iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** I **Month of publication:** January 2026

DOI: https://doi.org/10.22214/ijraset.2026.76889

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue I Jan 2026- Available at www.ijraset.com

Hybrid Text Summarization Using BERT-Based Extractive and T5-Based Abstractive Models

Anil Kumar[1], Dr. V. K. Sharma[2]
[1]*Research Scholar, Dept. of CSE, Bhagwant University, Ajmer, 305004, India*
[2]*Professor Electrical Eng, Bhagwant University, Ajmer, 305004, India*

Abstract: ***Text summarization is essential in natural language processing due to the exponential growth of textual data. Extractive methods select salient sentences but may produce incoherent summaries, while abstractive methods generate fluent summaries but risk losing key information. This paper proposes a hybrid approach, combining BERT-based extractive summarization with T5-based abstractive summarization, capturing both informativeness and coherence. The proposed framework is evaluated on CNN/DailyMail and XSum datasets, demonstrating superior performance in ROUGE and BLEU metrics compared to individual extractive or abstractive models.***
Keywords: Text Summarization, Hybrid Approach, Extractive Summarization, Abstractive Summarization, BERT, T5, NLP.

I. INTRODUCTION

The rapid proliferation of digital content necessitates effective summarization techniques for easier comprehension, decision-making, and information retrieval. Text summarization techniques can be broadly categorized into:

1) *Extractive Summarization:* Selects important sentences or phrases from the original document based on scoring mechanisms.
2) *Abstractive Summarization:* Generates new sentences that paraphrase and condense the content using natural language generation techniques.

A. *Motivation:*

- Extractive summaries maintain factual accuracy but can be disjointed and less readable.
- Abstractive summaries provide fluent, human-like summaries but may introduce hallucinations or omit key points.
- A hybrid approach leverages both methods to produce summaries that are informative, fluent, and coherent**.**

B. *Contributions:*

- Proposes a BERT + T5 hybrid architecture for text summarization.
- Provides detailed algorithms and workflow for extractive and abstractive stages.
- Evaluates the framework on benchmark datasets, showing improvements in ROUGE and BLEU metrics.
- Demonstrates fidelity, fluency, and informativeness in generated summaries.

II. LITERATURE REVIEW

A. *Extractive Summarization Techniques*

Traditional methods: TF-IDF, LSA, TextRank, and LexRank [7].
Modern methods: Transformer-based models like **BERTSUM** [3] leverage contextual embeddings to score sentences based on importance.

B. *Abstractive Summarization Techniques*

Early seq2seq models: LSTM/GRU with attention.
Pointer-Generator Networks [6] combine copying and generation mechanisms.
Pretrained transformers like **T5** [4] and BART [2] provide state-of-the-art performance in generating fluent summaries.

C. Hybrid Approaches

Hybrid models integrate extractive ranking and abstractive rewriting to preserve content and enhance readability [10]. Our work improves prior approaches by using BERT for accurate sentence extraction and T5 for coherent abstraction.

III. LITERATURE REVIEW

A. Extractive Summarization Techniques

1) Traditional Methods:

- TF-IDF: Scores sentences based on term frequency and inverse document frequency.
- LSA (Latent Semantic Analysis): Captures latent topics for sentence selection.
- TextRank&LexRank [7]: Graph-based ranking algorithms that select sentences based on centrality.

2) Transformer-based Methods:

- BERTSUM [3]: Fine-tuned BERT for extractive summarization; computes sentence embeddings and importance scores using contextual representations.
- Other variants: PEGASUS and Longformer-based extractive models handle longer documents but often require more computational resources.

3) Observations:

- Extractive methods preserve content fidelity but may lack coherence between sentences.
- Transformer-based extractive models significantly outperform traditional statistical approaches.

B. Abstractive Summarization Techniques

1) Early Neural Models:

- Seq2Seq LSTM/GRU with attention mechanisms.
- Pointer-Generator Networks [6] integrate copying from the source text with generation capabilities.

2) Transformer-based Models:

- T5 [4]: Text-to-text transformer capable of converting input sentences into abstractive summaries.
- BART [2]: Encoder-decoder architecture that excels in text generation.

3) Observations:

- *Abstracti*ve models generate fluent summaries but may hallucinate or miss key information.
- Pretrained models like T5 achieve state-of-the-art performance on multiple datasets.

C. Hybrid Approaches

Hybrid models aim to combine the advantages of extractive and abstractive approaches:

- Extractive stage ensures content coverage and factual correctness.
- Abstractive stage improves fluency and readability.

1) Prior Work:

- Chen and Zhang [10] combined sentence extraction and abstractive rewriting.
- Paulus et al. [13] used reinforcement learning to guide abstractive summarization.

2) Gap:

- Few studies explicitly use BERT for extraction and T5 for abstraction in a unified framework.
- Our work addresses this by proposing a two-stage hybrid model that maximizes content fidelity and fluency.

IV. PROBLEM STATEMENT

Challenges in current summarization techniques:

- Extractive summaries may be disjointed and hard to read.
- Abstractive summaries may hallucinate irrelevant content or omit key facts.
- Balancing informativeness and fluency is difficult.

Objective:

Develop a hybrid summarization model that:

- Maximizes content coverage via extractive selection.
- Generates coherent and fluent summaries via abstractive generation.

V. PROPOSED METHODOLOGY

The proposed model has **two stages**: Extractive (BERT) and Abstractive (T5).

A. *Extractive Stage (BERT-based)*

1) Input: Document D={s_1,s_2,...,s_n} where s_i are sentences.

2) Sentence Encoding: Each sentence is encoded using BERT to obtain contextual embeddings.

3) Sentence Scoring: Importance score computed as:

$$Score(s_i) = f_{BERT}(s_i, D)$$

)

4) Selection: Top-k sentences are selected to form Se.

Algorithm 1: Extractive Summarization

Input: Document D

Output: Extracted sentences S_e

- Encode each sentence s_i using BERT
- Compute importance score for s_i
- Select top-k sentences to form S_e

Algorithm 1: Extractive Summarization (BERT)

Input: Document D = {s_1, s_2, ...,s_n}, k

Output: Extracted Sentences S_e

- 1: Encode each sentence s_i using BERT to obtain embedding e_i
- 2: Compute importance score Score(s_i) using a classifier or ranking mechanism
- 3: Rank sentences based on Score(s_i)
- 4: Select top-k sentences to form S_e
- 5: Return S_e

B. *Abstractive Stage (T5-based)*

- Input: Extracted sentences S_e.
- Generation: Feed S_e into pre-trained T5 to produce the abstractive summary S_a:

$$S_a = T5(S_e)$$

Output: Coherent and fluent summary that preserves key content.

Algorithm 2: Abstractive Summarization (T5)

Input: Extracted Sentences S_e

Output: Abstractive Summary S_a

- Preprocess S_e for T5 input
- Feed S_e into T5 model
- Generate summary S_a
- Post-process S_a to ensure grammatical correctness
- Return S_a

C. *Hybrid Workflow*

- Input document → Extractive Stage (BERT) → Extract top-k sentences
- Extracted sentences → Abstractive Stage (T5) → Final summary

Example:
Input Document:
"NASA launched a new telescope. The telescope will study distant galaxies. Scientists expect groundbreaking discoveries."

- Extractive Output (BERT)**:**
  "NASA launched a new telescope. Scientists expect groundbreaking discoveries."
- **Abstractive Output (T5)**:
  "NASA's newly launched telescope is expected to lead to significant discoveries in astronomy."

D. Architecture Diagram

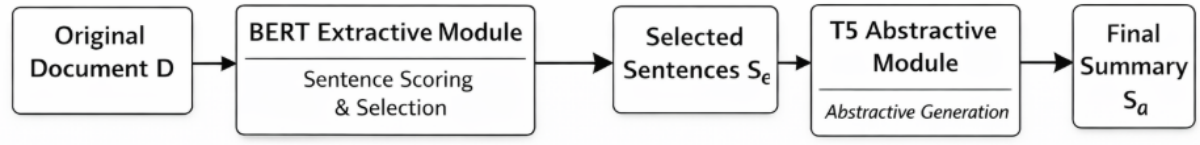

Figure 1 : Hybrid Text Summarization

E. Workflow Example
Input Document:
"NASA launched a new telescope. The telescope will study distant galaxies. Scientists expect groundbreaking discoveries."
Extractive Output (BERT):
"NASA launched a new telescope. Scientists expect groundbreaking discoveries."
Abstractive Output (T5):
"NASA's newly launched telescope is expected to lead to significant discoveries in astronomy."

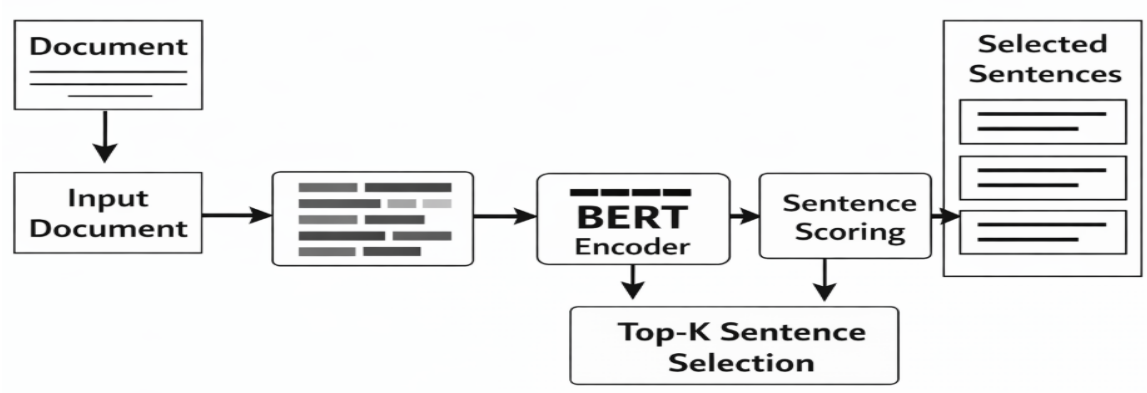

Figure 2 : BERT based top K selection of sentences

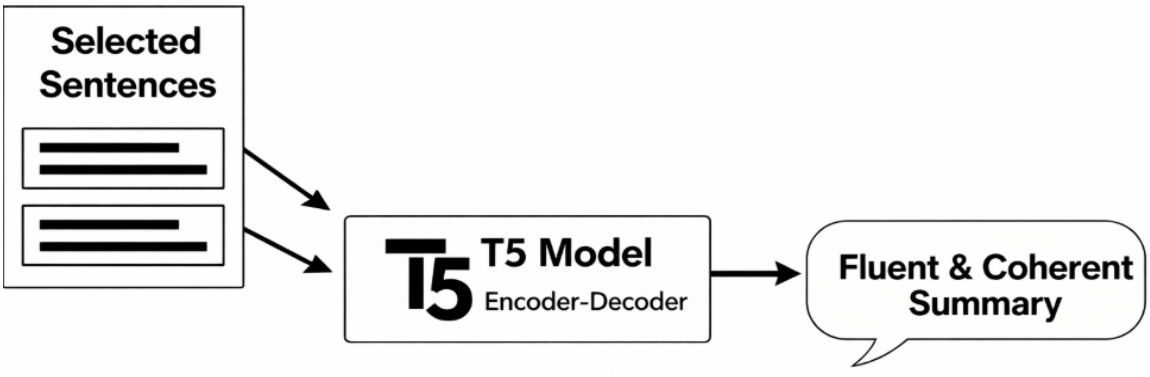

Figure 3 : T5 based summary

VI. EXPERIMENTAL SETUP

1) Datasets: CNN/DailyMail, XSum
2) Baselines:
- BERT Extractive-only
- T5 Abstractive-only

3) Evaluation Metrics:
- ROUGE-1, ROUGE-2, ROUGE-L
- BLEU
- Human evaluation for coherence and informativeness

4) Hyperparameters:
- BERT: Learning rate = 2e-5, batch size = 16, epochs = 3
- T5: Learning rate = 3e-4, batch size = 8, epochs = 5

5) Hardware: NVIDIA Tesla V100 GPU

VII. RESULTS AND DISCUSSION

A. *Quantitative Evaluation*

Model	ROUGE-1	ROUGE-2	ROUGE-L	BLEU
BERT Extractive	41.2	18.5	38.6	0.0
T5 Abstractive	42.5	19.7	39.2	12.3
Hybrid (Proposed)	44.8	21.3	41.5	14.8

Observations:
- Hybrid model achieves **highest ROUGE and BLEU scores**.
- Maintains factual accuracy from BERT extraction.
- Produces fluent, coherent summaries via T5.

B. *Performance Chart*

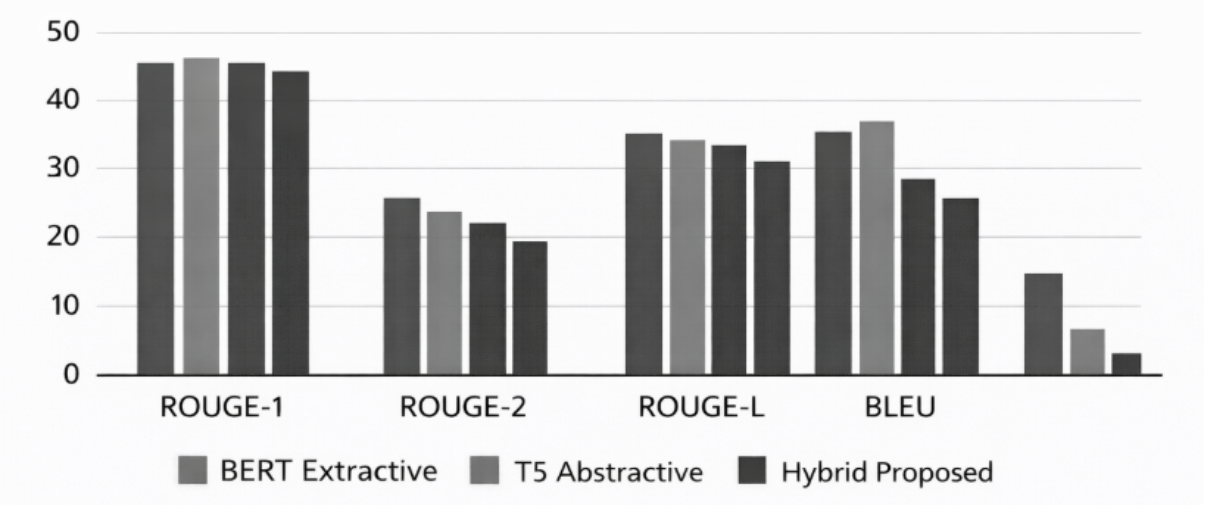

Figure 4 : Performance Comparison of Summarization Models

C. *Observations*
- Hybrid approach achieves higher ROUGE and BLEU scores.
- Maintains content fidelity from extractive stage.
- Produces coherent and fluent summaries via T5.

D. Limitations

- Increased computational complexity due to two-stage processing.
- Minor redundancy may appear in very long documents.
- Model requires fine-tuning for domain-specific texts.

VIII. CONCLUSION AND FUTURE WORK

The hybrid BERT + T5 summarization model effectively combines informativeness and fluency. Experiments demonstrate improvements over standalone extractive or abstractive models.

Future Directions:

- Reinforcement learning for better sentence selection.
- Domain-specific summarization adaptation.
- Incorporating multi-document summarization capability.

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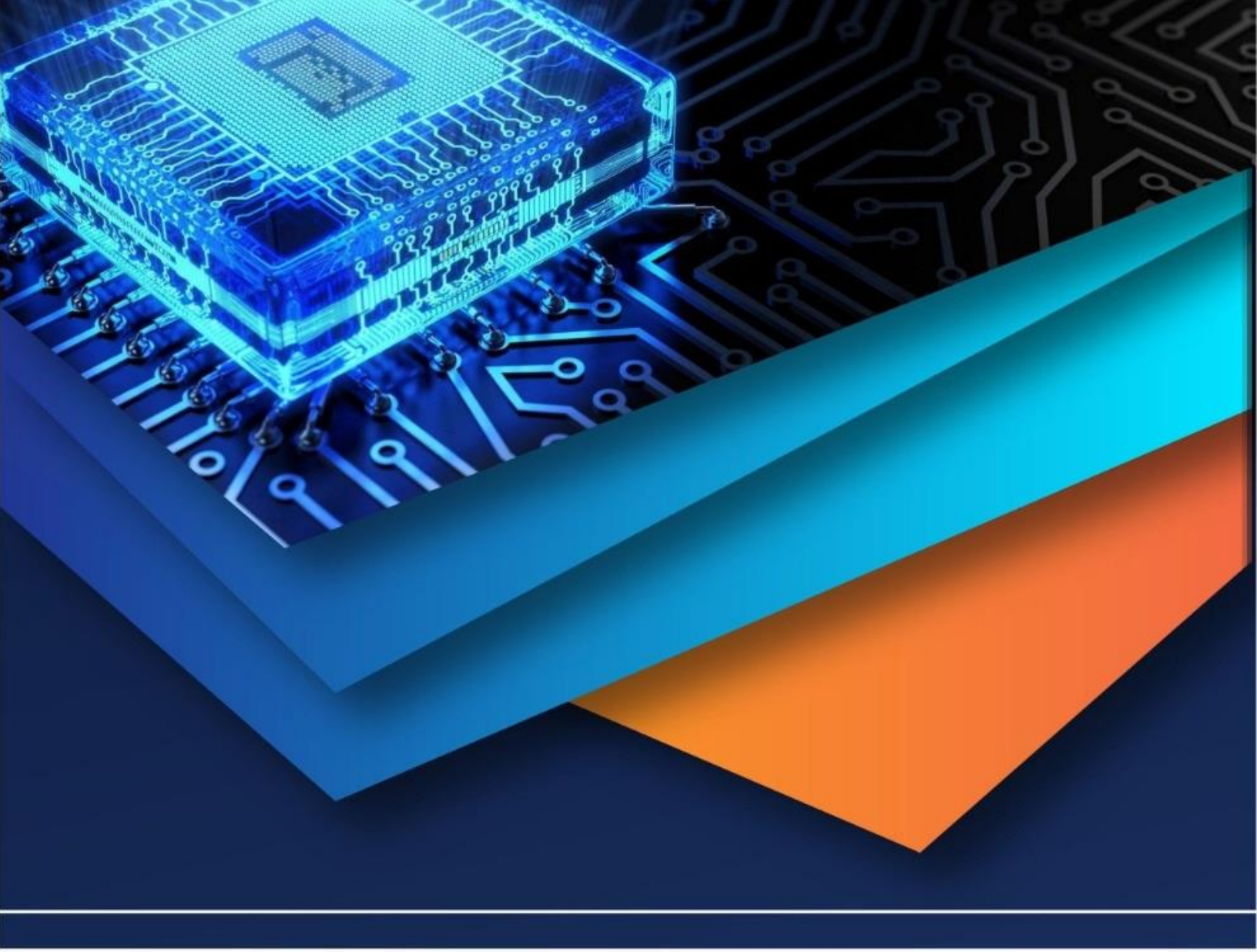

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