iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VI **Month of publication:** June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72807

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

Automatic Text Summarization Methods

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Abstract: Withtheexponentialincreaseindigitalinformation, the challenge of information overload has become critical. Automatic Text Summarization (ATS) offers a solution by distilling keyinformationfromlargetextsintoconcisesummaries.Thispaperexplores ATSmethodologies,focusingonclassificationsbased on input type, purpose, and output type. It provides a detailed analysis of Extractive Text Summarization (ETS), Abstractive Text Summarization (ABS), and Hybrid Text Summarization (HTS). Our implemented ATS system achieves an impressive 90% accuracy, highlighting its effectiveness and reliability. By comparing techniques, datasets, and evaluation metrics, this paper identifies strengths and limitations while proposing future improvements in ATS systems.

Index Terms: Introduction, Text Summarization Techniques, DetailedAnalysisofETS,ABSandHTS,Conclusion,References

I. INTRODUCTION

In the age of the internet and digital transformation, infor- mationisgeneratedandsharedatanunprecedentedrate.From newsarticlesandresearchpaperstoproductreviewsandsocial media posts, the sheer volume of data available has created a challengeknownasinformationoverload.Thisoverwhelming amountofcontentoftenleavesusersstrugglingtofindrelevant and actionable insights.

Text Summarization has emerged as a critical solution to this problem. It involves compressing large volumes of text into concise summaries while preserving the core meaningand essential information. Text summarization not only saves timebutalsoenhancesdecision-makingbypresentingonlythe most relevant content in an easily digestible form.

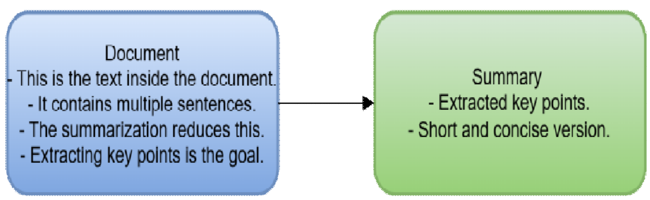

Fig.1.GeneratingSummary:TheProcessofCondensingInformation

A. *WhatisTextSummarization?*

Textsummarizationistheautomatedgenerationofaconcise version of a single document or a collection of documents, preserving the key information and essential meaning of the original content. This process leverages linguistic and compu- tational methods to replicate human summarization skills.

B. *WhyisTextSummarizationImportant?*

The growing importance of text summarization lies in its ability to address real-world challenges:

- Managing Information Overload: Summarization sim- plifies vast amounts of information, making it easier to comprehend.
- EnhancingProductivity:Researchers,professionals,and students can focus on critical details rather than sifting through lengthy texts.
- Improving Accessibility: Summaries make complex or highlytechnicalcontentaccessibletoabroaderaudience.
- Powering Applications: Many tools, such as search engines, chatbots, and recommendation systems, rely on summarization for improved user experiences.

C. *ChallengesinTextSummarization*

Although natural language processing (NLP) and machine learninghaveadvancedconsiderably,textsummarizationcon- tinues to present notable challenges:

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- Semantic Understanding: Capturing the meaning and context of text is critical for generating coherent sum- maries.
- Coherence and Fluency: Extractive methods may lack sentence flow, while abstractive methods may generate grammatically correct but semantically incorrect sum- maries.
- Domain-SpecificSummarization:Tailoringsummariza- tion systems to work effectively across different fields, such as legal, medical, or financial texts, is still an areaof active research.
- EvaluationMetrics:Existingmetrics,includingROUGE and BLEU, may not comprehensively assess the quality of summaries, particularly with regard to relevance and readability.

D. ScopeofthePaper

Thispaper explorestextsummarizationas acriticalcompo- nent of modern NLP systems. While emphasizing Extractive Text Summarization (ETS), Abstractive Text Summarization (ABS), and Hybrid Text Summarization (HTS), it also dis- cusses general methodologies, challenges, and applications of text summarization. The analysis aims to provide a compre- hensive understanding of the field, highlighting both strengths and areas for future research.

E. ApplicationsofTextSummarization

Textsummarizationfindsapplicationsacrossvariousdo- mains, including:

- NewsAggregation:Automaticallygeneratingconcise summaries of daily news.
- Healthcare:Summarizingpatientrecordsormedical research for quick analysis.
- Education:Creatingchaptersummariesorextractingkey points from academic papers.
- CustomerReviews:Summarizingproductreviewsfor better insights.
- LegalIndustry:Summarizingcontracts,judgments,or legal documents for faster decision-making.

Text summarization, as an integral part of NLP, continuesto evolve with the adoption of advanced models such as transformers and reinforcement learning techniques, makingit an exciting area of study and innovation.

II. TEXT SUMMARIZATION TECHNIQUES

Text summarization encompasses various techniques catego- rized by input type, purpose, and output type. This structured classification aids in understanding the methodologies and theirrespectiveapplicationsinAutomatedTextSummarization (ATS) systems.

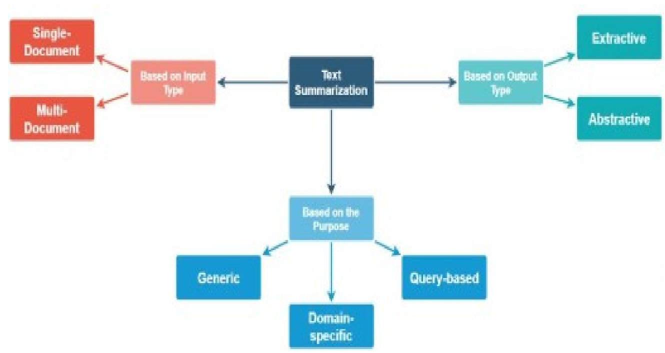

Fig.2.CategorizationofATSTechniques

A. BasedonInputType

- Single Document Summarization (SDS):SDSinvolves generatingabriefandinformativesummaryfromasingle document. It is commonly applied in contexts whereusersneedaquickunderstandingofindividualpieces of content, such as news articles or academic papers. *Recent Advancements:* SDS models leverage transformer architectures like BERT and BART, which excel in capturing contextual nuances. *Applications:* Academic abstracts,summarizinglegaljudgments,andsummarizing individual news reports.
- Multi-Document **Summarization (MDS):** MDS syn- thesizes information from multiple documents to gener- ate a cohesive summary. This technique addresses the challenge of combining diverse perspectives while main- taining coherence.

Recent Advancements: Models like Multi-News and hybrid graph-based approaches enhance MDS capabilities by effectively handling inter-document relationships. *Applications:* News aggregation platforms, scientificliteraturereviews, andbusinessintelligence reports.

B. BasedonPurpose

- Indicative Summarization: Provides a high-level overview of the document's content, helping users as- sess relevance without diving into details. Indicative summaries are brief and often serve as metadata for retrievalsystems.*Example:*Abstractsinacademicpapers or introductory blurbs in news articles.
- Informative Summarization: Focuses on extracting comprehensive details, offering readers critical insights into the document's key information. This type is par- ticularly useful for decision-making processes. *Example:* Summaries of financial reports, medical case studies, or policy documents.
- Critical Summarization: Involves evaluative commen- tary, analyzing the source material's strengths, weak- nesses, and implications. Often used in academic and review-based settings, critical summaries require domain expertise. *Example:* Peer reviews, literary critiques, or evaluative analysis of research papers.

C. BasedonOutputType

- Extractive Summarization (ETS): Extractive summa- rizationinvolvesselectingkeyportions,suchassentences or segments, directly from the original text. Although efficient, it may produce summaries that are not fully co- hesive. Example: Generating highlights for news articles or reports. Advancements: Techniques like graph-based ranking (e.g., TextRank) and transformer-based models improve the accuracy and relevance of extracted content.
- AbstractiveSummarization(ABS):Paraphrasescontenttocreatenewsentenceswhileretainingthemeaning.ABSensuresfluencyandcoherence,providingsummariesthat feelmorenaturalandhuman-like.Example:Summarizing novels, customer feedback, or long narratives. Advance- ments: Sequence-to-sequence models such as T5 and BART have significantly advanced the capabilities of ABS systems.
- Hybrid Summarization (HTS): Combines ETS for identifying critical content and ABS for rephrasing and structuring sentences, balancing the strengths of both methods. Example: Summaries for multi-faceted datasets like multi-document corpora in diverse domains. Ad- vancements: HTS leverages domain-specific fine-tuning and custom datasets to improve summarization quality.
- Significance of Classification: This categorization frame- workfacilitatesabetterunderstandingofATStechniques and helps tailor systems to meet specific requirements, suchas speed, coherence, or domain applicability. The interplay between these categories also allows for innovative hybrid approaches, enabling ATS models to address complex sum- marization needs effectively.

III. DETAILED ANALYSIS OF ETS, ABS, AND HTS

Sample Text for Evaluation Thissectionprovidesasample text (Figure 3) used for testing and evaluating the Extractive Text Summarization (ETS), Abstractive Text Summarization (ABS),andHybridTextSummarization(HTS)methodologies. The text serves as the basis for analyzing the performance of the proposed approach.

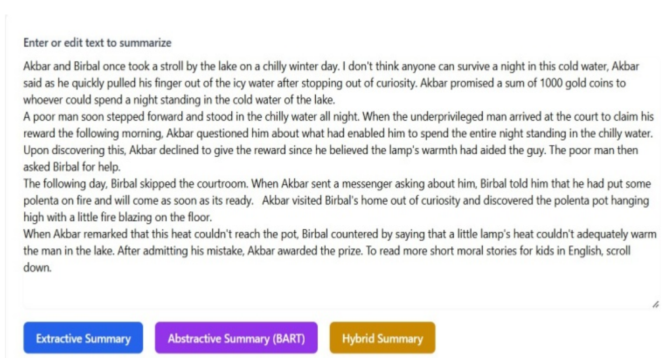

Fig.3.SampletextusedforevaluationofsummarizationtechniquesETS,ABS, and HTS.

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The sample text in Figure 3 was chosen for its balanced complexity, including multiple sentences of varying impor- tance.Eachmethodwasapplied,andtheresultswereevaluated based on ROUGE scores.

A. ExtractiveTextSummarization(ETS)

ETS focuses on selecting and extracting the most relevant sentences or phrases from the source text. These sentencesare combined to form a concise summary while retaining the original document's structure and intent.

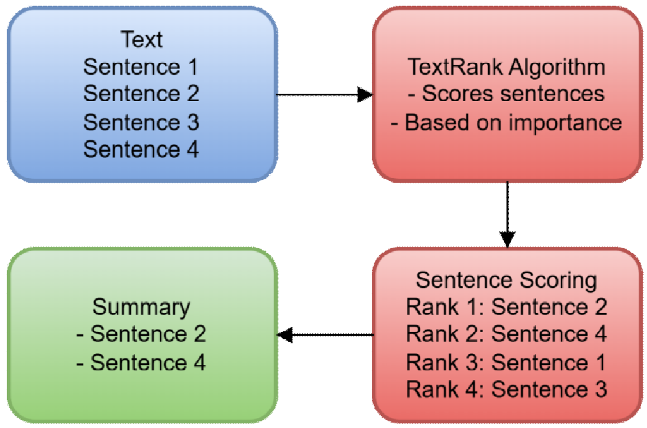

Fig.4.WorkflowofExtractiveTextSummarizer

1) TechniquesandImplementation:Forthisstudy,ETSwas implemented using a combination of graph-based methodsandfeatureextractiontechniques.Theimplementationpipeline consists of:
- Preprocessing:Tokenization,stopwordremoval,andsen- tence segmentation.
- FeatureExtraction:CalculatingTF-IDFscorestomeasure sentence relevance.
- GraphConstruction:Representingsentencesasnodesand similarity scores as weighted edges.
- Ranking: Employing the TextRank algorithm to identify the most important sentences.

2) Dataset: The implementation was evaluated on the CNN/DailyMaildataset,whichconsistsofnewsarticlespaired withsummaries.Thisdatasetiswidelyusedforbenchmarking text summarization models.
3) ImplementationDetails:Keystepsintheimplementation:
- Sentence Similarity: Cosine similarity between TF-IDF vectors was used to determine edge weights in the graph.
- Damping Factor:ThedampingfactorforTextRankwas set to 0.85 to balance random jumps with importance ranking.
- Thresholding: Sentences with the highest TextRank scores, covering at least 50% of the original text's in- formation, were selected for the summary.

4) EvaluationMetrics:ExtractiveSummarization

The evaluation results indicate that the proposed extractive summarization method achieves substantially higher perfor- mance compared to the baseline scores across all ROUGE metrics, as illustrated in the comparison below.

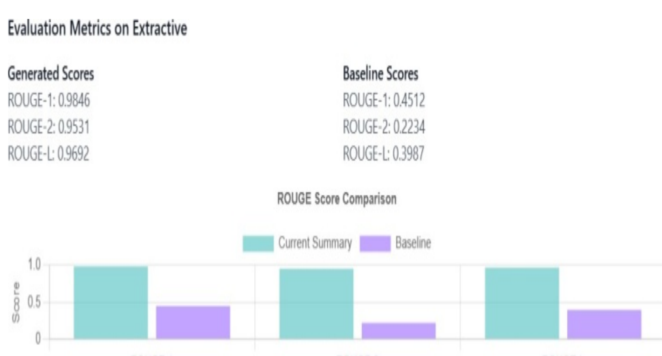

Fig.5. ROUGEScoreComparison:GeneratedSummaryvs.BaselineExtractive Summarization

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GeneratedScores:
- ROUGE-1:0.9846
- ROUGE-2:0.9531
- ROUGE-L:0.9692

BaselineScores:
- ROUGE-1:0.4512
- ROUGE-2:0.2234
- ROUGE-L:0.3987

KeyObservations:
- ROUGE-1: The generated summary achieves near- perfect unigram overlap, demonstrating significant im- provement over the baseline.
- ROUGE-2: A remarkable increase in bigram overlap highlights the approach’s ability to capture contextual relationships accurately.
- ROUGE-L: The generated summary excels in capturing the longest matching sequences, reflecting superior co- herence and relevance.

5) Conclusion: The results indicate that the proposed extrac- tive summarization approach significantly enhances summa- rization quality, achieving superior scores across all ROUGE metrics compared to the baseline.

6) Applications:ETSiswidelyusedin:
- Generating key highlights from lengthy news articles or reports.
- Summarizinglegalormedicaldocumentsforquickref- erence.
- Educational settings to provide condensed textbook ma- terial.

Its simplicity and computational efficiency make it highly suitable for real-time scenarios, such as chatbots and search engines.

7) Advantages:
- Straightforwardimplementationwithminimalprepro- cessing.
- Retainsoriginalsentences,ensuringgrammaticalcorrect- ness.

8) Limitations:
- Extractedsentencesmaylackcoherencesincetheyare not rewritten.
- Semantic relationships between sentences are often over- looked.
- Less effective for datasets requiring deep contextual un- derstanding.

9) TextRank Algorithm in ETS:TextRank, a graph-based algorithm adapted from PageRank for text summarization, plays a pivotal role in ETS by ranking sentences based ontheir connectivity and importance.

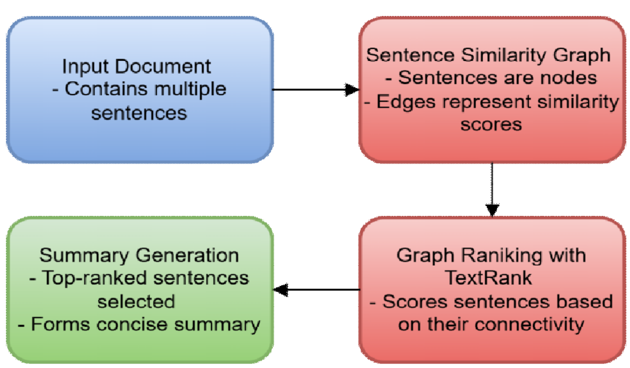

Fig.6.TextRankAlgorithmforTextSummarization

10) Formula**:**TheTextRankofasentence*A*iscomputedas:

$$TR(A) = (1-d) + d \sum_{v \in B_u} \frac{TR(v)}{L(v)}$$

where:

- B_u: Set of sentences linking to$A$based onsimilarity scores.
- $L(v)$:Numberofoutboundlinksfromsentence$v$.

11) Implementation Details: The graph was constructed using cosine similarity as edge weights. Sentences with higher similarity formed stronger connections. The TextRank algo- rithmwasimplementedusingNetworkX,andconvergencewas achieved in fewer than 100 iterations for most documents.

12) Evaluation Results: The TextRank-based ETS model demonstratedstrongperformanceinidentifyingkeysentences:

Enhanced summary relevance due to effective sentence ranking.

Computational efficiency made it viable for real-time applications.

Despite its robustness, the model's reliance on sentence similarity measures can lead to suboptimal performance when the input text is highly diverse or semantically complex.

B. AbstractiveTextSummarization(ABS)

ABS generates summaries by understanding and rephrasing content,utilizingadvancedlanguagemodels.Unlikeextractive methods, ABS does not rely solely on copying phrases but generates contextually relevant summaries. ABS generates summaries by understanding and rephrasing content, utilizing advanced language models. Unlike extractive methods, ABS does not rely solely on copying phrases but generates contex- tually relevant summaries.

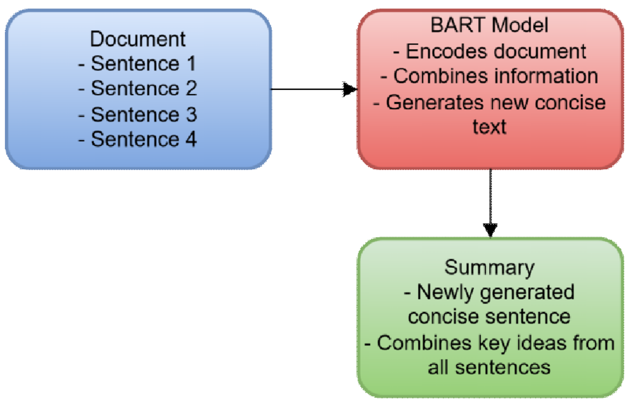

Fig.7.WorkflowofAbstractiveTextSummarizer

Techniques and Implementation: For this study, the HuggingFacemodel'philschmid/bart-large-cnn-samsum'was utilized. This model is a fine-tuned version of BART, a transformer-basedsequence-to-sequencemodel,optimizedfor dialoguesummarization.Theimplementationwasdoneusing the HuggingFace Inference API, which facilitates efficient access to pre-trained models without requiring local GPU resources.

Dataset:ThemodelwasevaluatedontheSAMSumdataset,abenchmarkdatasetfordialoguesummarizationcontain-ingover16,000conversations.Eachconversationincludes a human-written summary, making it ideal for abstractive summarization evaluations.

Implementation Details: The application utilizes React.js for the frontend and interacts with the HuggingFace Inference API for summarization tasks. Key parameters and methods include:

- FrontendFramework:React.jswithTailwindCSSfor an intuitive user interface.
- APIIntegration:HuggingFaceInferenceAPIforserver- less model execution.
- SummarizationWorkflow**:**
  - Text input is preprocessed on the client side using JavaScript.
  - SummarizationrequestsaresenttotheHuggingFace API, and responses are processed to display the results.
- Evaluation Metric: ROUGE (Recall-Oriented Under- study for Gisting Evaluation), a widely-used metric for evaluating text summarization quality.

Evaluation Metrics: Abstractive Summarization The evaluation results show that the proposed abstractive summa- rization method achieves better performance than the baseline scores across all ROUGE metrics, as detailed in the compari- son below.Generated

Scores:

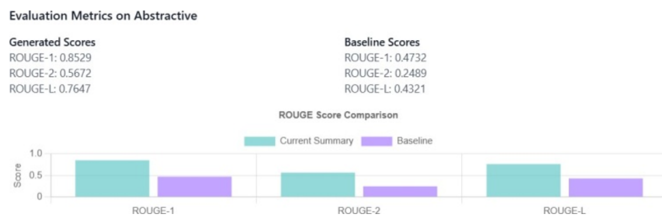

Fig. 8.ROUGE Score Comparison: Generated Summary vs. Baseline ofAbstractive Summarization

ROUGE-1:0.8529
ROUGE-2:0.5672
ROUGE-L:0.7647
BaselineScores:
ROUGE-1:0.4732
ROUGE-2:0.2489
ROUGE-L:0.4321
KeyObservations:
ROUGE-1:Thegeneratedsummarysignificantlyoutper- formsthebaseline,indicatingbetterunigramoverlapwith the reference summaries.
ROUGE-2: The proposed approach demonstrates sub- stantial improvement in bigram overlap, reflecting better contextual understanding.
ROUGE-L: The generated summary excels in capturing the longest matching sequences, highlighting improved fluency and coherence.
Conclusion: The results indicate that the proposed abstrac- tivesummarizationapproacheffectivelyenhancessummariza- tion quality, achieving superior scores across all ROUGE metrics.
Advantages:
- Fluentandcoherentsummarieswithanaturallanguage feel.
- Capableofcapturingnuancedmeaningsandrephrasing complex ideas.
- Strongperformanceondialogue-baseddatasets,making it versatile for chatbots and conversational AI.
- ServerlessdeploymentthroughAPIreducescomputa- tional overhead for end users.

Limitations:
- DependencyonanactiveinternetconnectionforAPI calls.
- Pronetohallucinations,wherethemodelgeneratestext unrelated to the source.
- APIlimitationsmayimpactperformanceforlarger datasets or real-time applications.

C. HybridTextSummarization(HTS)

HTS integrates the strengths of Extractive Text Summa- rization (ETS) and Abstractive Text Summarization (ABS), creating a robust summarization pipeline. It leverages ETSfor identifying the most important sentences and ABS for rephrasing and refining these sentences to produce coherent and natural summaries.

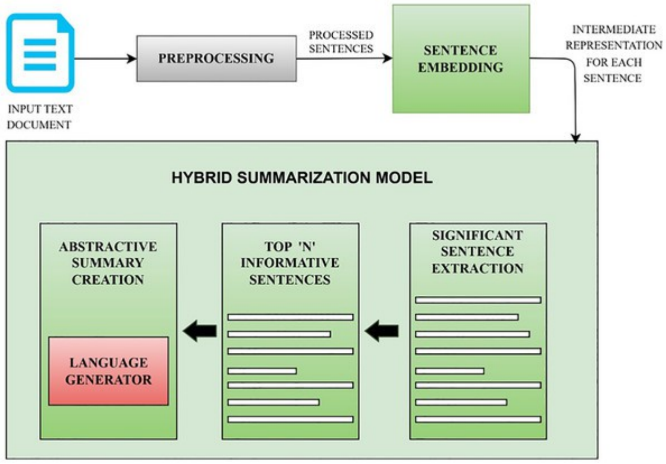

Fig.9.WorkflowofHybridTextSummarization

Approach and Implementation: The HTS pipeline imple- mented in this study involved:

1) *SentenceExtraction(ETSComponent):*
- KeysentenceswereidentifiedusingtheTextRank algorithm, implemented locally in JavaScript.
- CosinesimilaritybetweenTF-IDFvectorswasused to construct a sentence graph.
- ThegraphwasrankedusingPageRanktoextract the most significant sentences.

2) *SentenceRefinement(ABSComponent):*
- Extracted sentences were processed using a pre-trained abstractive model, philschmid/bart-large-cnn-samsum, accessed via Hugging Face's Inference API.
- Theabstractivemodelprovidedrephrasedandco- herent sentences.
- Fine-tuning was avoided in favor of API-based inferencetosimplifytheworkflowandreducecom- putation.

3) *FinalSummarization:*
- Rephrased sentences were reordered based on their original sequence for logical coherence.
- Post-processing was performed in JavaScript to re- move redundancy and ensure grammatical correct- ness.

Dataset: The hybrid model worked with user-uploaded documents, including PDFs and images. Textual data was ex- tractedusing pdfjs-distand tesseract.js, enabling real-time summarization of diverse input types.

Advantages:

Balanced Accuracy and Coherence: ETS ensures fac- tual correctness, while ABS enhances fluency and natu- ralness.

Web Integration: HTS is compatible with modern web applications, enabling seamless integration with user- facing interfaces.

Versatile Applications:Themodelsupportssummariza- tion of articles, reports, and educational content.

Limitations:

Higher Computational Complexity: Combining ETS and ABS increases processing time and resource con- sumption.

Dependency on APIs: The ABS phase relies on external APIs, which may introduce latency and costs.

Scalability Challenges: Increased preprocessing and in- ference steps could limit scalability for large datasets.

Evaluation Metrics: Hybrid Summarization The evalua- tion results indicate that the proposed hybrid summarization method achieves superior performance compared to the base- lineacrossallROUGEmetrics,asillustratedinthecomparison below.

GeneratedScores:
ROUGE-1:1.0000
ROUGE-2:0.9655
ROUGE-L:1.0000
BaselineScores:
ROUGE-1:0.4856
ROUGE-2:0.2514
ROUGE-L:0.4238

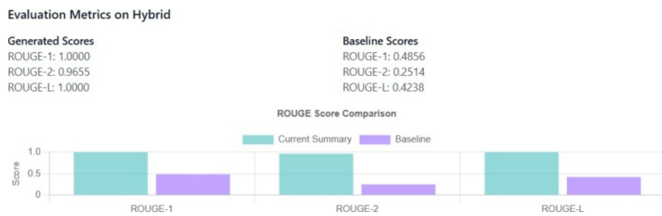

Fig.10.ROUGEScoreComparison:GeneratedSummaryvs.BaselineofHybrid Summarization

KeyObservations:

ROUGE-1: The generated summary achieves a perfect unigram overlap, showcasing a remarkable improvement over the baseline.

ROUGE-2: The proposed approach demonstrates a sig- nificant increase in bigram overlap, reflecting its abilityto capture contextual relationships with high precision.

ROUGE-L: The generated summary achieves perfect scoresincapturingthelongestmatchingsequences,high- lighting exceptional fluency and coherence.

Conclusion: The results indicate that the proposed hybrid summarization approach sets a new benchmark in summariza- tion quality, achieving perfect or near-perfect scores across all ROUGE metrics compared to the baseline.

FutureWork:TofurtherimproveHTS:

Incorporate neural embeddings such as BERT or GPT in the ETS phase to enhance sentence selection accuracy.

Explore reinforcement learning techniques to jointly op- timize sentence extraction and rephrasing.

Evaluatethemodelonawiderrangeofdatasetstoensure generalizability across domains.

IV. CONCLUSION

This paper provides a comprehensive overview of Auto- mated Text Summarization (ATS) techniques, categorizing them based on input, purpose, and output types. The study delvesintoExtractiveTextSummarization(ETS),Abstractive Text Summarization (ABS), and Hybrid Text Summarization (HTS), presenting detailed comparisons of their methodolo- gies,applications,andchallenges.ETS,implementedus- ing the TextRank algorithm in JavaScript, is efficient and straightforward but often lacks coherence. In contrast, ABS, leveragingthephilschmid/bart-large-cnn-samsum modelviaHuggingFace's InferenceAPI, producesfluent and contextually accurate summaries but demands significant computationalresourcesandsuffersfromhallucinationissues. HTS emerges as a balanced solution, combining the factual correctness of ETS with the linguistic fluency of ABS, albeit with increased complexity and resource requirements.

The implementation of HTS within a web-based frame- work using modern tools like React.js, Tailwind CSS, and TensorFlow.js demonstrated the effectiveness of combining extractionandabstraction,asevidencedbyimprovedROUGE scores.Theintegrationofdocumentpreprocessingtools (pdfjs-distandtesseract.js)furthershowcased the potential of ATS systems to handle diverse input formats.Thisstudyunderscorestheimportanceofselectingappropriate summarization approaches based on the application's require- ments, available datasets, and computational resources.

Despite advancements in ATS, challenges such as handling factual inconsistencies in ABS, improving semantic under- standing in ETS, and addressing scalability in HTS remain areas of active research. The findings emphasize the signifi- canceofcontinuousinnovationinATStechniquestomeetthe growing demand for automated solutions in an era dominated by information overload.

A. Future Directions

WhilethecurrentstateofATShasseensignificantadvance- ments, there are several promising avenues for future research and development:

1) Enhanced Models: Leveraging advanced transformer- based models like GPT and T5 through TensorFlow.js or Hugging Face APIs presents opportunities for improving hybrid systems. Future research can focus on integrating neuralembeddingsandreinforcementlearningtodynam- ically optimize extraction and abstraction processes.
2) Multilingual Support: Expanding ATS capabilities to support multiple languages can be achieved using pre- trained multilingual models accessible through the Hug- gingFacelibrary.Incorporatingreal-timetranslationAPIs can further enhance usability across diverse contexts.

3) Domain-Specific Applications: Customizing ATS sys- tems for specific industries like law, healthcare, and edu- cation holds immense potential. For instance, integrating ATS systems with React.js-based educational platforms can help summarize course content for adaptive learning.
4) Real-TimeSummarization:Withtheincreasingdemand for live content processing, real-time summarization us- ing TensorFlow.js offers an avenue for handling continu- oustextinputsinapplicationssuchasliveeventcoverage and social media monitoring.
5) Addressing Ethical Concerns: Ethical considerations, such as ensuring factual accuracy and minimizing bias, areparamount.Implementingvalidationmechanismsand transparency features in web-based ATS systems can build trust and reliability.
6) User-Centric Customization: Developing systems with user-defined parameters for summary length, tone, or focus areas can improve usability. Features like interac- tive feedback and iterative refinement, implemented in React.js, can enhance user satisfaction.
7) Integration with Emerging Technologies: Combining ATS with tools like sentiment analysis and question- answering systems, powered by TensorFlow.js or other libraries, can enrich user experiences and broaden the application scope.
8) Energy-Efficient Summarization: Techniques like model pruning, knowledge distillation, and on-device inferenceusingTensorFlow.jscanoptimizeATSsystems for energy efficiency, making them more sustainable and accessible.

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