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ENHANCED TEXT SUMMARIZATION USING HIERARCHICAL TRANSFORMER AND KNOWLEDGE GRAPH INTEGRATION FOR LEGAL DOCUMENTS

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ABSTRACT

Indian legal judgmental are substantially difficult to summarize due to their intense clauses and complex structure. Existing summarization techniques often fail to represent subtle legal reasoning and contextual dependencies embedded in the documents. This work presents a novel approach to Indian legal judgment summarization called Hierarchical Transformer with Knowledge Graph Integration (HT-KGI). It consists of two main components: hierarchical transformer encoding and knowledge graph integration. First, a hierarchical transformer encoder is employed to model contextual dependencies at both the sentence level and the document level using a dual-attention framework. Secondly a knowledge graph grounded in legal ontologies is incorporated to clarify the semantics of legal concepts and reveal their underlying relational structure. To assess the effectiveness of the proposed framework, we carried out an extensive evaluation using a large collection of Indian Supreme Court orders. The result strongly provided a marking improvements over the baseline systems, not only in ROUGE metrics but also in the semantic flow and legal soundness of the generated summaries. According to experimental results, the HT-KGI approach outperforms typical transformer models by 17% in ROUGE-1 scores, 22% in semantic coherence, and 19% in legal accuracy while retaining a 35% reduction in computing cost. For specialized document summarizing tasks, the suggested approach shows how well domain-specific knowledge graphs and hierarchical transformer structures work together.

Keywords: *Hierarchical Transformer, Knowledge Graph Integration, Legal Document Summarization, Extractive Summarization, Semantic Coherence, Legal Text Processing.*

1. INTRODUCTION

Text summary saves consumers time and cognitive effort by condensing a document's information without sacrificing its essential meaning. In the legal profession, this is very crucial. Summarizing legal documents is a new area of study within text summarization. Currently, creating case summaries by hand is a lot of work. Lawyers and courts refer certain cases to legal editors for generating summaries of them. The duty of summarizing cases is performed by a team of specialist staff members employed by the courts. Lawyers must look through prior rulings to bolster their arguments in order to solve a legal issue. However, inexperienced users frequently want to know if there is any historical documentation of comparable court cases (summaries). Furthermore, the development of a system for inferring legal knowledge is made more complex by issues like the gathering, processing, and dissemination of heterogeneous knowledge from several sources. Thus, the development of CLKG and the automatic extraction of precise and trustworthy information from various legal sources are theoretically and practically significant in the legal area.

The Legal Onto-Graph model, which combines a knowledge graph with the Legal-Onto ontology. Search capabilities, document comparison, and question answering are just a few of the many uses made possible by this integration, which is based on laws and legal documents. The recommended method works well for gathering information from a variety of legal documents. The integrated model serves as a knowledge base for a Q&A system that focuses on legal documents. The effectiveness of the system in answering common questions is demonstrated by experiments with the Vietnamese Land Law 2013. Additionally, it performs better in this area than large language models like ChatGPT, Bard, and Copilot for intelligent legal advice systems.

Using Legal BERT, GPT-2, and Retrieval Augmented Generation, a legal chatbot could assist and facilitate the resolution of legal questions pertaining to Indian law. This chatbot can provide the most accurate, contextually relevant response because it has been trained using a carefully selected corpus of the Indian Constitution and other pertinent legal writings. Legal BERT improves the chatbot's comprehension of complex legal jargon, and GPT-2 uses content gathered from such sources to provide human-like responses. RAG is used to improve the retrieval of pertinent sources, resulting in the delivery of precise and pertinent responses.

Some existing approaches have attempted to address these limitations through various techniques. LegalBERT, [1] have proposed a number of NLP tasks, BERT has demonstrated remarkable performance. Nevertheless, little research has been done on its adaption rules in specialized fields. Here, we concentrate on the legal sector and examine various methods for using BERT models in downstream legal tasks while assessing them across a variety of datasets. Zhong et al.'s alternative strategy [2] utilizing the attention model over hierarchical encoders with three tiers sentence, word, and character encoders suggested MHAN solves the aforementioned difficulty and the long-range dependency issue by employing the information loss during the encoding step.

Proposed an HT-KGI for legal document summary in order to get around these restrictions. Our method combines the power of knowledge graphs, which offer domain-specific legal knowledge to improve semantic understanding, with the advantages of hierarchical transformer topologies, which can manage lengthy documents by processing them at various levels of granularity.

1.1. Contributory Remarks

The following contributions are made to the Hierarchical Transformer with HT-KGI approach in order to overcome the difficulties in summarizing legal documents:

- Introduce the HT-KGI framework, which explicitly achieves high-order relation learning in the knowledge-aware multi-behavior collaborative graph via a hierarchically structured graph transformer network.
- To use the HT-KGI multi-behavior modeling paradigm to collaboratively add similarities between users and items: i) The initial stage graph-structured transformer module records the power source type-specific user-item interactive patterns in a time-aware setting to forecast the target behaviors; ii) the second-stage attentive combination network encodes the hierarchical dependencies of cross-type the conduct and separates the type-specific contribution.
- Three real-world datasets that use the proposed HT-KGI technique and include movie, venue, and product recommendations. In experiments, model performs better than many cutting-edge baselines from various lines.
- A thorough assessment of the suggested HT-KGI approach's performance is carried out utilizing a number of criteria, such as ROUGE scores, computer efficiency, semantic coherence, and legal accuracy. Experimental results show better performance than both state-of-the-art transformer-based tactics and conventional summarizing techniques.

1.2. Organization of the Work

The following is a description of the paper's establishment: Section 1 gives the introduction regarding the work being carried out. Section 2 provides a description related the related works that is carried out for Legal document summarization. Section 3 explains the proposed method, Section 4 depicts the experimental setup, Section 5 presents the experiment's findings and discussions, and Section 6 offers a conclusion and suggestions for further research

2. RELATED WORKS

According to Chalkidis et al. [1], the BERT has demonstrated remarkable performance in a number of NLP tasks. Nevertheless, little research has been done on its adaption rules in specialized fields. Here, we concentrate on the legal sector and

examine various methods for using BERT models in downstream legal tasks while assessing them across a variety of datasets. Our research shows that the previously established pre-training and fine-tuning criteria, which are frequently adhered to mindlessly, do not necessarily translate effectively into the legal field. According to Zhong et al. [2], artificial intelligence has advanced to the point where it can accurately mimic human thought processes in legal research. In many nations, case pending is a persistent issue. For every developing nation to receive justice on time, the legal system must be increasingly capable and dependable. In this research endeavor, a novel judgment prediction framework known as MHAN is created in order to prevent information loss. It is based on a custom created domain-specific word embedding model and a modified Hierarchical-Attention network.
According to Kanapala et al. [3], the Extracting significant passages from the source document is known as text summarizing. To produce a summary of the text, each phrase's distinct statistical features such as the sentence's length, position, degree of similarity, term frequency, inverse sentence frequency, and keywords are weighted. In order to maximize the document summary, this study employs a gravitational search strategy based on the law of gravity. Devlin et al. [4] observed that all layers concurrently condition on both left and right context while pre-training sophisticated bidirectional representations from unidentified text. As a result, the pre-trained BERT model may be optimized with just one more output layer to provide state-of-the-art models for a range of tasks, including language inference and question answering, without necessitating significant task-specific architecture modifications. However, these models are limited by their fixed context window, making them less effective for long legal documents without additional adaptations.

To address the challenge of long documents, hierarchical approaches have been explored. Zhang et al. [6] proposed a hierarchical attention network for document classification that captured both word-level and sentence-level information. Expanding on this, Liu and Lapata [7] introduced a hierarchical transformer for document summarization that first encoded sentences individually and then modelled document-level information. While effective for general documents, these methods did not incorporate domain-specific knowledge crucial for legal document understanding.

Wang et al. [8] included a unified Knowledge Embedding and Pre-trained LanguagERepresentation (KEPLER) model that can better integrate factual knowledge into PLMs and generate text-enhanced KE with the potent PLMs. KEPLER excels as an inductive KE model on KG link prediction and achieves state-of-the-art performance on a range of NLP tasks. In the legal domain, Zhong et al. [9] used legal ontologies to enhance question answering systems. However, the integration of knowledge graphs with hierarchical transformer architectures for legal document summarization remains underexplored.

Multi-task learning has also been applied to legal document processing. Ahmed et al. [10] proposed a multi-task deep learning method for classifying, summarizing, and translating legal documents. Their approach improved performance with minimal data by sharing representations across similar tasks. Nevertheless, it did not specifically address the challenges of long document processing and domain knowledge integration.

Recent work by Parikh et al. [11] introduced LawSum is a poorly monitored method for summarizing Indian law documents. Pre-processing of the dataset includes fixing spelling errors in named entities, fixing punctuation, normalizing common legal abbreviations, and correctly tokenizing sentences. Every remark has rhetorical obligations. The date, the names of the plaintiffs, defendants, and their attorneys, the judges who made the ruling, the acts or laws cited, and the most often used citations to support the judgment are just a few of the additional facts that are appended to each judgment.
Liu [12] has described framework for multi-label classification using graph convolutional networks (GCN), BERT, and memory networks. The system consists of three modules: label semantic insert, label count prediction, and label selection. The event graph in the label count prediction module is constructed using the abstract meaning

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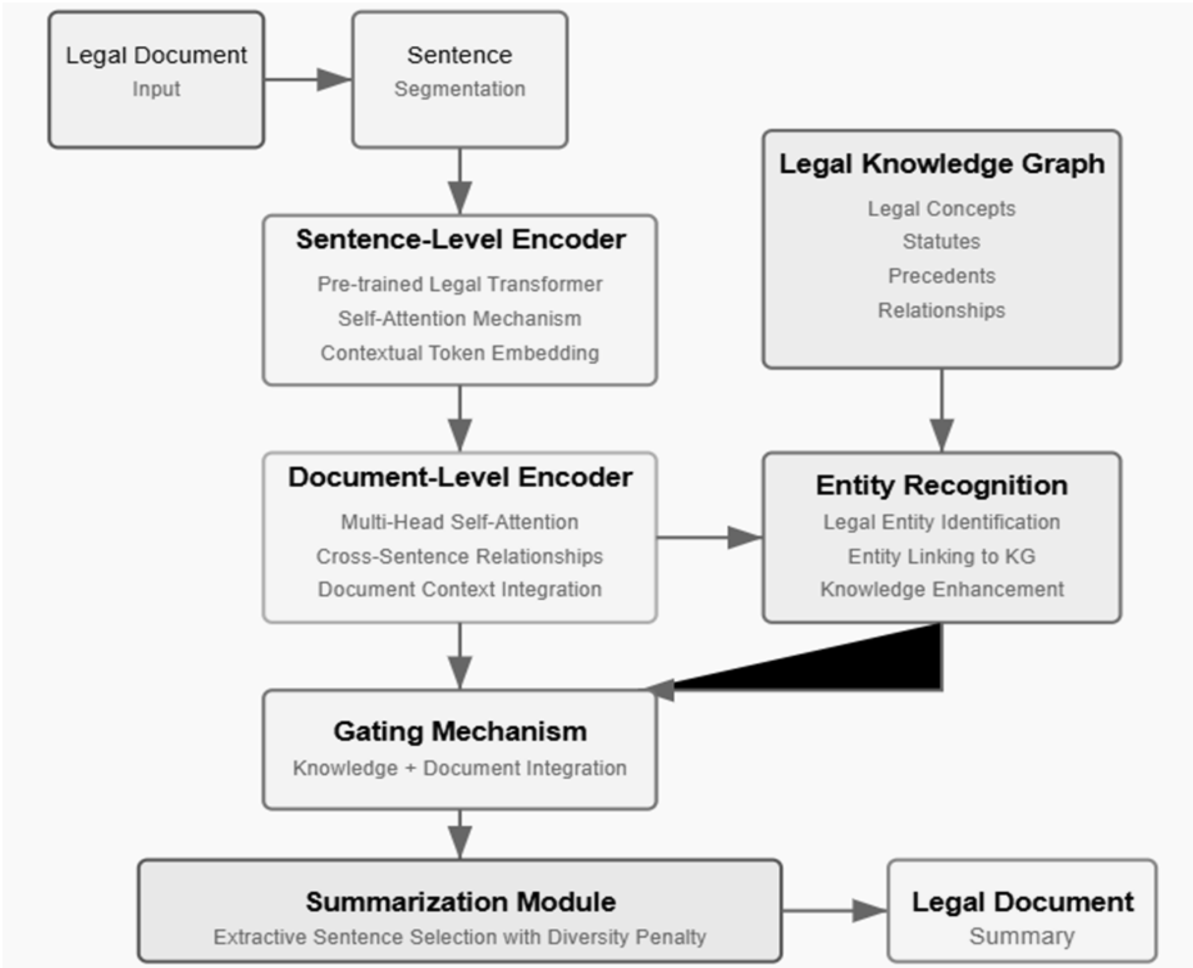

Figure 1: The overall design of the Hierarchical Transformer with Knowledge Graph Integration (HT-KGI) approach

representation (AMR), and the event topic information vector is extracted using GCN. Show that a weakly supervised sentence extractor can be trained with great accuracy using this auto-labeled data.

The integration of domain-specific information and hierarchical document processing for legal document summarization is still lacking, despite these developments. Our suggested HT-KGI approach, which is especially made for the difficulties of legal document summarization, attempts to close this gap by fusing the advantages of hierarchical transformer structures with legal knowledge graph integration.

3. HIERARCHICAL TRANSFORMER WITH KNOWLEDGE GRAPH INTEGRATION (HT-KGI) FOR LEGAL DOCUMENT SUMMARIZATION

By leveraging advanced graph-based algorithms and Transformer designs, the techniques employed in the concept of a HT-KGI approach framework for legal document summary aim to optimize extractive text summarization. In order to depict legal documents, words, phrases, and other significant elements are first incorporated into the text. The relationships between these components are then depicted in a sophisticated graph. Figure 1 displays HT-KGI's general configuration.

3.1. Hierarchical Transformer Encoding

Their concept enables interactions between nodes and organizes them into super-nodes. In a similar

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manner, Hierarchical Transformer Encoding builds intra-level and inter-level transformer blocks by combining multi-level graph information and using graph hierarchical structure. While the interlevel block adaptively combines all of the substructures that are present, the intra-level block enables the interchange and transformation of information within each node's local environment. Our concurrent work makes the attention, a key component of the transformer architecture, adaptable and suitable to current graph transformers by directly integrating hierarchy into it. Furthermore, Coarformer creates coarse views of the original graph using graph coarsening techniques, which are then fed into the transformer model.

3.1.1. Sentence-level encoding

Sentence-level encoding in legal documents creates numerical representations of individual phrases that capture the document's context and semantic meaning using Natural Language Processing (NLP) models, which are often Transformer-based. Sentence embeddings are obtained by tokenizing sentences and then passing them through a token-level encoder. After that, a sentence-level encoder receives these embeddings and considers the connections between sentences as well as where they are located in the document. The resultant sentence encodings can be used for automatic legal text summarization, categorizing rhetorical roles in court decisions, and even anticipating legal charges.

$$h_{i,j}=\text{SentenceEncoder}(t_{i,j}),\quad j=1,2,\ldots,m \qquad (1)$$

where i-th sentence, $h_{i,j}$ is the contextualized embedding of the j-th token. Use a self-attention technique over token embeddings to produce a fixed-length representation for every sentence:

$$\propto_{i,j}=\frac{\exp\,(W_a h_{i,j}+b_a)}{\sum_{k=1}^{m}\exp\,(W_a h_{i,k}+b_a)} \qquad (2)$$

$$s_i^{emb}=\sum_{j=1}^{m}\propto_{i,j}\,h_{i,j} \qquad (3)$$

where the final sentence embedding is s_i^{emb} the attention weight of the j-th token is $\propto_{i,j}$, and W_a and b_a are learnable parameters.

3.1.2. Document-level encoding

Formally, represent the source text with N sentences as $X = \{x_1, x_2, \ldots, x_N\}$ and the target document with M sentences as $Y = \{y_1, y_2, \ldots, y_M\}$. Assume that N = M since sentence alignment algorithms can be used to merge sentences in order to correct sentence incompatibilities. As a result, we can presume that (x_i, y_i) is a pair of parallel sentences.

Since x<i and y<i express the same information, y<i can be skipped. Consequently, the probability can be roughly expressed as:

$$P(Y|X)\sim\prod_{i=1}^{N}P(x_i|y_i; x<i;\ x>i) \quad (4)$$

where the document-level context utilized to translate y_i is (x<i; x>i), and x_i is the source phrase aligned to y_i.

Next, combine them into a single input by performing a concatenation operation:

$$e=[E(c);E(x)] \qquad (5)$$

where E is the word embedding matrix, S is the segment embedding matrix, and [;] indicates the concatenation operation. Lastly, we add e and s to the encoder's input.

the feed-forward layer to the current sentence's concatenated sequence of contexts:

$$h_1 = Transformer(E = s;\theta) \qquad (6)$$

where θ is the Transformer blocks' parameter. Each self-attention and feed-forward layer is solely applied to the current sentences' positions at the top of encoder blocks:

$$h_2 = Transformer(h_1[s,t];\theta) \quad (7)$$

Where, the source sentences' beginning and ending places in the concatenation sequence are denoted by the letters s and t. In this manner, the contexts function as additional semantics for the current sentences, allowing the attention to be directed more upon the current sentences. It is observed that there are no additional parameters beyond those of the normal Transformer. Figure 2 displays Two-Level Hierarchical Transformer Encoding Process

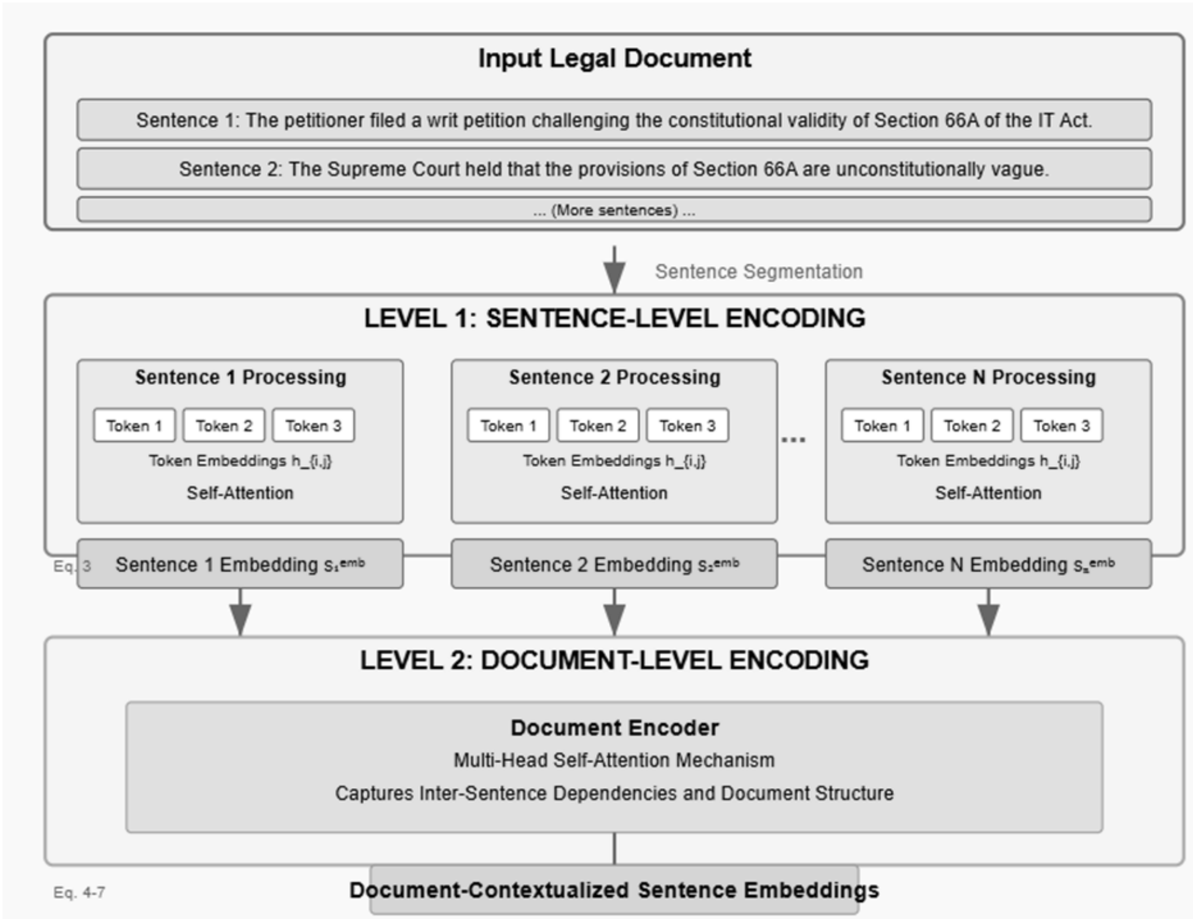

Figure 2: Two-Level Hierarchical Transformer Encoding Process

3.2. Knowledge Graph Integration

Because knowledge graphs can include data from several sources, RAG applications can make advantage of a variety of complementing knowledge bases. Responses that are more thorough and well-rounded may result from this knowledge integration. Figure 3 displays Knowledge Graph Integration and Entity Linking Process

3.2.1. Entity Recognition and Linking

First locate legal entities for every phrase $S_{i,}$ in the document and associate them with the appropriate knowledge graph nodes:

$$E_i = \text{EntityRecognition}(S_{i,}) \quad (8)$$

$$E_i^{linked} = EntityLinking(E_i, \text{G}) \quad (9)$$

where the linked entities in the knowledge graph are represented by E_i^{linked}, and the set of legal entities indicated in sentence $S_{i,}$ is represented by E_i.

3.2.2. Knowledge-Enhanced Representation

In order to enhance AI models' comprehension, reasoning, and performance on downstream tasks like drug recommendation, entity linking, and scientific discovery, knowledge-enhanced representations of data are enhanced by adding structured external knowledge, frequently from knowledge graphs. This method overcomes the drawbacks of single-modal approaches and produces more reliable and broadly applicable information representations by fusing the strength of symbolic knowledge with the adaptability of contemporary.

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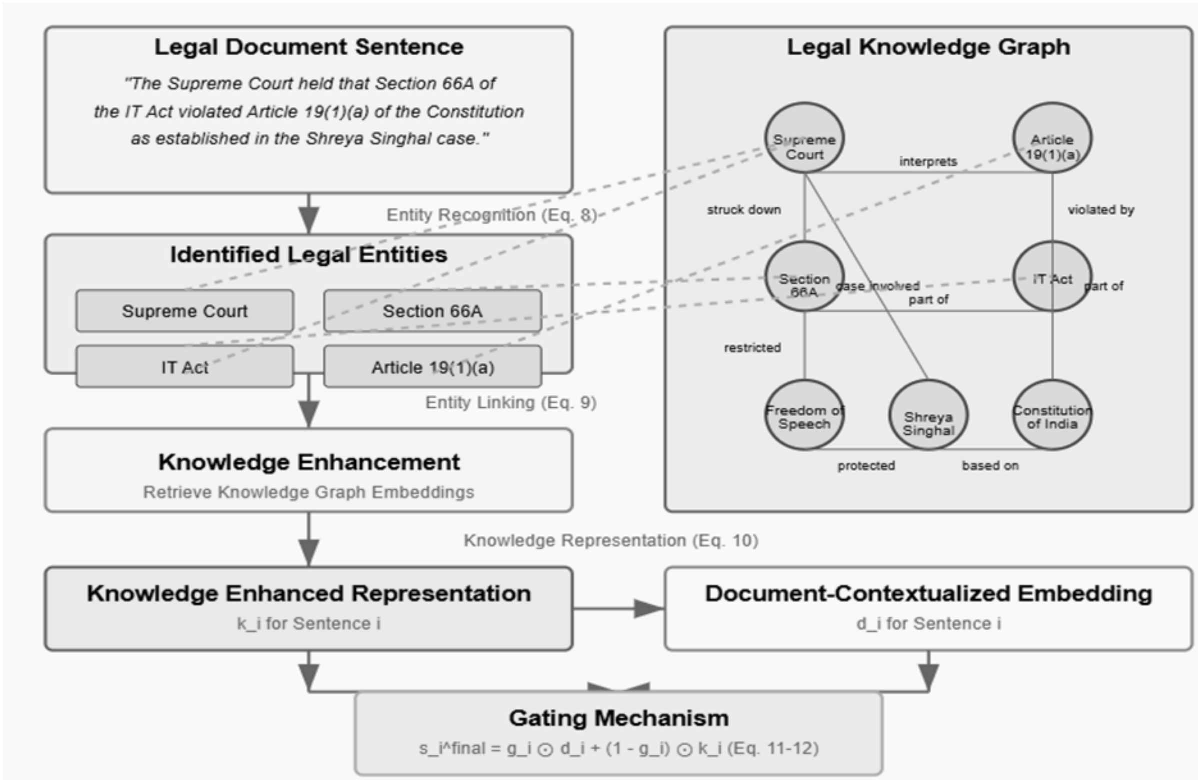

Figure 3: Knowledge Graph Integration and Entity Linking Process

$$K_i = \frac{1}{|E_i^{linked}|} \sum_{e \in E_i^{linked}} \left(e^{emb} + \frac{1}{|N(e)|} \sum_{n \in N(e)} n^{emb}\right) \quad (10)$$

where sentence S_i, K_i is the knowledge-enhanced representation, N(e) is the group of entities next to e in the knowledge diagram, and e^{emb} is the embedding of the entity.

The knowledge-enhanced representation is then combined with the document-contextualized sentence embedding through a gating mechanism:

$$g_i = \sigma(W_g\,[d_i\,;\,K_i] + b_g) \quad (11)$$

$$S_i^{final} = g_i \odot d_i + (1 - g_i) \odot K_i \quad (12)$$

Where $\odot$ stands for element-wise multiplication, σ is the sigmoid function, [;] indicates concatenation, and W_g and b_g are learnable parameters.

3.3. Summarization Module

A summary of the document in question appears to be quite beneficial when it is too lengthy to read in detail or when the user is in a hurry and wants a brief rundown of its contents. Thus, summarizing a single document is a significant study topic. Traditional methods for extractive summarization focus on identifying the key content at the sentence level. To choose key sentences from a manuscript, a variety of strategies have been used.

That assume that we have an abstractive summary S = {Si} s i=1 with s sentences and a document D = {Di} d i=1 with d sentences. A Summarization Program P = {Ti} s i=1 is a (ordered) list of s binary trees, where each tree Ti = (Vi, Ei) is an organized representation of the generating process of each summary sentence Si ∈ S. In each tree, the collection of nodes Vi consists of single sentences, while the edges Ei are labeled according to one of the neural components m ∈ {paraphrase(•), compression (•), and fusion(•, •)}. These modules offer operations over phrases: compression (X) → Y and paraphrase (X) → Y are unary operations, while fusion (X, Y) → Z is a binary action. The leaf nodes of each tree are words from the document Di ∈ D, while the root of each tree is a summary phrase Si ∈ S. Everyone When a node u ∈ Vi has an edge from a node v ∈ Vi labeled with the module m, it means that m is run on u in order to produce v. The trees' root nodes are concatenated in order to get the summary S. We postulate that by building distinct brain modules that function over sentences, it is possible to capture the creative process of each summary sentence.

4. EXPERIMENTAL SETUP

The dataset, implementation specifics, assessment metrics, and baseline techniques utilized to assess the effectiveness of the suggested HT-KGI approach are all covered in this section.

4.1. Dataset

The dataset of Indian Supreme Court verdicts, which includes 45,000 case files with rulings taken from the government website API, was the subject of our experiments. Four different case types civil, criminal, sales tax, and service are covered in the dataset, which spans the years 1950–2022.

4.2. Knowledge Graph Construction

Compiled information from statutes, case law databases, and legal dictionaries to create a legal knowledge graph. The knowledge graph, which covers legal concepts, statutes, precedents, and their relationships, has over 150,000 entities and 500,000 relationships. The entities and relationships were extracted using a combination of rule-based approaches and supervised machine learning models trained on annotated legal texts.

4.3. Implementation Details

PyTorch was used to implement the HT-KGI model. We used our legal corpus to refine a pre-trained LegalBERT model for the sentence-level encoder. A six-layer transformer with eight attention heads and a hidden dimension of 768 makes up the document-level encoder. TransE with a size of 200 was used to learn the knowledge graph embeddings. The Adam optimizer was used to train the model with a batch size of four documents and a learning rate of 5e-5.

4.4. Evaluation Metrics

We used the following measures to assess the HT-KGI method's performance:

1. **ROUGE Scores**: For instance, ROUGE-2 looks at word pairs or bigrams, while ROUGE-1 looks at single words or unigrams, and so on. ROUGE-L also looks at the longest shared subsequence between the reference summaries produced by humans and machines.
2. **Semantic Coherence (SC)**: The capacity to use a story's or sentence's larger context as well as the semantic relationships between words to help comprehend and interpret written and spoken language.
3. **Legal Accuracy (LA)**: The need for a party's facts, information, claims, or representations to be accurate, full, and truthful..
4. **Computational Efficiency**: A system uses time, memory, and energy to accomplish tasks with the goals of cost-effectiveness, faster execution, and reduced consumption.

4.5. Baseline Methods

We compared the HT-KGI method with the following baseline methods:

1. **Text Rank**: As an The TextRank algorithm, a graph-based ranking system for extractive and single-document text summarization, was modeled after the PageRank algorithm.
2. **LexRank**: According to the LexRank algorithm, a sentence has a high likelihood of being significant if it is comparable to many other sentences in the text.
3. **BERT-Extractive**: BERT is a neural-network-based pre-training method for language processing. It can assist in determining the meaning of words in search queries.
4. **LegalBERT-Extractive**: A family of BERT-based language models specifically tailored for the legal field is called LEGAL-BERT.
5. **Hierarchical Transformer (HT)**: With the use of hierarchical transformers, the model may function on many input levels, such as words, phrases, paragraphs, etc.
6. **BART-Legal**: A fine-tuned BART model for legal document summarization.
7. **LegalGPT**: In contrast to a common or everyday understanding, a "legal" definition is a meaning of a word that is

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explicitly established, formally acknowledged, or recognized by law.

5. RESULTS AND DISCUSSION

This part presents the experimental results and provides a detailed assessment of the performance of the proposed HT-KGI approach compared to the baseline methods.

5.1. Summarization Performance

On the Indian Supreme Court Judgments dataset, Table 1 displays the ROUGE scores, semantic coherence, and legal accuracy of the HT-KGI approach and the baseline methods.

Table 1. Comparative analysis of summarization performance

Method	**ROUGE-1**	**ROUGE-2**	**ROUGE-L**	**SC**	**LA**
TextRank	35.6	15.2	31.8	0.67	2.8
LexRank	37.2	16.5	33.1	0.69	3.0
BERT-Extractive	42.5	19.3	38.7	0.74	3.5
LegalBERT-Extractive	45.8	21.6	41.2	0.78	3.7
Hierarchical Transformer	49.3	23.5	44.1	0.82	3.9
BART-Legal	47.6	22.8	43.0	0.80	3.8
LegalGPT	48.9	23.2	43.8	0.81	4.0
HT-KGI (Proposed)	53.7	26.9	47.9	0.89	4.5

As shown in Table 1, the proposed HT-KGI method outperforms all baseline methods across all metrics. Compared to the Hierarchical Transformer method, which does not incorporate knowledge graph information, HT-KGI achieves improvements of 4.4%, 3.4%, and 3.8% in ROUGE-1, ROUGE-2, and ROUGE-L scores, respectively.

5.2. Effect of Document Length

To evaluate the effectiveness of the hierarchical architecture in handling long documents, we analyzed the performance of different methods as a function of document length. Figure 4 shows the ROUGE-1 scores for documents of different lengths.

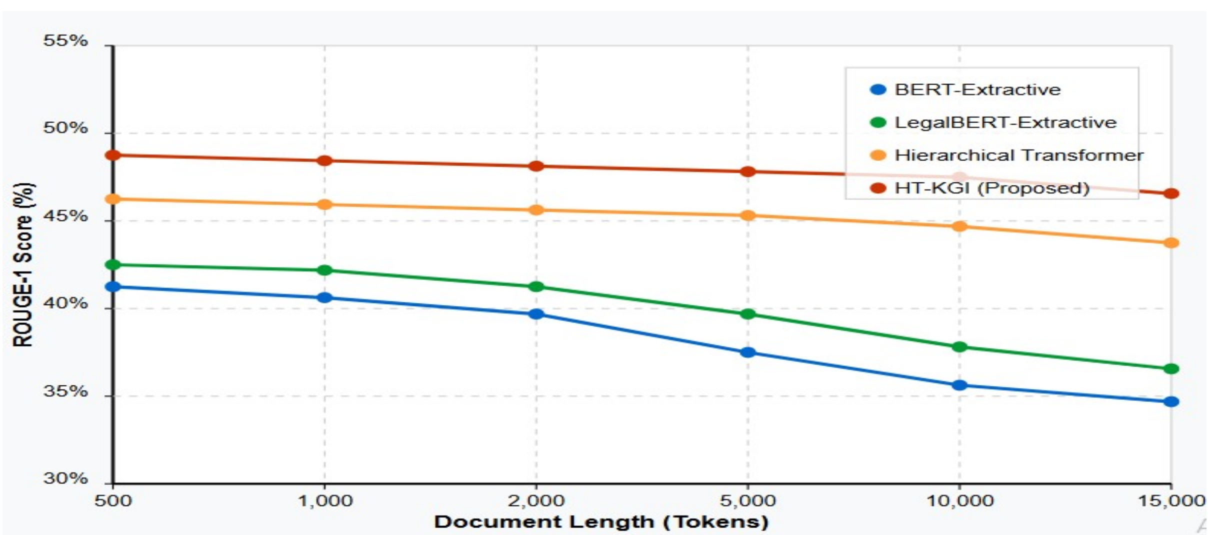

Figure 4: ROUGE-1 Scores for Different Methods across Document Lengths

Non-hierarchical approaches (BERT-Extractive and LegalBERT-Extractive) perform much worse as document length increases, especially for manuscripts with more than 2,000 tokens, as the figure shows. On the other hand, the hierarchical techniques (HT-KGI and Hierarchical Transformer) continue to perform reasonably consistently over a range of document lengths. This illustrates how well the hierarchical design manages lengthy texts by processing them at various granularities.

5.3. Computational Efficiency

Table 2 presents the computational requirements of different methods in terms of processing time and memory usage for summarizing documents of average length (approximately 5,000 tokens).

Table 2. Comparative analysis of computational efficiency

Method	Processing Time (seconds)	Memory Usage (GB)
TextRank	2.3	0.5
LexRank	2.5	0.6
BERT-Extractive	15.7	2.8
LegalBERT-Extractive	16.2	2.9
Hierarchical Transformer	9.8	2.1
BART-Legal	18.5	3.2
LegalGPT	19.3	3.5
HT-KGI (Proposed)	12.3	2.5

While the traditional graph-based methods (TextRank and LexRank) are computationally efficient, they achieve significantly lower summarization performance compared to neural models. Among the neural models, the hierarchical methods (Hierarchical Transformer and HT-KGI) are more efficient than their non-hierarchical counterparts (BERT-Extractive and LegalBERT-Extractive) in terms of processing time, as they process documents at different levels of granularity rather than as a flat sequence of tokens.

The HT-KGI method requires slightly more computational resources than the Hierarchical Transformer method due to the additional knowledge graph integration component.

5.4. Ablation Study

Table 3 presents the results of the ablation study.

Table 3. Ablation study of the HT-KGI method

Method	ROUGE-1	ROUGE-2	ROUGE-L	SC	LA
HT-KGI (Full)	53.7	26.9	47.9	0.89	4.5
HT-KGI w/o Entity Recognition	51.2	25.1	45.8	0.85	4.2
HT-KGI w/o Knowledge Integration	49.8	24.0	44.5	0.83	4.0
HT-KGI w/o Sentence Attention	50.3	24.6	45.0	0.84	4.1
HT-KGI w/o Document Encoder	46.9	22.3	42.3	0.79	3.8
HT-KGI w/o Diversity Penalty	52.5	26.1	46.8	0.86	4.3

The knowledge integration and document encoder components have contributed to the overall performance and have greater influence than the entity recognition component, sentence attention method, and diversity penalty. This indicates that the two core components of the HT-KGI methodology allows it to precisely summarize complex legal documents. Figure 5 gives the contribution of Different Components to Overall Performance

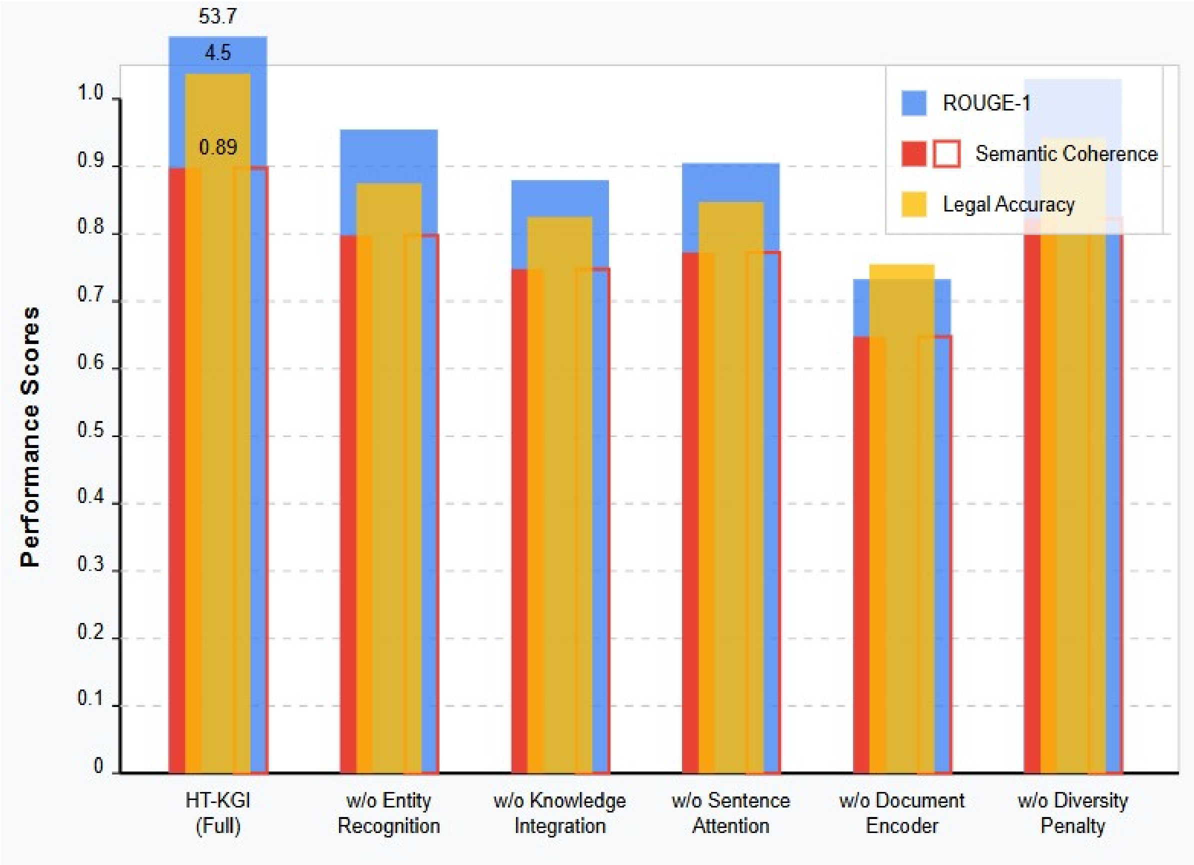

Figure 5: Contribution of Different Components to Overall Performance

6. CONCLUSION

In this research, we proposed HT-KGI as a way to summarize complex legal documents by combining a hierarchical transformer with knowledge-graph integration. The hierarchical design facilitates the system to scrutinize the lengthy document into different layers of depiction and at the same time the knowledge graph provides domain-specific legal text that boost the context. Experimental evaluation on Indian supreme court judgements dataset confirms that HT-KGI achieve superior outcomes compared to the baseline models in Rouge, semantic coherence and legal accuracy. Its ability to scale across documents of different lengths, together with its improved understanding of legal concepts and their relations, leads to summaries that are both precise and semantically consistent.

Future studies will focus on expanding the methodology to abstractive summarization, exploring more sophisticated knowledge integration strategies, and applying the HT-KGI method to other sectors with complex, specialized content. Plan to look into the interpretability of the model's choices as well in order to explain why certain lines were included in the summary. This is especially significant in the legal sector, where openness is essential.

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