations in legal terminology. This algorithm allows for flexible matching when querying documents, reducing instances of missed results due to minor linguistic differences. Once relevant documents were retrieved, we structured the data according to their **outgoing** and **incoming relationships**. In Fig. 5. outgoing relationships represented forward connections within a case (such as appeals or referenced statutes), while incoming relationships denoted precedents or cases cited. This structuring allowed the model to maintain the context of legal cases accurately when parsing data into the large language model (LLM).

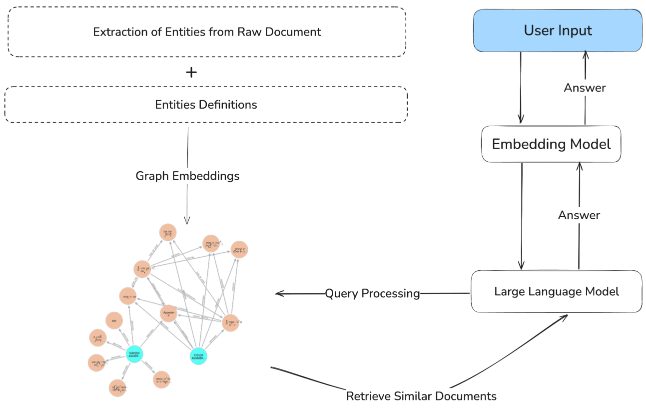

Fig. 5. Methodology of the study with reference to GraphRAG architecture by incorporating the Knowledge Graph for enhancing retrieval and reducing LLM hallucination.

The final step involved parsing the structured data into the LLM. The retrieved and structured graph data, along with the user query vector, was input to the LLM to generate a final response. The LLM, informed by both structured graph data and vectorized input, produced an answer aimed at maintaining legal accuracy and contextual relevance. This dual-input approach helped in reducing hallucinations by reinforcing factual consistency, which is essential in legal Q/A tasks.

IV. Results And Analysis

The ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric, introduced by Chin-Yew Lin in their pivotal work, is a cornerstone in the field of natural language processing, particularly for evaluating automatic summarization and machine translation [35]. ROUGE assesses the quality of a summary by comparing it with reference summaries, usually human generated. This section discusses the journey of evaluation for burmese language with ROUGE scores. However, for morphologically rich and low-resource languages like Myanmar, traditional ROUGE metrics face significant limitations due to complex morphological variations, limited standardization of word boundaries and contextual meaning dependencies. To address these challenges, this study proposes a novel cluster-based evaluation methodology that operates at the semantic cluster level rather than individual word matches.

A. Cluster Matching Framework

Given a set of predicted clusters c_p and ground truth c_g, we define our evaluation metrics as follows:

Cluster Matching Score: For any predicted cluster $c_p \in c_p$ and ground truth cluster, we define a matching score as:

$$match(c_p, c_g) = \frac{|c_p \cap c_g|}{max(|c_p|, |c_g|)} \quad (1)$$

where, $|c_p \cap c_g|$ represents the cardinality of the intersection between clusters, $max(|c_p|, |c_g|)$ normalizes the score based on the larger cluster size. Then, we calculate for Precision and Recall by measuring the best matching scores.

$$Precision = \frac{1}{|C_p|} \sum_{c_p \in c_p} maxmatch_{c_g \in c_g}(c_p, c_g) \quad (2)$$

$$Recall = \frac{1}{|C_g|} \sum_{c_g \in c_g} maxmatch_{c_g \in c_g}(c_p, c_g) \quad (3)$$

Finally, by using the F1 formula, we calculate the result.

$$F1 = 2 * \frac{precision * recall}{precision + recall} \quad (4)$$

To evaluate our approach, by leveraging our proposed equation, cluster matching ROUGE scores was used to calculate ROUGE scores while using four state-of-the-art models employing both our proposed GraphRAG method and a baseline retrieval-augmented generation (RAG) framework. The models used in our experiments were GPT-4o, GPT-4o mini, GPT-3.5 turbo, and LLAMA 3.1 70B. The scores for each model are presented in Table II. Our results show that the GraphRAG approach consistently outperforms the baseline RAG across all models, with notable improvements in F1 scores for each ROUGE metric. The GPT-4o model achieved the highest performance, yielding the score of over 87% while the other three models resulted in over 69%. According to the result, our approach improved the ROUGE score resulting in mitigating the LLM hallucination. Therefore, we can say that by leveraging the GraphRAG, we can definitely reduce the LLM hallucination by the exact information retrieval.

TABLE II. ROUGE SCORE RESULTS OF GRAPHRAG

		F1 Score		
Model	Methodology	ROUGE 1	ROUGE 2	ROUGE L
GPT 4 o mini	GraphRag	0.8050	0.7595	0.7925
	RAG	0.5120	0.2242	0.2530
	Improvements	+57.23%	+238.76%	+213.24%
GPT 4 o	GraphRag	0.8779	0.8538	**0.8732**
	RAG	0.5049	0.1980	0.2689
	Improvements	+73.88%	+331.21%	+224.73%
GPT 3.5 turbo	GraphRag	0.8646	0.8305	0.8599
	RAG	0.3622	0.1429	0.1732
	Improvements	+138.71%	+481.18%	+396.48%
LLAMA 3.1 70 B	GraphRag	0.7052	0.6648	0.6942
	RAG	0.4682	0.1751	0.2609
	Improvements	+50.62%	+279.67%	+166.08%

B. Model limitations

Below are some of the main limitations of GraphRAG, as confirmed by our experiment.

1. *Complexity of legal language.* One of the main challenges in using GraphRAG to search legal documents is its inherent complexity. Legal texts often contain specialized terminology, intricate sentence structures, and context-dependent meanings, hindering effective searching and summarization. Although GraphRAG's graph-based approach aims to capture semantic relationships, the variability and ambiguity of legal language can still lead to misinterpretations or incomplete retrieval.

2. *Dependence on the quality of input data*. GraphRAG's effectiveness heavily depends on the quality of the input data. The resulting graphical representation may not accurately reflect the underlying legal concepts if the processed legal documents are poorly structured, incomplete, or contain errors.

3. *Limitations in summarization methods***.** While GraphRAG incorporates advanced abstracting techniques, these techniques may not always produce satisfactory results, particularly in legal documents.

4. *Scalability and Computing Resources.* GraphRAG's graph nature can lead to scalability issues, particularly when dealing with large volumes of legal documents. As the graph size increases, the computational resources required to process and query the graph can become significant.

5. *Ethical and Privacy Considerations.* Using automated systems to search legal documents raises ethical and privacy concerns, particularly regarding handling sensitive legal information.

6. *Limited Contextual Understanding.* While GraphRAG aims to capture relationships between legal documents, its ability to understand the broader contextual factors that influence legal cases may be limited. Legal outcomes are often shaped by social, political, and historical contexts that may not be well represented in the graph structure.

C. Contribution to the field of study

The scientific contributions of the GraphRAG approach to retrieving and summarizing archival case documents are multifaceted. It addresses significant challenges in legal information retrieval while improving accessibility, efficiency, and relevance in the legal field. This section describes the main contributions of GraphRAG, supported by the relevant literature.

1. Improving retrieval efficiency with graph representations. GraphRAG's use of graph representations enables a more detailed understanding of the relationships between legal documents, which is critical in legal information retrieval. By representing cases, statutes, and principles as interconnected nodes in a graph, GraphRAG facilitates efficient traversal and querying of legal information [28].

2. Improved summarization methods for legal documents. Using advanced natural language processing techniques, GraphRAG can extract important information from legal texts, allowing users to quickly understand key points without browsing through extensive materials [29].

3. Addressing the Complexity of Legal Language. Legal documents are often characterized by complex language and specialized terminology, which can present significant challenges for traditional search engines. GraphRAG addresses this issue by using its graph structure to capture the semantic relationships inherent in legal texts [30]. GraphRAG improves the accuracy of search results by improving the understanding of legal language, thereby supporting lawyers in their research and case preparation [31].

4. *Facilitating Access for Non-Experts.* One of GraphRAG's notable contributions is its potential to democratize access to legal information for non-experts. By using text mining techniques that allow users to search legal documents using everyday vocabulary, GraphRAG can assist individuals who may not be familiar with professional legal terminology [32]. This approach increases access to legal information and enables the general public to interact more effectively with legal processes.

5. *Integrating domain knowledge and ontologies.* Incorporating domain knowledge and ontologies into GraphRAG improves its effectiveness in processing legal documents. By integrating structured legal knowledge into the search framework, GraphRAG can better understand legal concepts' nuances and increase the relevance of retrieved cases [33].

V. Conclusion

In this paper, we propose a novel Graph-Rag-based approach for multilingual legal information retrieval, specifically focusing on the Burmese language. The proposed approach takes care of nuances in the legal system while addressing steep challenges in multilingual scenarios. Additionally, it helps mitigate hallucination. The results underline the robustness of the proposed approach. With its applicability in multilingual legal information retrieval, the proposed methodology can be extended to other low-resource languages. Additionally, this work can be extended to attain scalability and tested on a larger dataset.

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