Extractive Summarization with Mamba-Transformer Hybrids for Low-Resource Scenarios

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Abstract

Extractive summarization of long documents is hindered by truncation imposed by transformer-based models, which disrupts inter-sentence dependencies and degrades summarization accuracy, particularly in resource-constrained settings. We introduce the first Mamba-Transformer hybrid for extractive summarization, combining the semantic strength of pre-trained transformers with Mamba's ability to process full documents without truncation and capture inter-sentence dependencies. The architecture includes: (1) a transformer encoder for sentence-level semantics, (2) a Mamba state space model to capture inter-sentence dependencies across the full document, and (3) a linear classifier for sentence relevance prediction. Across news, argumentative, and scientific domains under low-resource conditions, our method achieves: (1) large gains over BERTSUM and MATCHSUM, including $+0.23$ ROUGE-1 on ArXiv and statistically significant improvements on all datasets ($p < 0.001$); (2) consistent advantages across domains, strongest on the longest documents; and (3) robust summarization accuracy with limited training data, with the additional benefit of 24–27% faster inference on news summarization (CNN/DailyMail), while inference cost on longer-document domains is comparable to or higher than baselines.

1 Introduction

Text summarization is a crucial task in Natural Language Processing (NLP) that generates concise text containing the most significant information from original documents. Summarization has become critical across domains including news, scientific literature, and argumentative text, with approaches ranging from extractive methods (Dong et al., 2025; Le and Luu, 2024) to abstractive techniques (Bao et al., 2025; Zhang et al., 2024). Recent deep neural approaches achieve strong performance but require substantial computational resources and large-scale training data (Zhang et al., 2023; An et al., 2022; Sun and Li, 2021). However, these advances face critical challenges, particularly in low-resource settings where only limited training data is available. Transformer-based summarization models rely on self-attention mechanisms that impose quadratic computational complexity, forcing truncation of long documents. This truncation disrupts inter-sentence dependencies — the contextual relationships between sentences that are critical for accurate sentence selection. In low-resource settings, the truncation-induced dependency loss is more damaging, since the model cannot compensate for lost context through large-scale learning. As a result, summarization accuracy degrades significantly. To address this truncation challenge while maintaining effective semantic understanding, we propose, for the first time, a Mamba-Transformer hybrid architecture for extractive summarization. In this approach, pre-trained transformer encoders generate rich sentence-level representations, which are then processed through Mamba's state space model to capture inter-sentence dependencies while processing full-length documents without truncation. This design preserves complete contextual information and proves especially effective for very long documents such as scientific papers, where transformers often fail to retain all context. The main contributions of this work are:

1. We propose the first Mamba-Transformer hybrid model for extractive summarization in low-resource settings.

2. We demonstrate improved extractive summarization accuracy on long documents, with largest gains on the longest documents, confirming that full document processing without truncation directly improves accuracy in low-resource settings.

3. We provide comprehensive cross-domain evaluation under low-resource conditions across news (CNN/DailyMail), argumentative (DebateSum), and scientific (ArXiv) domains.

4. We achieve significant ROUGE-1 improvements over strong baselines: $+0.23$ on ArXiv, $+0.21$ on DebateSum, and $+0.17$ on CNN/DailyMail, with statistically significant gains ($p < 0.001$) across all domains, with the additional benefit of 24–27% faster inference on news summarization.

2 Related Work

2.1 State Space Models

State space models (SSMs) have emerged as efficient alternatives to transformer-based architectures for sequence modeling. Mamba (Gu and Dao, 2023) offers linear $O(L)$ complexity, allowing it to process full-length documents without truncation, preserving complete inter-sentence dependencies critical for accurate sentence selection. Recent works demonstrate their potential in text ranking (Xu et al., 2025) and machine translation (Pitorro et al., 2024), matching transformer performance with fewer resources. However, their effectiveness for extractive summarization in low-resource settings remains under-explored, motivating our proposed hybrid architecture.

2.2 Extractive Summarization

Transformer-based approaches dominate extractive summarization. BERTSUM (Liu, 2019) established sentence-level extraction paradigms, while MATCHSUM (Zhong et al., 2020) introduced semantic matching between sentences and summaries. However, these methods require large annotated datasets and are not competitive in low-resource settings, where limited training data significantly degrades their accuracy. Methods like COLO (An et al., 2022) and DiffuSum (Zhang et al., 2023) achieve strong performance but inherit quadratic complexity, forcing truncation of long documents and limiting their applicability in low-resource scenarios. Some works address low-resource summarization through disentangled representation learning (Yuan et al., 2023) and paraphrasing reformulation (Tang et al., 2023), but these approaches do not address truncation-induced dependency loss. Our contribution differs by introducing the first Mamba-Transformer hybrid architecture for extractive summarization that processes full documents without truncation, capturing complete inter-sentence dependencies and improving summarization accuracy in low-resource settings.

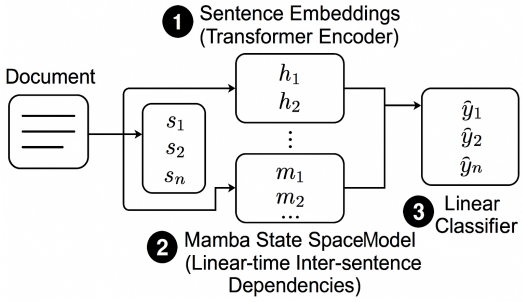

Figure 1: Overview of the proposed Mamba–Transformer hybrid architecture for extractive summarization.

3 Method

Figure 1 depicts the architecture of our proposed method.

3.1 Problem Formulation

We formulate extractive summarization as a document-level sentence classification task. Given a document $D = \{s_1, s_2, \ldots, s_n\}$ consisting of n sentences, our objective is to classify each sentence as relevant ($y_i = 1$) or not relevant ($y_i = 0$) for the summary, while considering inter-sentence relationships within the document context.

3.2 Architecture Overview

Our approach consists of three key components that process documents at the sentence-sequence level.

3.2.1 Sentence Encoding with Transformers

For each document $D = \{s_1, s_2, \ldots, s_n\}$, we first apply a pre-trained transformer (BERT) to generate semantic embeddings [CLS] for each sentence independently:

$$h_i = \text{Transformer}(s_i) \in \mathbb{R}^d$$

where h_i represents the sentence-level semantic encoding for sentence s_i.

3.2.2 Document-Level Sequential Processing with Mamba

We then construct a sequence of sentence embeddings $H = [h_1, h_2, \ldots, h_n] \in \mathbb{R}^{n \times d}$ and process this sequence through the Mamba state space model

to capture inter-sentence dependencies within the document:

$$M = \text{Mamba}(H) = [m_1, m_2, \ldots, m_n] \in \mathbb{R}^{n \times d}$$

This step enables the model to capture document structure and sentence relationships while maintaining linear computational complexity $\mathcal{O}(n)$ with respect to the number of sentences.

3.2.3 Binary Classification for Sentence Relevance

Finally, we apply a linear classifier to each position in the Mamba output sequence to predict sentence-level relevance:

$$\hat{y}_i = \sigma(W \cdot m_i + b)$$

where m_i is the Mamba encoding for sentence i, $W \in \mathbb{R}^d$ is the weight matrix, b is the bias term, and σ is the sigmoid function. This produces relevance probabilities for each sentence in the document.

4 Experimental Setup

4.1 Dataset

Following prior work on low-resource summarization (Xu et al., 2020; Reza et al.), we use 200 documents per dataset, reflecting settings with limited annotation and compute. We used these datasets: (1) CNN/DailyMail (Hermann et al., 2015): News articles with multi-sentence highlights; (2) DebateSum (Roush and Balaji, 2020): Debate evidence requiring argumentative structure understanding; and (3) ArXiv (Cohan et al., 2018): Scientific papers with abstracts, ideal for evaluating long-document summarization.

Preprocessing: We generated sentence-level binary labels using a greedy ROUGE-2 maximization approach. For dataset diversity, we applied K-means clustering (500 clusters) using TF-IDF representations, then randomly selected 200 documents. Text is segmented using NLTK, tokenized with HuggingFace, and document-level truncation is not applied. Documents are split 120/40/40 (train/val/test) at document level to prevent data leakage.

4.2 Implementation Details

Our architecture consists of a BERT-base-uncased encoder (110M parameters, 768-dimensional embeddings) followed by a Mamba-130M state space model (NF4 quantized, $d_{\text{state}} = 16$, $d_{\text{conv}} = 4$) and a linear classifier mapping from 768 to 1 with a sigmoid activation. Training was performed using the Adam optimizer (learning rate 1×10^{-5}), binary cross-entropy loss, batch size of 1 with gradient accumulation, for 2 epochs. We applied 0.2 dropout and gradient clipping with $\text{max_norm} = 1.0$. Data preprocessing used the BERT tokenizer with a maximum length of 128 tokens per sentence, ROUGE-2 greedy labeling for supervision, and no document truncation. Experiments were conducted on an NVIDIA A100 GPU (40GB) using PyTorch 2.6.0+cu124 and HuggingFace Transformers 4.35.0, with random seeds $\{42, 123, 456\}$. Evaluation was performed using ROUGE-1, ROUGE-2, and ROUGE-L F1 scores, with paired t-test significance testing.

Dataset	Avg doc length (tokens)	Avg sents/doc	Positive (%)
CNN/DailyMail	781	29.4	18.2
DebateSum	643	24.1	22.7
ArXiv	1,247	41.8	16.9

Table 1: Dataset statistics.

5 Results

5.1 Overall Performance

Across three domains, MAMBA-BERT consistently outperforms transformer-only baselines in ROUGE scores. On CNN/DailyMail (news), it achieves 0.61/0.51/0.53 (ROUGE-1/2/L), a significant gain over BERTSUM (+0.17 ROUGE-1) and MATCHSUM (+0.21 ROUGE-1). On DebateSum (argumentative), improvements are smaller but consistent. The largest gains occur on ArXiv (scientific), where MAMBA-BERT surpasses BERTSUM by +0.23 ROUGE-1 and MATCHSUM by +0.56. Notably, summarization accuracy increases with document length. ROUGE-1 rises from 0.57 on DebateSum (643 avg tokens) to 0.61 on CNN/DailyMail (781 avg tokens) and 0.73 on ArXiv (1,247 avg tokens). This confirms that Mamba's ability to process full documents without truncation becomes increasingly advantageous as document length grows, precisely where transformer-based baselines struggle most due to forced truncation and loss of inter-sentence dependencies. MATCHSUM's low ROUGE-1 on ArXiv (0.17) reflects its inability to recover lost context on long inputs — precisely the failure mode our method addresses. Statistical significance testing confirms these improvements are not due to random variation, with MAMBA-BERT significantly outperforming BERTSUM on ROUGE-1 across all

Model	ROUGE-1	ROUGE-2	ROUGE-L	Time (s/sample)
CNN/DailyMail				
MAMBA-BERT	**0.61**	**0.51**	**0.53**	**13.7**
BERTSUM	0.44	0.28	0.33	18.0
MATCHSUM	0.40	0.18	0.27	18.6
DebateSum				
MAMBA-BERT	**0.57**	**0.54**	**0.56**	0.65
BERTSUM	0.50	0.35	0.40	0.52
MATCHSUM	0.46	0.34	0.37	0.12
ArXiv				
MAMBA-BERT	**0.73**	**0.64**	**0.64**	8.14
BERTSUM	0.50	0.26	0.27	3.67
MATCHSUM	0.17	0.04	0.12	0.45

Table 2: ROUGE scores and inference times.

Statistical significance testing ($p < 0.001$, paired t-test, $n = 40$): MAMBA-BERT vs BERTSUM on ROUGE-1 across all datasets.

domains (paired t-test over per-document scores, $p < 0.001$, $n = 40$ for CNN/DailyMail, DebateSum, and ArXiv). These results indicate statistical significance across datasets. We attempt to evaluate MemSum as a recent extractive baseline; however, under our low-resource setting (200 documents), the model produces unstable and illogical outputs. We therefore exclude MemSum from quantitative comparison, noting this as a limitation of evaluation under strict low-resource conditions. These results are obtained with only 200 documents per dataset, demonstrating the effectiveness of MAMBA-BERT for extractive summarization in low-resource settings.

5.2 Inference Efficiency

We report inference time per sample as an additional analysis of practical runtime efficiency. On CNN/DailyMail, MAMBA-BERT reduces inference time by approximately 24–27% compared with the baselines. However, this runtime advantage is not consistent across datasets. On DebateSum, MAMBA-BERT requires 0.65s per sample, compared with 0.52s for BERTSUM and 0.12s for MATCHSUM. On ArXiv, MAMBA-BERT requires 8.14s per sample, compared with 3.67s for BERTSUM and 0.45s for MATCHSUM. Thus, while Mamba provides linear sequence modeling at the document-level sentence sequence, the hybrid MAMBA-BERT architecture does not always translate this theoretical advantage into lower inference time. This suggests that the practical efficiency of MAMBA-BERT is dataset- and implementation-dependent.

6 Error Analysis

Manual examination of the lowest-performing cases reveals two primary failure modes:

- **Over-selection of peripheral details:** MAMBA-BERT consistently selects excessive contextual details instead of the most central summary content. These sentences are semantically related to the document topic, but they are less important for the summary.

- **Missing critical information:** In 75% of the examined low-performing cases, the model fails to select sentences containing key information. These omissions include named entities (e.g., organizations, digital platforms), main events (e.g., key actions, decisions, or announcements), contextual information (e.g., explanatory details, characterizing quotes), and attribution details (e.g., source information or age details).

The error analysis shows a limitation specific to low-resource settings: The model learns to identify semantically relevant sentences but struggles with importance ranking and entity prioritization. This suggests that MAMBA's sequential modeling could be further enhanced.

7 Conclusion

We introduce the first Mamba-Transformer hybrid for extractive summarization. By combining transformer-based semantic encoding with Mamba's linear complexity, the model processes full-length documents without truncation and preserves the inter-sentence dependencies critical for sentence selection. Across news, argumentative, and scientific domains under low-resource conditions, our approach significantly outperforms BERTSUM and MATCHSUM ($p < 0.001$), with the largest gains on the longest documents and 24–27% faster inference on news summarization.

8 Limitations

Our approach has several limitations. Inter-sentence dependency modeling does not explicitly capture sentence importance, leaving room to better distinguish central from contextually related sentences. Our test set is small (40 documents per domain), and we evaluate only one backbone configuration (BERT-base + Mamba-130M) without an ablation isolating Mamba's contribution. We also exclude MemSum, which produced unstable outputs under our low-resource conditions.

References

Chenxin An, Ming Zhong, Zhiyong Wu, Qin Zhu, Xuanjing Huang, and Xipeng Qiu. 2022. Colo: A contrastive learning based re-ranking framework for one-stage summarization. In *Proceedings of the 29th International Conference on Computational Linguistics, Gyeongju, Republic of Korea*, pages 5783–5793.

T. Bao, H. Zhang, and C. Zhang. 2025. Enhancing abstractive summarization of scientific papers using structure information. *Expert Systems with Applications*, 261:125529.

Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. A discourse-aware attention model for abstractive summarization of long documents. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics*, pages 615–621.

Xiangyun Dong, Wei Li, Yuquan Le, Zhangyue Jiang, Junxi Zhong, and Zhong Wang. 2025. Termdiffusum: A term-guided diffusion model for extractive summarization of legal documents. In *Proceedings of the 31st International Conference on Computational Linguistics, Abu Dhabi, UAE*, pages 3222–3235.

Albert Gu and Tri Dao. 2023. Mamba: Linear-time sequence modeling with selective state spaces. *Computing Research Repository*, arXiv:2312.00752. Version 1.

Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In *Advances in Neural Information Processing Systems*, pages 1684–1692.

Thang Le and Anh Tuan Luu. 2024. Extractive summarization with text generator. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 157–174.

Y. Liu. 2019. Fine-tune bert for extractive summarization. *Computing Research Repository*, arXiv:1903.10318. Version 2.

Hugo Pitorro, Pavlo Vasylenko, Marcos Treviso, and André Martins. 2024. How effective are state space models for machine translation? In *Proceedings of the Ninth Conference on Machine Translation*, pages 1107–1124.

Tasnim Reza, Mayank Anand, Juan Santamaria, and Tanuka Bhowmick. An evaluation framework for legal document summarization. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 4105–4112.

Allen Roush and Arvind Balaji. 2020. Debatesum: A large-scale argument mining and summarization dataset. In *Proceedings of the 7th Workshop on Argument Mining, Online*, pages 1–7.

Shichao Sun and Wenjie Li. 2021. Alleviating exposure bias via contrastive learning for abstractive text summarization. *Computing Research Repository*, arXiv:2108.11846. Version 1.

Moming Tang, Chengyu Wang, Jianing Wang, Cen Chen, Ming Gao, and Weining Qian. 2023. Parasum: Contrastive paraphrasing for low-resource extractive text summarization. In *Knowledge Science, Engineering and Management*, pages 106–119.

Jiacheng Xu, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020. Discourse-aware neural extractive text summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5021–5031.

Zhichao Xu, Jinghua Yan, Ashim Gupta, and Vivek Srikumar. 2025. State space models are strong text rerankers. In *Proceedings of the 10th Workshop on Representation Learning for NLP (RepL4NLP-2025),Albuquerque, NM*, pages 152–169.

Ruifeng Yuan, Shichao Sun, Zili Wang, Ziqiang Cao, and Wenjie Li. 2023. Separating context and pattern: Learning disentangled sentence representations for low-resource extractive summarization. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 7575–7586.

Haopeng Zhang, Xiao Liu, and Jiawei Zhang. 2023. DiffuSum: Generation enhanced extractive summarization with diffusion. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 13089–13100.

Yusen Zhang, Nan Zhang, Yixin Liu, Alexander Fabbri, Junru Liu, Ryo Kamoi, Xiaoxin Lu, Caiming Xiong, Jieyu Zhao, Dragomir Radev, Kathleen McKeown, and Rui Zhang. 2024. Fair abstractive summarization of diverse perspectives. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers),Mexico City, Mexico*, pages 3404–3426.

Ming Zhong, Pengfei Liu, Yiran Chen, Danqing Wang, Xipeng Qiu, and Xuanjing Huang. 2020. Extractive summarization as text matching. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6197–6208.