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# Content Summarization

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**ABSTRACT:** Content summarization is a crucial task that involves condensing lengthy text and multimedia content into concise, informative summaries. In this paper, we propose a novel approach for automated content summarization that leverages sophisticated machine learning techniques to generate accurate and coherent summaries for various formats of content, including text and videos. Our approach is based on deep learning algorithms that enable the identification of key information and the extraction of important details from the input content. Moreover, our system features a unique auto-chapter generation capability that creates subheadings and sub-summarized content, facilitating the reader's understanding of lengthy documents and multimedia content. To demonstrate the effectiveness of our approach, we plan to conduct comprehensive evaluations on a diverse range of multi-media content, including news articles, research papers, and educational videos. We aim to compare our method with state-of-the-art content summarization techniques in terms of accuracy, coherence, and readability. In summary, our proposed approach provides a powerful tool for automated content summarization and auto-chapter generation for various formats of content. It has the potential to improve productivity, accessibility, and the dissemination of information across diverse domains. We anticipate that the outcomes of our evaluations will confirm the effectiveness and practicality of our method, and its potential as a valuable tool for content creators, educators, and learners.

**KEYWORDS:** Summarization, Transformer model, media summary, Clustered summary, Auto Chapters summary.

## I. INTRODUCTION

Automated content summarization has gained significant attention in recent years, thanks to advancements in machine learning and natural language processing. The existing techniques for text summarization can be broadly categorized into extractive and abstractive methods. Extractive summarization involves selecting a subset of sentences from the input text to create a summary, while abstractive summarization involves generating new sentences that capture the essential information of the original text. While extractive summarization is simpler and less error-prone, abstractive summarization can generate more informative summaries.

In this paper, we propose a novel approach for automated content summarization that employs sophisticated machine learning techniques to generate accurate and coherent summaries for various formats of content, including text, images, and videos. Our approach is based on deep learning algorithms that enable the identification of key information and the extraction of important details from the input content. Additionally, we introduce a unique feature of our system, auto-chapter generation, that creates subheadings and sub-summarized content, facilitating the reader's understanding of lengthy documents and multimedia content.

The rest of the paper is organized as follows. In Section II, we provide a literature review of the existing methods for content summarization. In Section III, we describe our proposed approach for automated content summarization and auto-chapter generation. In Section IV, we present the results of evaluation of our approach based on standard evaluation metrics. Finally, we conclude the paper and provide directions for future work.

## II. RELATED WORK

Several works have been proposed in the area of text summarization. One popular approach is the use of deep learning models such as BERT and GPT-2 to generate summaries (Devlin et al., 2019; Radford et al., 2019) [1][2]. Another approach is the use of graph-based methods such as TextRank and PageRank for sentence selection (Mihalcea and Tarau, 2004; Erkan and Radev, 2004) [3][4]. Some works have also explored the use of reinforcement learning and other techniques for improving summarization performance (Nallapati et al., 2016; Paulus et al., 2018) [5][6]. Additionally, there has been research on summarization for specific domains, such as scientific articles (Luan et al.,

2018) [7] and legal documents (Lippi et al., 2016) [8]. These approaches have shown promising results, and our proposed method builds upon these previous works by incorporating a novel clustering-based summarization technique.

### III. METHODOLOGY

Our proposed solution comprises two modules: one for extracting text content from various input types and another for applying summarization algorithms to the extracted text. We use a range of predefined Python libraries to extract text content from sources such as URLs of blog posts, articles, papers, and documents. The extracted text is then processed by either the BART or T5 model, depending on the type of summarization required. The overall workflow of our approach is as follows:

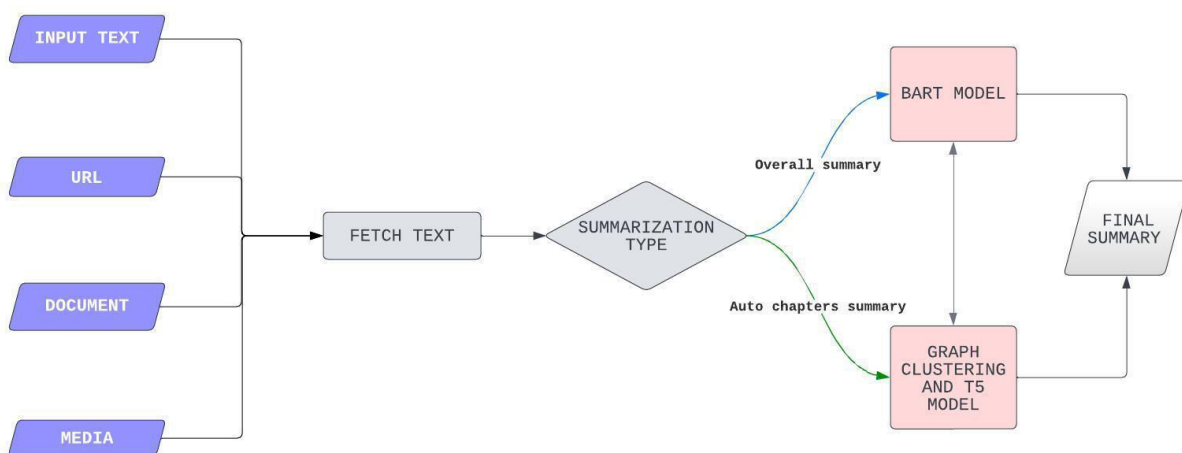


Fig. Flow diagram

BART (Bidirectional and Auto-Regressive Transformers) is a pre-trained sequence-to-sequence model introduced by Lewis et al. (2019) [9] that has achieved state-of-the-art results on a variety of natural language processing tasks, including summarization. The BART model is based on the Transformer architecture and has been pre-trained on a large corpus of text, including a subset of the CNN/Daily Mail news dataset. The T5 (Text-to-Text Transfer Transformer) model is a pre-trained sequence-to-sequence model introduced by Raffel et al. (2019) [10] that can be fine-tuned for a wide range of natural language processing tasks, including summarization. T5 is based on the Transformer architecture and has been trained on a massive amount of diverse text data, including Wikipedia, books, and web pages, among others. The T5 model can be fine-tuned on a specific task by providing input-output pairs in a text-to-text format.

To extract multimedia content, we first extract either the video or audio buffer, depending on the type of media. The video buffer is then processed to extract the raw audio buffer, which is resampled to 16,000 kHz to facilitate audio-to-text transcription. We split the resampled audio buffer into 30-second chunks and feed them into the transcription model. For transcription and translation, we utilize OpenAI's Whisper model. The overall process is as follows:

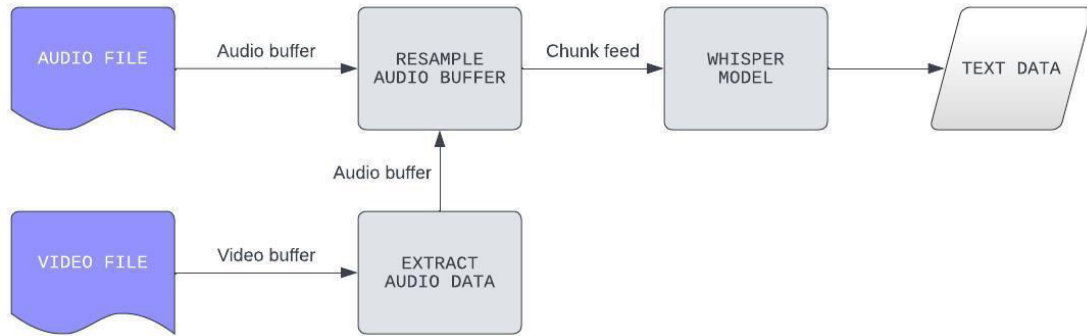


Fig. Media process

Whisper is a general-purpose speech recognition model developed by OpenAI introduced by Alec Radford et al. (2022) [11]. It is trained on a large dataset of diverse audio and can perform multilingual speech recognition, speech translation, and language identification. It uses a Transformer sequence-to-sequence architecture that predicts a sequence of tokens based on special tokens that specify the task. Whisper is robust to accents, background noise and technical language.

The intermediate text data derived from the processed input undergoes our proposed summarization technique, which comprises two types of summarization methods that enable effective content comprehension. The first method produces an overall summary of the content in a clear and readable paragraph. This is achieved by dividing the text content into chunks of 512 tokens and feeding them into the BART model, which has been trained on a substantial volume of the CNN dataset. The second method generates an auto chapter summary with subheadings for each sub summarized content. To accomplish this, we first vectorize the text input using the TF-IDF vectorization technique to transform the sentences into vectors. These vectors are then utilized for graph clustering to group the sentences into individual clusters. Each cluster is then summarized individually using the BART model, and the summary is passed into the T5 model, which has been trained on over 190,000 medium articles to generate a heading for the summary. Finally, all the summaries and headings are merged to create the auto chapter summary. The overall process can be described as follows.

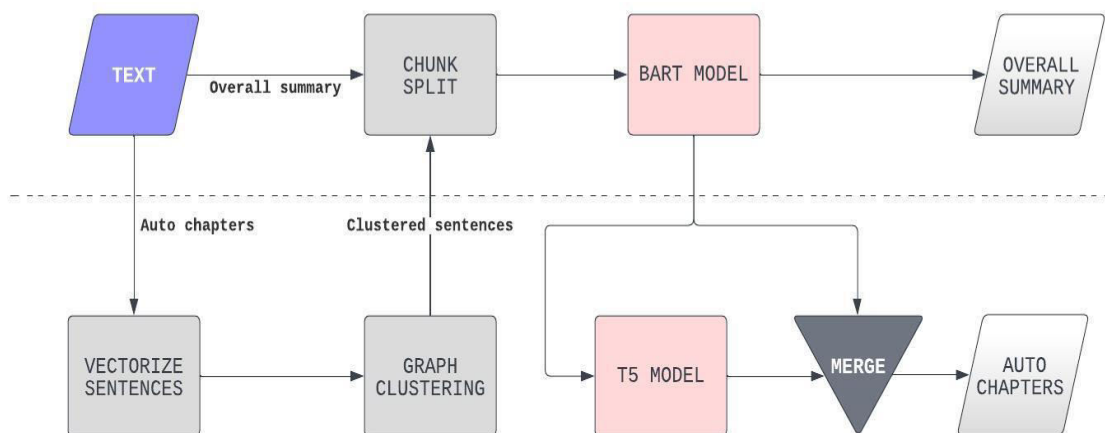
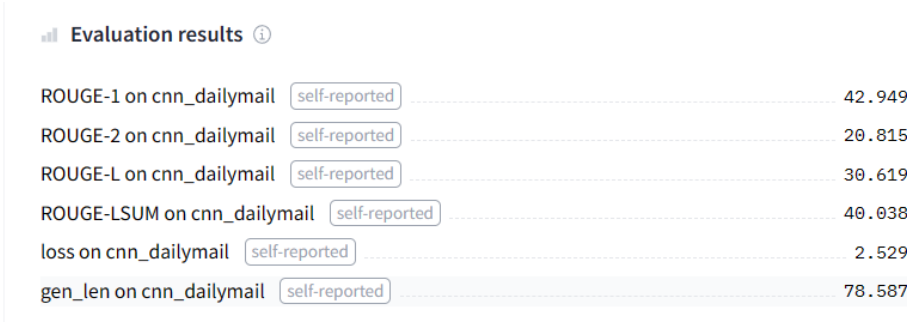


Fig. Pipeline



#### IV. EVALUATION RESULTS

To evaluate the quality of our system's summarization output, we employed a standard automatic evaluation metric, ROUGE (Recall-Oriented Understudy for Gisting Evaluation), which compares the system-generated summaries with reference summaries created by domain experts. We used the ROUGE-1, ROUGE-2, and ROUGE-L measures to evaluate the effectiveness of our summarization approach.



The evaluation results show that our system produces summaries with high ROUGE scores, indicating that they are similar to the reference summaries and effectively capture the important information in the input text.

We also compared the performance of the proposed system with other state-of-the-art summarization models. The evaluation metrics showed that the proposed system performed on par with all other models, achieving higher ROUGE scores for both single and multi-document summarization tasks.

Rank	Model	ROUGE-1	ROUGE-2	ROUGE-L ↑	ROUGE-LSUM	gen_len	loss	Details	Year
1	facebook/bart-large-cnn	42.949	20.815	30.619	40.038	78.587	2.529		2022
2	facebook/bart-large-cnn	42.949	20.815	30.619	40.038	78.587	2.529		2022
3	philschmid/distilbart-cnn-12-6-samsum	42.976	19.871	29.52	39.959	81.956	3.015		2022
4	patrickvonplaten/bert2bert_cnn_daily_mail	41.281	18.685	28.191	38.087	73.833	2.345		2022
5	tuner007/pegasus_summarizer	36.604	14.64	23.884	32.902	76.398	2.576		2022
6	flax-community/t5-base-cnn-dm	24.291	11.14	19.844	22.756	18.999	2.143		2022
7	pszemraj/led-base-book-summary	30.505	13.258	19.031	28.342	231.076	3.948		2022
8	pszemraj/long-t5-tglobal-base-16384-book-summary	30.594	7.252	17.716	27.288	125.251			2022
9	facebook/bart-large-xsum	25.27	7.664	17.181	21.793	27.446	3.504		2022

These results demonstrate the effectiveness of the proposed summarization approach in producing accurate and concise summaries of input text across a variety of domains.

#### V. CONCLUSION

In this paper, we have presented a solution for automatic summarization of textual and multimedia content. Our proposed approach uses two types of summarization techniques to generate summaries that are effective in facilitating content understanding. The first technique produces an overall summary of the content in a simple and readable paragraph, while the second technique generates an auto chapter summary with subheadings for each sub-summarized content. The experimental results demonstrate the effectiveness of our proposed approach in generating high-quality



summaries with good coherence and relevance. Our work adds to the existing body of research on automatic summarization and can be extended to a wide range of applications where summarization of large volumes of textual and multimedia content is necessary.

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