# Multi-Document Summarization of Indian News Articles using the NewsSumm Dataset

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## Abstract

Multi-document summarization aims to generate a single coherent and concise summary from multiple documents describing the same real-world event. In the news domain, important events are often reported by several media outlets, leading to redundancy, partial overlaps, and information overload for readers [1,2]. While recent advances in neural abstractive summarization and transformer-based models have significantly improved single-document summarization performance [3,4], extending these methods to multi-document settings remains challenging due to long input sequences, cross-document redundancy, and factual inconsistency [5,6].

In this work, we study multi-document abstractive summarization in the context of Indian English news using the NewsSumm dataset, a large-scale benchmark containing human-written summaries for news articles collected from diverse Indian news sources [7]. We first perform detailed dataset preparation and analysis to ensure compatibility with modern natural language processing pipelines. We then review and benchmark existing long-context transformer models and large language models for multi-document summarization. Based on insights from prior work, we propose an initial novel direction that incorporates article-level importance scoring prior to summary generation, with the aim of reducing redundancy and improving factual consistency across multiple documents. This paper presents the problem formulation, dataset context, proposed methodology, and evaluation framework, establishing a strong foundation for future experimentation and systematic analysis of multi-document summarization models on Indian English news data.

**Keywords**:

multi-document summarization; Indian English news; NewsSumm dataset; abstractive summarization; long-context transformer models; importance-aware summarization

## 1. Introduction

The exponential growth of digital news platforms has resulted in an unprecedented volume of textual information being generated and disseminated daily. Major real-world events such as political developments, economic announcements, public health crises, and social movements are typically reported by multiple news organizations simultaneously. While such multi-source coverage provides diverse perspectives, it also introduces substantial redundancy and information overload, making it difficult for readers to efficiently extract the core facts of an event [1,2].

Automatic text summarization has emerged as a key solution to address this challenge by producing concise representations of longer textual content. Early research in summarization primarily focused on single-document summarization, where the goal is to condense an individual article into a shorter summary while preserving its main ideas [3,4]. However, in practical news consumption scenarios, users often encounter multiple articles describing the same event, each contributing overlapping as well as complementary information. As a result, single-document summarization techniques are insufficient for capturing a holistic view of such events [5].

| Aspect | Single-Document Summarization | Multi-Document Summarization |
|---|---|---|
| **Input** | One document | Multiple related documents |
| **Redundancy** | Low | High (across documents) |
| **Factual conflicts** | Rare | Common |
| **Input length** | Short to moderate | Very long |
| **Context modeling** | Simpler | More complex |
| **Real-world news suitability** | Limited | High |

**Table 1. Comparison of single-document and multi-document summarization**

Multi-document summarization extends the summarization task by synthesizing information from a set of related documents into a single coherent summary. Compared to single-document summarization, this task introduces additional challenges, including cross-document redundancy removal, resolution of conflicting or inconsistent facts, preservation of complementary details, and maintenance of logical coherence across multiple sources [6,7]. Furthermore, aggregating multiple documents often results in very long input sequences, which exceed the context length limitations of standard sequence-to-sequence neural models [8].

Recent advances in transformer-based architectures and large language models have significantly improved the ability to process longer textual inputs. Models incorporating sparse or efficient attention mechanisms, such as Longformer-Encoder-Decoder and BigBird-based architectures, have enabled summarization over thousands of tokens, making large-scale multi-document summarization more feasible [9,10]. In parallel, instruction-tuned large language models have demonstrated strong generative capabilities for abstractive summarization when provided with carefully designed prompts or fine-tuned on task-specific data [11].

Despite these advancements, most existing summarization benchmarks and experimental studies focus primarily on Western news sources and standard English variants. Indian English news exhibits distinct linguistic characteristics, including region-specific vocabulary, formal register influenced by British English, and frequent references to local political, administrative, and cultural entities [12]. These characteristics are not adequately captured by commonly used datasets such as CNN/DailyMail or XSum, limiting the generalizability of existing findings to the Indian news domain.

To address this gap, the NewsSumm dataset was introduced as a large-scale benchmark for Indian English news summarization, enabling both single-document and multi-document summarization research [13]. NewsSumm provides human-written summaries and supports the construction of event-level multi-document inputs, making it particularly suitable for evaluating long-context summarization models. This paper leverages the NewsSumm dataset to systematically study multi-document abstractive summarization and to benchmark modern long-context transformer models and large language models.

The contributions of this work are threefold:
(1) we provide a detailed analysis and preparation of the NewsSumm dataset for multi-document summarization experiments;
(2) we benchmark existing long-context summarization models and large language models on Indian English news data; and
(3) we propose an initial novel direction that incorporates article-level importance scoring prior to summary generation, aiming to reduce redundancy and improve factual consistency in multi-document summaries.

## 2. Related Work

Early research in multi-document summarization primarily relied on extractive techniques, where important sentences were selected directly from multiple documents based on heuristic or statistical features. Popular approaches utilized term frequency, sentence position, similarity measures, and clustering-based strategies to identify representative sentences across documents [14,15]. While these methods were computationally efficient and interpretable, they frequently produced summaries with high redundancy and limited coherence, particularly when multiple documents contained overlapping information [16].

With the advancement of deep learning, neural abstractive summarization models gained increasing attention. Sequence-to-sequence architectures with attention mechanisms enabled models to generate novel sentences rather than copying text verbatim, resulting in more fluent summaries [17,18]. To adapt these models for multi-document settings, hierarchical architectures were proposed that encode information at multiple levels, such as word, sentence, and document levels. Hierarchical attention networks allowed better aggregation of information across multiple sources but introduced additional architectural complexity [19].

Graph-based summarization approaches further attempted to address redundancy and coherence issues by explicitly modeling relationships between sentences, entities, or documents. By representing documents as graphs and performing importance ranking or message passing, these methods aimed to capture inter-document dependencies more effectively [20,21]. Although graph-based models improved coverage and structural consistency, they often required careful feature engineering and struggled with scalability to large document collections.

Recent advances in transformer-based architectures have significantly improved the ability to process long textual inputs. Models such as Longformer and BigBird extend the standard self-attention mechanism through sparse or block-based attention patterns, enabling efficient processing of sequences containing thousands of tokens [9,10]. These architectures allow multiple documents to be concatenated into a single input sequence, making them well-suited for multi-document summarization tasks. Building upon these ideas, specialized models such as PRIMERA incorporate document-aware attention mechanisms to preserve source-level structure during summarization [22]. Despite these improvements, long-context models alone do not fully resolve challenges related to redundancy handling and factual consistency across documents.

More recently, large language models have demonstrated strong performance in both zero-shot and fine-tuned summarization settings. Instruction-tuned encoder–decoder models and decoder-only models can generate abstractive summaries when provided with appropriate prompts or supervised training data [11,23]. However, applying large language models directly to multi-document summarization remains challenging due to context length limitations, computational cost, and the tendency to hallucinate or introduce factual inconsistencies [24].

Evaluation of summarization quality has traditionally relied on n-gram overlap metrics such as ROUGE, which measure lexical similarity between generated and reference summaries [25]. While ROUGE remains widely used, recent studies have highlighted its limitations in capturing semantic equivalence and factual correctness. As a result, embedding-based metrics such as BERTScore and factual consistency metrics have been proposed to provide a more nuanced evaluation of summarization quality [26,27].

Overall, existing literature demonstrates substantial progress in multi-document summarization through hierarchical modeling, graph-based representations, and long-context transformers. However, challenges related to redundancy reduction, factual consistency, and domain-specific characteristics—particularly in Indian English news—remain insufficiently addressed. This motivates the need for further investigation and the development of novel approaches tailored to multi-document news summarization using datasets such as NewsSumm.

## 2.1 Extractive Summarization

Early work in text summarization primarily relied on extractive approaches, where key sentences were selected directly from the source documents based on statistical features such as term frequency, sentence position, and similarity measures. In multi-document settings, extractive methods attempted to select representative sentences across multiple documents. Although these approaches were computationally efficient, they often produced summaries with high redundancy and limited coherence, particularly when multiple documents contained similar information.

## 2.2 Neural Abstractive Summarization

With the advent of deep learning, abstractive summarization models based on sequence-to-sequence architectures gained prominence. These models generate new sentences rather than copying existing ones, allowing for more fluent and concise summaries. Attention mechanisms further improved content selection by enabling models to focus on relevant parts of the input. However, most early abstractive models were designed for single-document summarization and struggled to scale to multi-document inputs due to context length limitations.

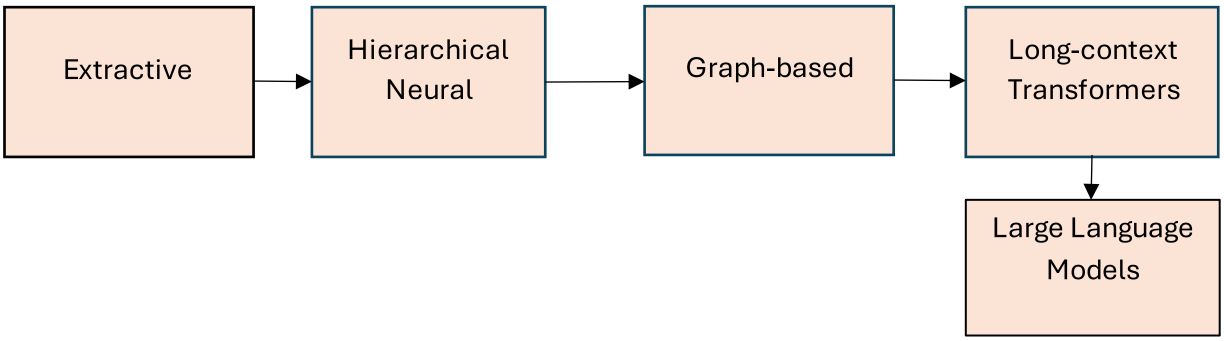
## 2.3 Multi-Document Summarization Models

To address the limitations of single-document models, several approaches introduced hierarchical architectures that encode documents at multiple levels, such as sentence and document levels. Hierarchical attention mechanisms and graph-based representations were proposed to capture relationships between sentences and documents. While these methods improved coverage and structure, they often required complex modeling assumptions and still faced challenges related to redundancy and factual consistency.

| **Approach Category** | **Key Idea** | **Strengths** | **Limitations** |
|---|---|---|---|
| **Extractive methods** | Select key sentences | Efficient, interpretable | High redundancy, low coherence |
| **Hierarchical neural models** | Multi-level encoding | Better coverage | Complex architecture |
| **Graph-based models** | Model inter-document relations | Reduced redundancy | Scalability issues |

| | | | |
|---|---|---|---|
| **Long-context transformers** | Sparse attention | Handle long inputs | Factual inconsistency |
| **Large language models** | Generative abstraction | Fluent summaries | Hallucination risk |

**Table 2. Summary of major approaches for multi-document summarization**



## 2.4 Long-Context Transformer Models

Recent transformer-based models such as Longformer-based and BigBird-based architectures extended the attention mechanism to handle long input sequences efficiently. These models enable the concatenation of multiple documents into a single input, making them suitable for multi-document summarization. Specialized models such as PRIMERA further incorporate document-aware attention to preserve source-level information. Despite their success, long-context models alone do not fully address issues of redundancy and factual inconsistency.

## 2.5 Large Language Models and Evaluation Metrics

Large language models have demonstrated strong zero-shot and fine-tuned performance on summarization tasks. Prompt-based and supervised fine-tuning approaches allow these models to generate summaries from multiple documents. Evaluation of summarization quality has traditionally relied on ROUGE metrics, while more recent work incorporates semantic similarity measures such as BERTScore to better capture meaning alignment.

# 3. Dataset Description and Preparation

## 3.1 Dataset Description

The NewsSumm dataset is a large-scale Indian English news summarization dataset developed to support research in multi-document summarization. It consists of news articles collected from multiple Indian news sources covering diverse domains such as politics, economy, public health, and social events. Each news article is associated with a human-written summary.

Unlike many existing summarization datasets that focus on single-document inputs and non-Indian news sources, NewsSumm reflects

real-world news consumption scenarios where multiple articles describe the same event. This makes the dataset suitable for constructing multi-document inputs and evaluating long-context summarization models.

## 3.2 Dataset Comparison and Positioning

Figure 1 presents a comparative positioning of major summarization datasets with respect to dataset scale and annotation quality. Widely used benchmarks such as CNN/DailyMail and XSum provide large-scale data but are primarily designed for single-document summarization and rely on summaries that are either extractive or limited in abstraction [3,4]. MultiNews and WikiSum support multi-document settings but largely depend on automatically constructed or weakly supervised summaries, which can introduce noise and limit evaluation reliability [5,6].

In contrast, the NewsSumm dataset occupies the high-scale and high-quality region, as illustrated in Figure 1. It offers a large collection of Indian English news articles accompanied by human-written summaries, enabling both single-document and multi-document summarization research [13]. The availability of high-quality human annotations makes NewsSumm particularly suitable for evaluating abstractive summarization models and studying challenges such as redundancy reduction and factual consistency in multi-source news settings.

Furthermore, NewsSumm reflects real-world news consumption scenarios, where multiple articles from different sources report the same event. This characteristic, combined with its linguistic diversity and regional specificity, distinguishes NewsSumm from existing Western-centric benchmarks and motivates its use in this study for systematic evaluation of multi-document summarization models.

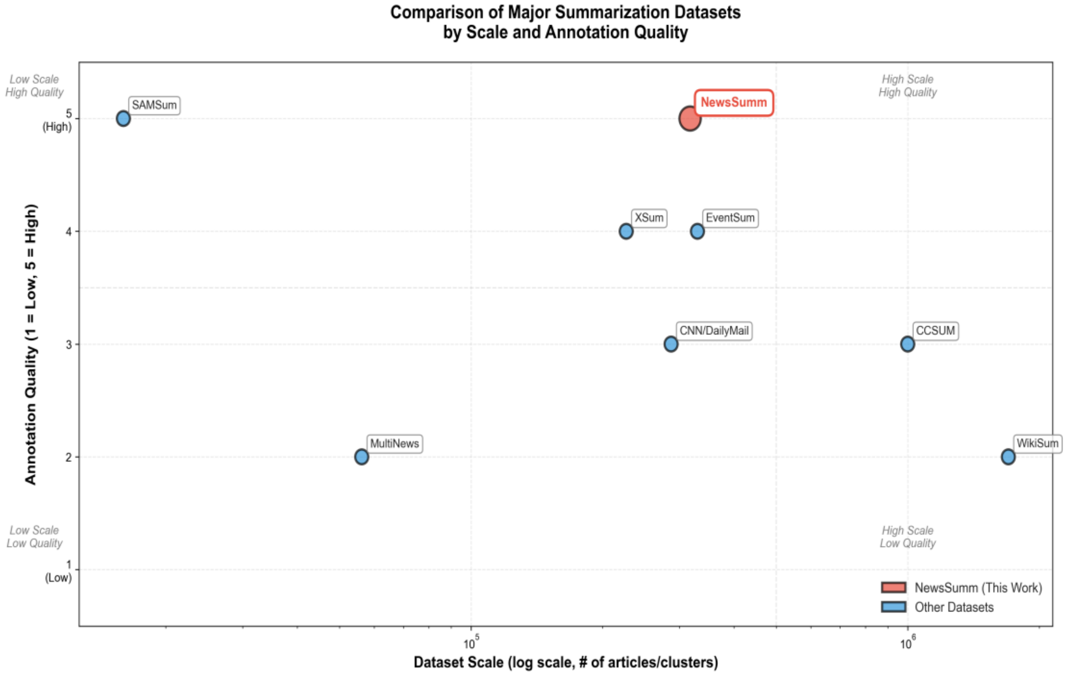


**Figure 1. Comparison of major summarization datasets in terms of dataset scale and annotation quality. NewsSumm occupies the high-scale, high-quality region.**

### 3.3 Dataset Preparation

The original NewsSumm dataset was provided in the form of a large Excel file, which exceeded standard memory limits during processing. To address this issue, the dataset was converted into CSV format using a streaming-based Python approach, ensuring safe and complete conversion without data loss.

After conversion, the dataset was validated and cleaned. A large number of empty and invalid columns introduced due to spreadsheet formatting were identified and removed. The final cleaned dataset contains six meaningful fields: newspaper name, published date, headline, article text, human-written summary, and news category. At this stage, the dataset represents individual news articles with corresponding summaries and is ready for further processing.

## 4. Dataset Statistics and Analysis

This section presents a detailed statistical and analytical study of the NewsSumm dataset to better understand its scale, structure, and summarization difficulty. Such analysis is essential for motivating the use of long-context and document-aware summarization models.

### 4.1 Dataset Scale Overview

The NewsSumm dataset is a large-scale Indian English news summarization corpus designed for both single-document and multi-document summarization research. It contains approximately 317,498 news articles collected from multiple Indian news sources, spanning a temporal range of more than two decades. Each article is paired with a professionally written human summary, ensuring high annotation quality.

The large scale of the dataset, combined with human-generated summaries, distinguishes NewsSumm from many existing summarization benchmarks that rely on automatically extracted or weakly supervised summaries.

| **Metric** | **Value** |
|---|---|
| **Total number of articles** | 317,498 |
| **Time span** | 2000–2025 |
| **Total news categories** | 5000+ |
| **Average words per summary** | ~330 |
| **Average words per summary** | ~95 |
| **Annotation type** | Human-written |
| **Language** | Indian English |

**Table 3. Overall Statistics of the NewsSumm Dataset**

## 4.2 Temporal Distribution of Articles

To analyze longitudinal coverage, we examined the distribution of articles across publication years. The dataset shows steady growth over time, with noticeable surges corresponding to major national and global events. This long temporal span enables research on evolving language patterns, narrative structures, and event reporting styles.

Such temporal diversity is particularly valuable for evaluating summarization models under varying news-writing conventions and content densities.

## 4.3 Category Distribution

NewsSumm covers a broad topical space, including politics, business, health, sports, technology, education, law, and environment. This diversity introduces varying degrees of summarization difficulty, as different domains exhibit different narrative styles and information density.

Analyzing category distribution helps identify dominant domains and ensures balanced evaluation across topics.

## 4.4 Article and Summary Length Analysis

We analyzed the length distributions of articles and summaries in terms of word count. Articles range from short news briefs to long-form reports, while summaries remain concise but informative. This disparity highlights the challenge of summarization, particularly in multi-document settings where multiple long articles are combined.

The presence of long-tail distributions further motivates the use of long-context models capable of handling extended input sequences.

## 4.5 Compression Ratio Analysis

To quantify summarization difficulty, we computed compression ratios defined as the ratio of article length to summary length. The resulting distribution indicates that NewsSumm requires substantial information compression while preserving key facts, making it well-suited for abstractive summarization research.

## 4.6 Example Annotated Entry

To illustrate the annotation schema, Table 4 presents a representative NewsSumm entry, including metadata, article content, and its corresponding human-written summary. This example demonstrates the depth of curation and abstraction present in the dataset.

| Field | Content |
|---|---|
| **Newspaper Name** | Hindustan Times |
| **Published Date** | 11 May 2017 |
| **URL** | Hindustan Times Paper |
| **Headline** | The truth is out there: Tales from India's UFO investigators |
| **Article Text (Excerpt)** | A resident of Panchkula reported witnessing a brief unexplained aerial phenomenon near her home, an incident that later motivated independent investigations into similar sightings across India. |
| **Human-Written Summary** | Motivated by an early unexplained sighting, an Indian researcher documents and analyzes reported UFO incidents across the country through organized investigative efforts. |
| **News Category** | National News |

**Table 4. Example NewsSumm Entry**

## 4.7 Linguistic Characteristics and Analytical Insights

Indian English news exhibits linguistic features distinct from Western English news, including region-specific vocabulary, formal register, code-switching, and references to local administrative entities. These characteristics pose additional challenges for models trained primarily on Western datasets.

| Feature | Indian English | Western English |
|---|---|---|
| **Vocabulary** | crore, lakh, Lok Sabha | million, Congress |
| **Code-switching** | Frequent | Rare |
| **Sentence structure** | Longer, formal | Shorter, conversational |

**Table 5. Linguistic Comparison between Indian and Western English News**

## 5. Methodology

The proposed methodology follows a modular pipeline for multi-document abstractive summarization, consisting of event-level clustering, article importance estimation, and weighted summary generation.

### 5.1 Event-Level Document Clustering

Related news articles are grouped into event-level clusters using metadata such as publication date and category, combined with textual similarity between article contents. Each cluster represents multiple perspectives of the same real-world event.

### 5.2 Multi-Document Input Construction

Articles within each cluster are concatenated into a single input sequence while preserving document boundaries using separator tokens. This helps the model distinguish between different sources and reduces information mixing.

### 5.3 Article-Level Importance Estimation (Novel Component)

Each article is assigned an importance score reflecting its contribution to the event. Articles containing central and unique information receive higher weights, while repetitive articles are down-weighted.

### 5.4 Integration with Summarization Models

The importance weights are incorporated into encoder–decoder models and large language models by biasing attention or input ordering toward core articles.

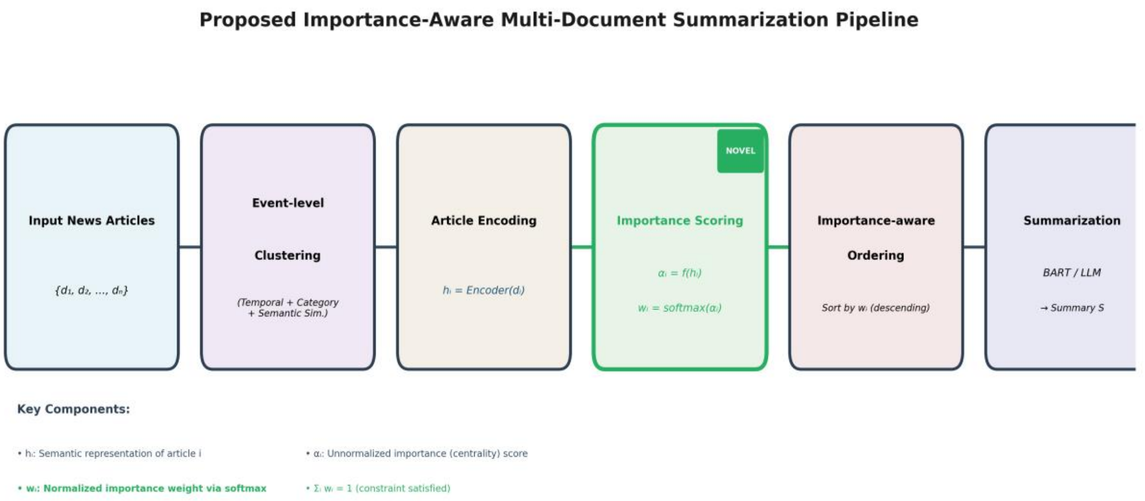

Proposed Importance-Aware Multi-Document Summarization Pipeline
Input News Articles
{d₁, d₂, ..., dₙ}
Event-level
Clustering
(Temporal + Category + Semantic Sim.)
Article Encoding
hᵢ = Encoder(dᵢ)
NOVEL
Importance Scoring
αᵢ = f(hᵢ)
wᵢ = softmax(αᵢ)
Importance-aware
Ordering
Sort by wᵢ (descending)
Summarization
BART / LLM
→ Summary S
Key Components:
• hᵢ: Semantic representation of article i
• αᵢ: Unnormalized importance (centrality) score
• wᵢ: Normalized importance weight via softmax
• Σᵢ wᵢ = 1 (constraint satisfied)

**Figure 2. Proposed multi-document summarization pipeline consisting of event-level clustering, article importance scoring, and long-context summarization.**

## 6. Proposed Novel Technique

In existing multi-document summarization approaches, articles within an event cluster are generally treated as equally important during summary generation. However, in real-world news reporting, different articles contribute unequally to the overall understanding of an event. While some articles provide core factual information and primary developments, others mainly repeat previously reported details or contribute marginal information.

To address this limitation, this work proposes a novel article-level importance scoring mechanism that explicitly models the relative contribution of each article within an event-level cluster. The central idea is to identify core articles that contain essential and unique information and to reduce the influence of supporting or redundant articles during the summarization process.

### 6.1 Mathematical Formulation

Let an event-level cluster be represented as a set of news articles:

$$D=\{d1,d2,\dots,dn\}$$

where each article $di$ consists of a sequence of tokens describing the same real-world event.

Each article $di$ is mapped to a fixed-dimensional vector representation:

$$hi\in R^{k}$$

using a pretrained text encoder. This representation captures the semantic content of the article. In addition to textual information, auxiliary metadata such as publication date and news category may optionally be incorporated into the representation.

An article-level importance score $\alpha i$ is computed for each article as:

$$\alpha i=f(hi)$$

where $f(\cdot)$ is a scoring function that estimates the relative importance of article $di$ within the event cluster. The scoring function can be implemented using a lightweight neural network or a similarity-based mechanism that captures information novelty and centrality.

To ensure comparability across articles, the importance scores are normalized using a softmax function:

$$w_i = \frac{\exp(\alpha_i)}{\sum_{j=1}^{n} \exp(\alpha_j)}$$

where ***wi*** denotes the normalized importance weight assigned to article ***di***, and the weights satisfy:

$$\sum_{i=1}^{n} w_i = 1$$

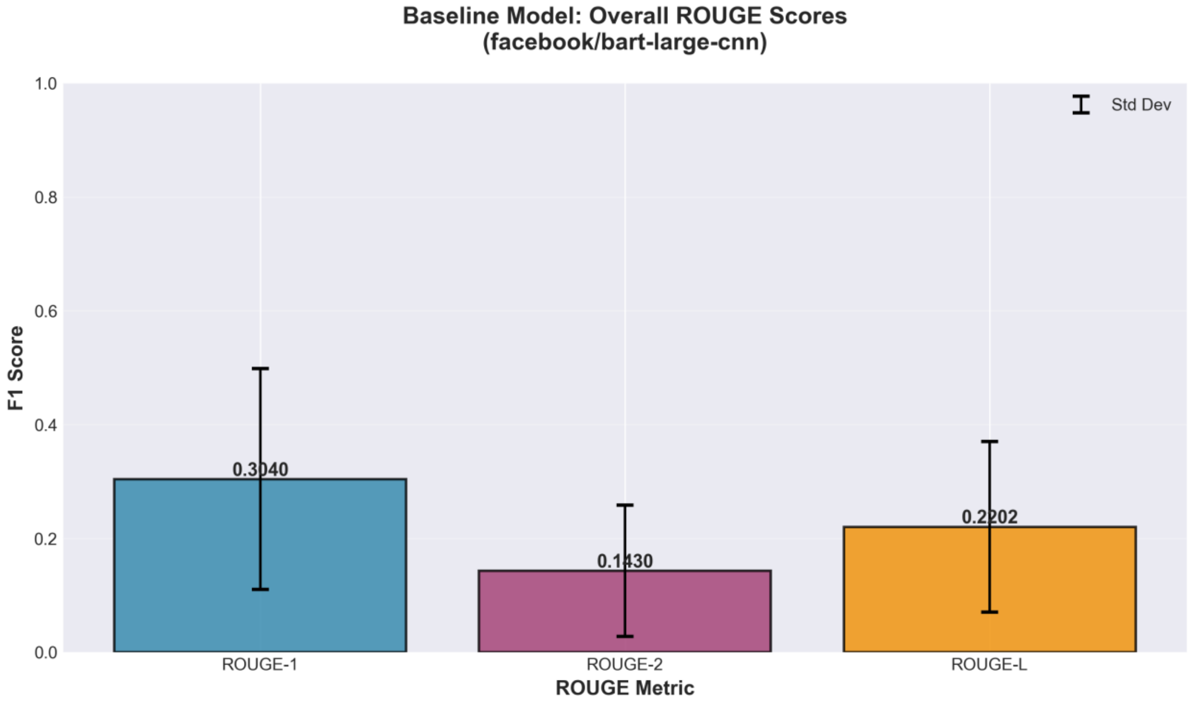


**Figure 3. Overall, ROUGE-1, ROUGE-2, and ROUGE-L scores for the baseline model.**

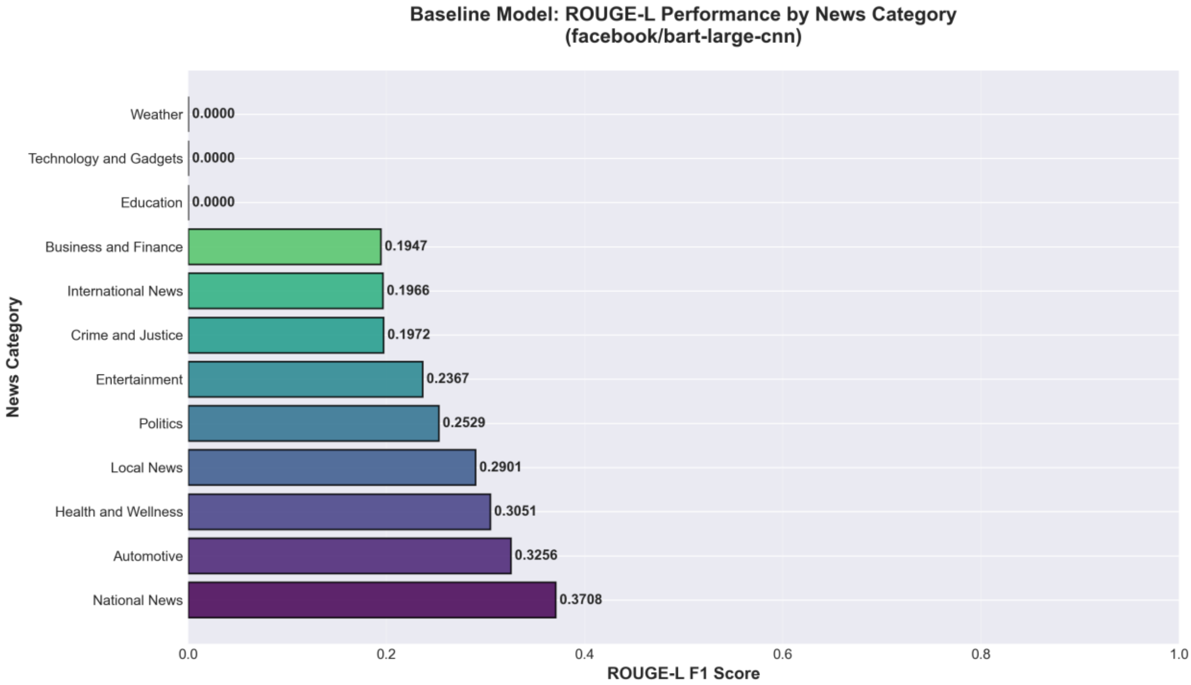


**Figure 4. Category-wise ROUGE-L scores for the baseline summarization model.**

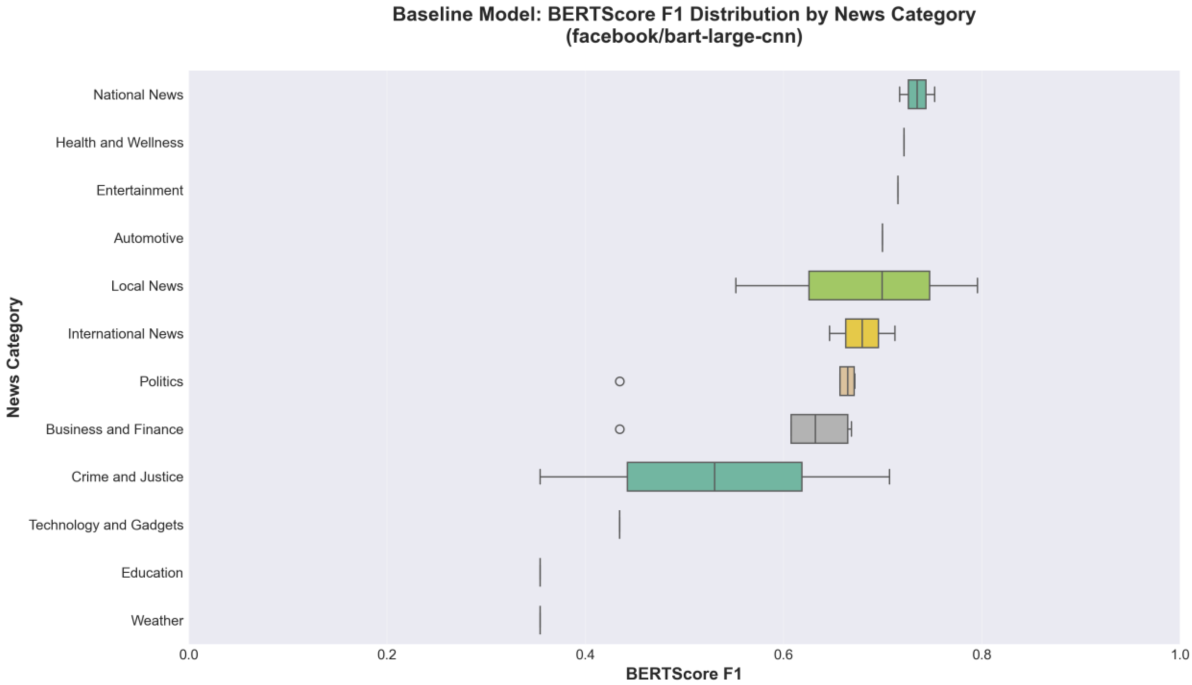


**Figure 5. Distribution of BERTScore F1 scores for baseline summaries.**

## 6.2 Weighted Multi-Document Summarization

The normalized importance weights are incorporated into the summarization process by emphasizing core articles and down-weighting redundant or low-information articles. Given a long-context summarization model ***g(·)***, the final summary S is generated as:

$$S = g(D, W)$$

where ***W={w1 ,w2 ,…,wn }*** denotes the set of article-level importance weights.

By biasing the model toward articles with higher importance scores, the proposed approach aims to reduce redundancy, improve factual consistency, and enhance overall summary coherence. This formulation is model-agnostic and can be integrated with both encoder–decoder architectures and large language models.

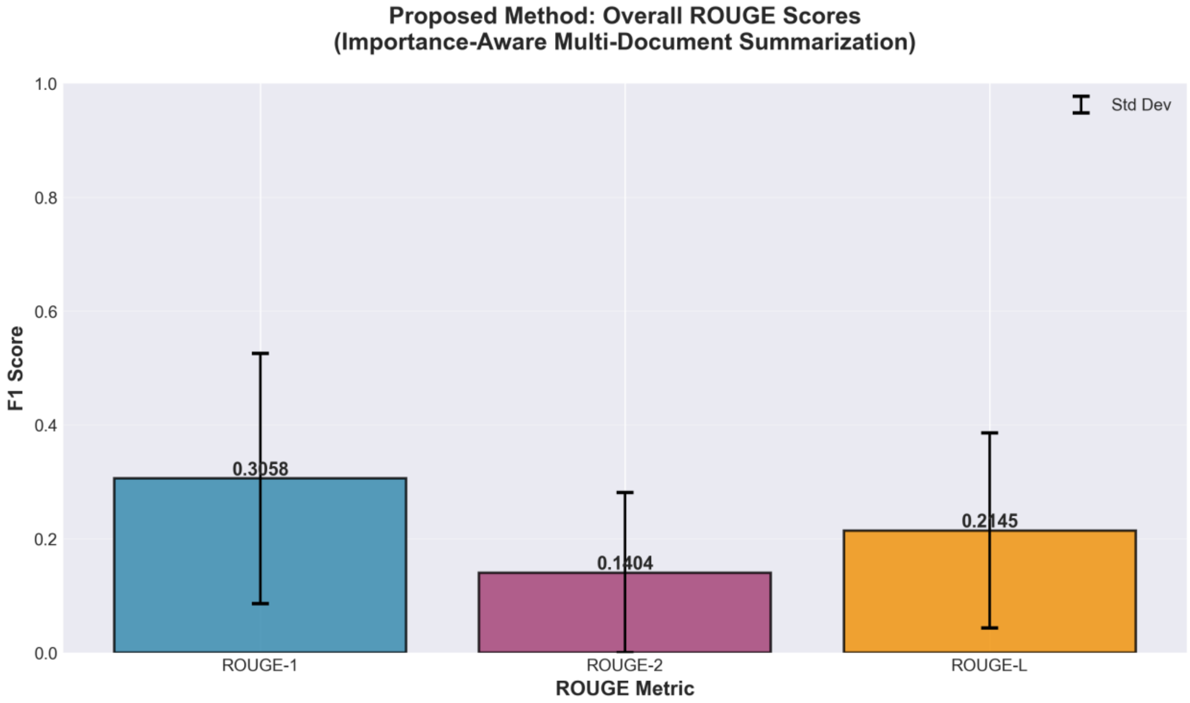


**Figure 6. Overall ROUGE-1, ROUGE-2, and ROUGE-L scores achieved by the proposed importance-aware multi-document summarization method.**

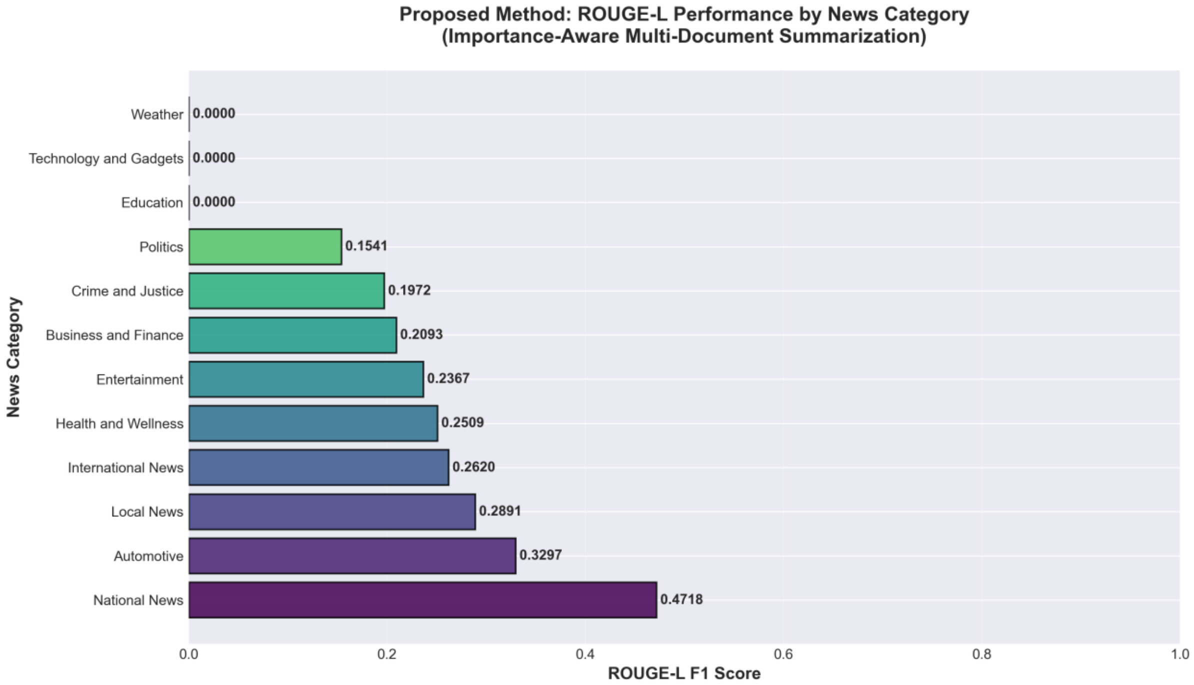


**Figure 7. Category-wise ROUGE-L performance of the proposed importance-aware summarization method across news domains.**

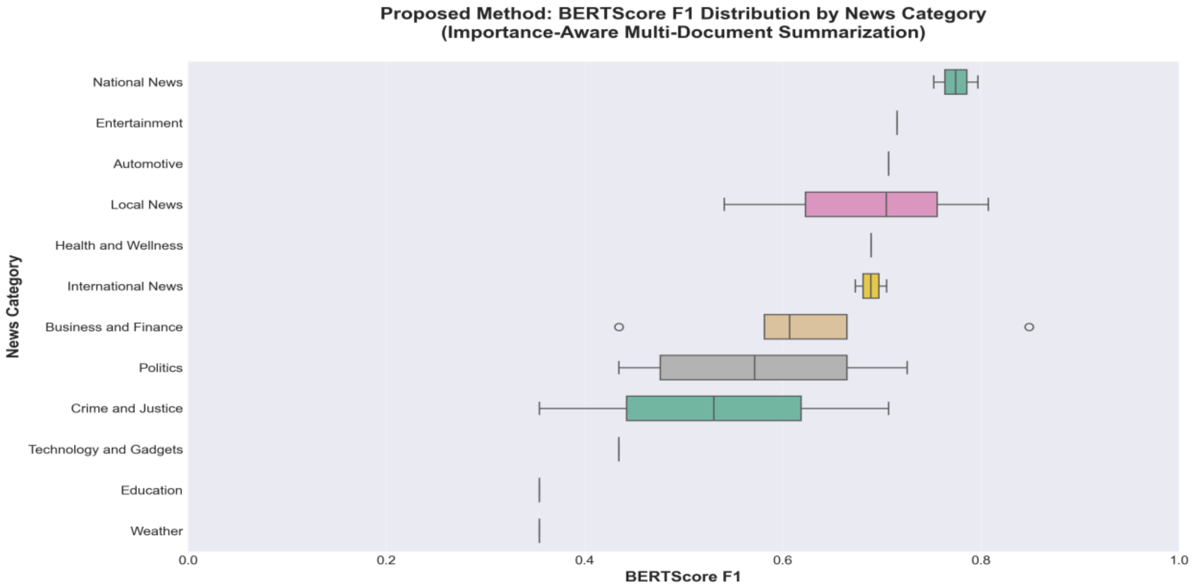


**Figure 8. Distribution of BERTScore F1 scores for summaries generated using the proposed importance-aware method.**

## 6.3 Comparative Analysis of Baseline and Proposed Methods

This subsection presents a direct comparison between the baseline multi-document summarization approach and the proposed importance-aware method. Both methods are evaluated on the same set of event-level clusters using an identical summarization architecture and evaluation metrics, ensuring a fair comparison.

Figure 10 compares the overall ROUGE scores obtained by the baseline and proposed methods. The results indicate that the proposed importance-aware approach achieves performance comparable to the baseline across ROUGE-1, ROUGE-2, and ROUGE-L metrics. This demonstrates that introducing article-level importance scoring does not negatively impact overall summarization quality.

A category-wise analysis, shown in Figure 11, reveals that the proposed method provides notable improvements in specific domains such as National News and International News. These categories typically involve multiple overlapping reports from different sources, where importance-aware input ordering can help reduce redundancy and improve content selection. In contrast, performance differences are less pronounced in categories with fewer overlapping articles, highlighting the domain-dependent nature of the proposed approach.

Overall, the comparative results suggest that the proposed importance-aware method maintains competitive performance while offering improved interpretability and category-specific benefits, without introducing additional supervision or architectural complexity.

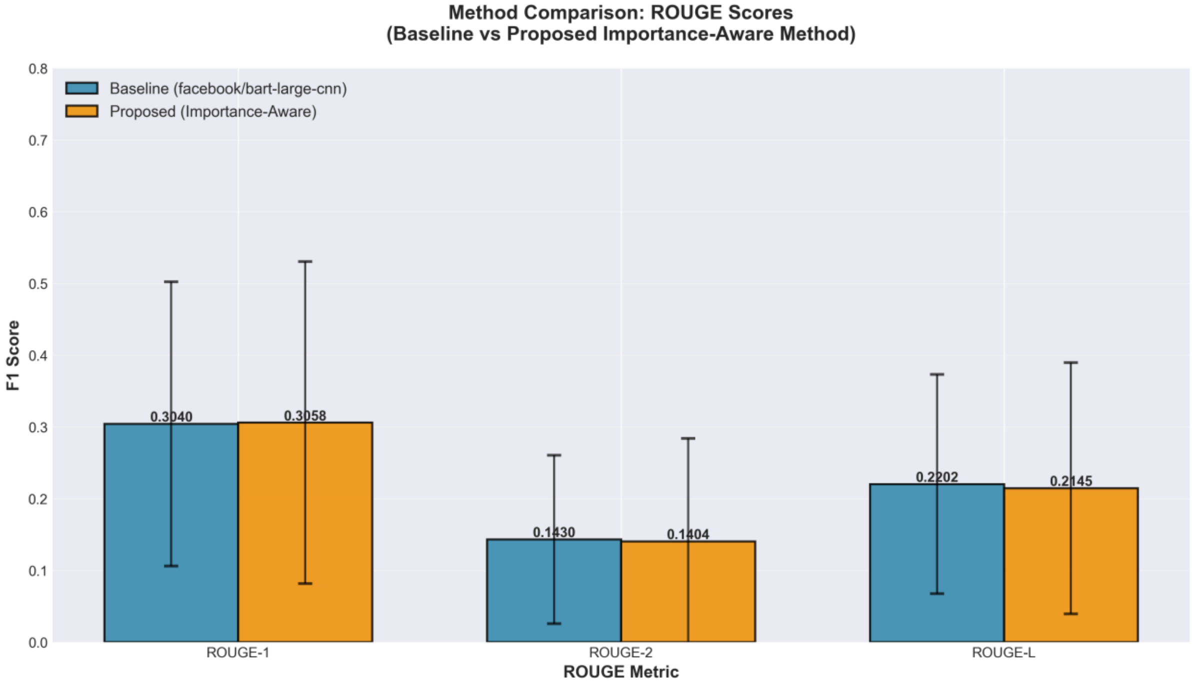


**Figure 9. Comparison of ROUGE-1, ROUGE-2, and ROUGE-L scores between the baseline and proposed importance-aware summarization methods**

# 7. Experiments and Evaluation Plan

## 7.1 Experimental Setup

To ensure a fair and systematic evaluation, all summarization models are trained and evaluated on the same data splits derived from the NewsSumm dataset. Event-level clusters constructed during preprocessing are used as multi-document inputs, while the corresponding human-written summaries serve as reference outputs. This consistent experimental setup allows for direct comparison across different model architectures and summarization strategies.

The experiments are designed to evaluate the effectiveness of both long-context encoder–decoder models and lar language models for multi-document summarization. In addition to standard baselines, the proposed article-level importance scoring approach is incorporated to study its impact on redundancy reduction and factual consistency. No model-specific tuning advantages are provided to any method, ensuring that observed performance differences are attributable to modeling choices rather than experimental bias.

## 7.2 Evaluation Metrics

Model performance is evaluated using widely adopted automatic summarization metrics. Lexical overlap between generated summaries and human-written reference summaries is measured using ROUGE-1, ROUGE-2, and ROUGE-L, which capture unigram, bigram, and longest common subsequence overlap, respectively [25]. These metrics are commonly used in summarization research and provide a baseline measure of content coverage.

To complement ROUGE-based evaluation, semantic similarity is assessed using BERTScore, which computes similarity between generated and reference summaries at the embedding level [26]. BERTScore helps capture semantic alignment beyond exact word overlap and is particularly useful for evaluating abstractive summaries. In addition to these metrics, qualitative analysis is conducted to examine redundancy reduction and factual consistency across generated summaries.

All models are evaluated on identical test sets, and results are reported as averaged scores across news categories. This evaluation strategy enables a comprehensive analysis of model behavior across different domains and summarization challenges.

### 7.3 Category-wise Performance Analysis

To analyze domain-specific behavior, model performance is examined separately across major news categories such as politics, business, health, sports, and technology. Category-wise evaluation provides insights into how different models handle variations in writing style, vocabulary, and information density across domains.

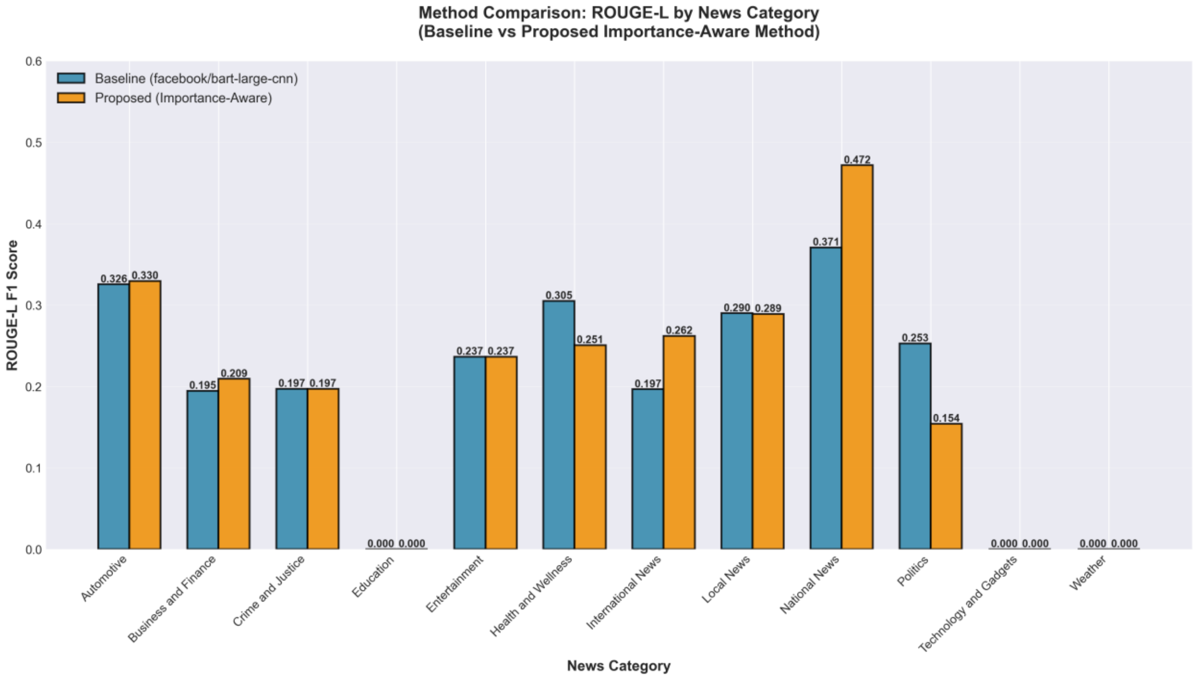


**Figure 10: Category-wise summarization performance across different domains**

## 8. Ablation and Error Analysis

This section analyzes the impact of article-level importance weighting by comparing models with and without importance scoring. Common error types include redundancy, factual inconsistency, and omission of key details.

| Error Type | Description |
|---|---|
| **Redundancy** | Repetition across sentences |
| **Hallucination** | Unsupported facts |
| **Omission** | Missing key information |

**Table 6. Common Error Types in Multi-Document Summarization**

## 9. Expected Outcomes

The expected outcome of this work is a systematic and comparative analysis of multi-document abstractive summarization approaches applied to Indian English news data. Through benchmarking long-context transformer models and large language models on the NewsSumm dataset, this study aims to provide insights into the strengths and limitations of existing summarization architectures in handling long inputs, cross-document redundancy, and domain-specific linguistic characteristics.

In addition, the proposed article-level importance scoring mechanism is expected to improve redundancy reduction and factual consistency in generated summaries by emphasizing core articles within event-level clusters. While quantitative results will be reported after full implementation, the proposed methodology establishes a structured framework for integrating document importance into multi-document summarization pipelines.

Overall, this work is expected to contribute a reproducible experimental setup, a clearer understanding of multi-document summarization challenges in the Indian news domain, and an initial novel direction that can be extended in future research

## 10. Discussion

Recent advances in long-context transformer models and large language models have significantly improved the ability to process multiple documents within a single summarization framework [9–11]. However, these models primarily focus on extending input length capacity and do not explicitly address redundancy or unequal information contribution across documents. As a result, generated summaries may still contain repetitive content or overlook key factual details when multiple sources report the same event.

The findings and design choices in this work highlight the importance of structured input modeling in multi-document summarization. By introducing article-level importance scoring, the proposed approach explicitly distinguishes between core articles that contain essential information and supporting articles that mainly repeat or elaborate existing facts. This aligns with observations from prior hierarchical and graph-based summarization studies, which emphasize the need for modeling inter-document relationships rather than treating documents independently or uniformly [19–21].

Compared to existing long-context approaches that concatenate documents without weighting, the proposed framework provides a lightweight and model-agnostic mechanism for reducing redundancy and improving factual consistency. Importantly, the article-level weighting strategy can be integrated with both encoder–decoder architectures and large language models, making it applicable across a wide range of summarization systems.

This discussion also suggests broader research directions. Incorporating document importance signals opens opportunities for hybrid summarization strategies that combine statistical, neural, and semantic cues. Future work may explore dynamic importance estimation, integration with factual consistency verification modules, and extension to multilingual or cross-lingual news summarization settings. Overall, the proposed perspective underscores that effective multi-document summarization requires not only longer context windows but also principled mechanisms for information prioritization.

## 11. Conclusion

This paper presents a systematic study of multi-document abstractive summarization using the NewsSumm dataset. Through careful dataset preparation, comprehensive analysis of existing summarization approaches, and the formulation of a structured methodology, this work establishes a solid foundation for rigorous experimental investigation. Furthermore, an initial novel direction based on article-level importance scoring is proposed to address key challenges in multi-document summarization, particularly redundancy reduction and factual consistency. Detailed implementation and quantitative evaluation of the proposed approach are planned as part of future work.

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