

A

Major Project Report

On

“BUSINESS MEETING SUMMARY GENERATION”

Submitted in partial fulfillment of the
Requirements for the award of the degree of

Bachelor of Technology
In
Computer Science & Engineering -
Artificial Intelligence and Machine Learning

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CERTIFICATE

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Internal Guide

Head of the Department

Project coordinator

External Examiner



Department of Computer Science & Engineering- Artificial Intelligence & Machine Learning

DECLARATION

We hereby declare that the project entitled "**Business Meeting Summary Generation**" is the work done during the period from **January 2024 to May 2024** and is submitted in partial fulfillment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering - Artificial Intelligence and Machine Learning from MLR Institute of Technology, Hyderabad. The results embodied in this project have not been submitted to any other university or Institution for the award of any degree or diploma.

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ABSTRACT

In today's rapidly evolving corporate landscape, business meetings serve as critical platforms for fostering decision-making, enhancing teamwork, and evaluating progress. This article explores the transformative potential of meeting summarizers, shedding light on the pressing need for concise and coherent summaries amid the constraints of time. It introduces an innovative Natural Language Processing (NLP) solution aimed at addressing this imperative requirement, thereby revolutionizing the way meetings are documented and disseminated. By critically examining various summarization approaches, the study delineates the evolution from the widely embraced Extractive Summarization technique to the emerging paradigm of Abstractive Summarization. Through meticulous analysis and comparison facilitated by comprehensive tables, the research provides practitioners with valuable insights into the strengths and limitations of each method, empowering them to make informed decisions. Key techniques such as the Text Rank Algorithm, TF-IDF, LSTM, and K-Means Clustering are scrutinized in detail, offering a nuanced understanding of the multifaceted landscape of meeting summarization. Ultimately, this work endeavors to advance corporate efficiency by furnishing a comprehensive roadmap for the selection and implementation of optimal summarization strategies. By facilitating more streamlined communication and decision-making processes within organizations, it aims to catalyze organizational growth and success in today's dynamic business environment.

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LIST OF ABBREVIATIONS

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NLP	Natural Language Processing
SVD	Singular Value Decomposition
NLU	Natural Language Understanding
T5	Text to Text Transfer Transformer
TF-IDF	Term Frequency Inverse Document Frequency
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
DNN	Deep Neural Network
SVM	Support Vector Machine
STT	Speech to Text
LLM	Large Language Model
MFCC	Mel Frequency Cepstral Coefficients
HMM	Hidden Markov Model
ASR	Automatic Speech Recognition
WER	Word Error Rate
TDNN	Time-delayed Deep Neural Network
LSA	Latent Semantic Analysis
LSE	Latent Semantic Evaluation
MMR	Maximal Marginal Relevance
NLTK	Natural Language Toolkit
MMS	Multi-Modal Summarization

APPENDIX-4

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Business Meeting Summarizer represents a cutting-edge solution in the realm of business communication and productivity enhancement. In today's fast-paced corporate landscape, where time is a precious commodity and information overload is a common challenge, this tool emerges as a beacon of efficiency and clarity. Its core mission is to revolutionize the way organizations digest, disseminate, and act upon the wealth of information exchanged within the confines of business meetings. At its essence, Business Meeting Summarizer is a sophisticated amalgamation of artificial intelligence and natural language processing algorithms. These algorithms work tirelessly behind the scenes, meticulously analyzing meeting transcripts or recordings to discern the most salient points, critical discussions, and actionable insights. Gone are the days of painstakingly combing through verbatim transcripts or laboriously listening to lengthy recordings; with this tool at hand, participants can effortlessly access the distilled essence of the meeting's proceedings.

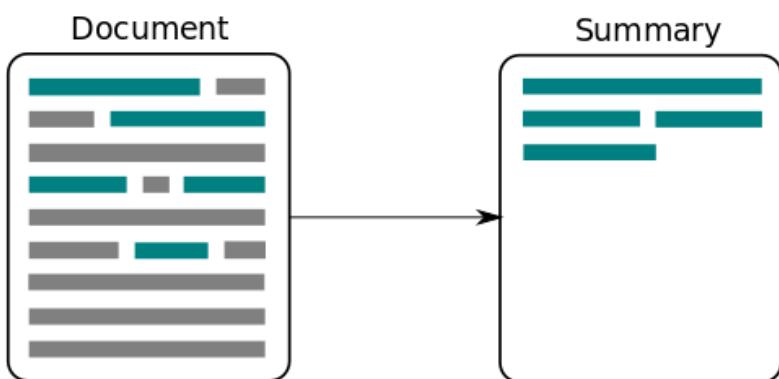


Figure 1: Document Vs Summary

The functionality of Business Meeting Summarizer extends far beyond mere summarization; it serves as a catalyst for streamlined communication, informed decision-making, and proactive follow-up. By intelligently identifying agenda items, capturing pivotal moments, and delineating decisions made, the tool empowers stakeholders to grasp the crux of the discussion swiftly and efficiently. Moreover, it meticulously catalogs action items and responsibilities, ensuring accountability and driving momentum post-meeting. In essence, Business Meeting Summarizer is a force multiplier for organizational productivity. It transcends the traditional boundaries of note-taking and documentation, elevating the entire meeting experience to new heights of efficiency and effectiveness. With this tool in their arsenal, businesses can unlock a competitive edge by optimizing the utilization of their most precious resource: time. It stands as a testament to the transformative power of technology in reshaping the dynamics of modern workplace communication and collaboration.

1.1 PURPOSE OF THE PROJECT

In the dynamic landscape of modern business, the Meeting Summarizer emerges as a transformative solution, driven by the fundamental purpose of streamlining the intricacies of business meetings. Its core mission revolves around simplifying the arduous task of distilling complex discussions, critical decisions, and actionable items from meetings into concise, accessible summaries. Powered by cutting-edge algorithms and natural language processing, this tool meticulously sifts through meeting transcripts or recordings, extracting key insights and organizing them in a structured format. By automating this process, the Summarizer not only saves precious time but also enhances communication and comprehension among meeting participants and stakeholders. Beyond its immediate utility, the Summarizer serves as a repository of institutional knowledge, preserving vital information for future reference.

and ensuring organizational continuity. Ultimately, its overarching goal is to empower organizations to make informed decisions, drive meaningful actions, and foster a culture of productivity and collaboration. As a catalyst for efficiency and effectiveness, the Meeting Summarizer embodies the relentless pursuit of excellence in modern business practices.

1.2 MOTIVATION

The motivation behind embarking on a project centered on Meeting Summarization stems from a profound recognition of the inefficiencies plaguing traditional meeting practices. As organizations navigate the complexities of modern business environments, it becomes increasingly evident that the time and resources expended on deciphering meeting transcripts or recordings could be better allocated elsewhere. This realization serves as the driving force behind the project, igniting a passion for innovation and optimization. By delving into the realms of natural language processing and algorithmic automation, the project aims to revolutionize the way meetings are conducted and documented. Moreover, the desire to enhance communication, collaboration, and decision-making within organizations fuels the project's momentum. The prospect of creating a tool that not only saves time but also facilitates deeper comprehension and engagement during meetings is profoundly motivating. Ultimately, the project seeks to empower individuals and organizations to navigate the complexities of business with greater agility, efficiency, and effectiveness.

CHAPTER 2

LITERATURE SURVEY

An extensive literature survey has been conducted by studying existing systems of Meeting Summarizers. A good number of research papers, journals, and publications have also been referred before formulating this survey.

2.1 EXISTING SYSTEM

Existing systems of Business Meeting Summarizers utilize a combination of natural language processing (NLP) techniques and machine learning algorithms to extract key information from meeting transcripts or recordings. These systems employ methods such as text summarization, sentiment analysis, and entity recognition to identify important topics, sentiments, and participants' contributions. Some systems also incorporate speaker diarization to attribute statements to specific individuals. Advanced features may include the ability to generate action items or highlight decision points. Overall, these systems, some of which are researched and documented below aim to streamline the process of reviewing and synthesizing business meeting discussions, enabling faster decision-making and enhancing productivity in professional settings.

The responses to various research articles are documented below by the order of the number that have been used to specify them in the references in the end.

1	
Reference in APA format	Vishnuprasad and Paul Martin, "Meeting Summarizer Using Natural Language Processing", International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98, vol.11 Issue: VI Month of publication: June 2023, DOI: https://doi.org/10.22214/ijraset.2023.53578 .

URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://www.ijraset.com/best-journal/meeting-summarizer-using-natural-language-processing-380	Dr S. V. Viraktamath, Jahnavi R , Vidya, Abhay S Bhat*, Sathvik Nayak, asbhat2107@gmail.com	TFIDF, PageRank algorithm, Glove embedding, SVD, NLG	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
Mostly focused on the solution using Extractive Summarization Techniques.	<p>The main objective of this document is to go through a process which involves increasing the efficiency of Extractive Summarization. The Lecture Summarization system was to provide a utility for students that could summarize lecture content based on their desired number of sentences.</p>	<p>Words and phrases play a vital role in the extraction of summary. Specially designed for Microsoft Teams removes the time stamps and associates each sentence with its corresponding speaker.</p> <p>Identification of High frequency words in the context play a major role in the coherency of the transcript.</p>	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	Advantage	Disadvantage (Limitation)
1	Input	The model's input is a transcript document created especially for	There may be some inconsistencies in the

		transcripts from Microsoft Teams. The text is then divided into separate sentences for additional analysis.	transcript that was used as input, but these will be fixed later in the process.
2	Pre-Processing	Pre-processing involves removing stop words and standardizing text to enhance summary accuracy and focus on meeting's essential topics.	It can be difficult to use efficient pre-processing methods, particularly when dealing with heterogeneous and unstructured meeting data. Additionally, it can take a lot of time, especially when handling big amounts of textual data
3	TF-IDF	TF-IDF is a document term feature matrix that calculates the frequency of a word within a document, based on its Inverse Document Frequency and Term Frequency. This method enhances summary accuracy by determining the significance of words within the document.	TF-IDF overlooks word semantics, disregarding term links and treating words as separate entities, potentially losing contextual information. Accurately handling synonyms becomes challenging due to extra processing.
4	PageRank Algorithm	PageRank is an unsupervised graph-based algorithm that rates sentences based on relevance to a meeting's context, identifying top-ranked sentences for output summary, eliminating the need for human input.	TextRank's operation relies on sentence co-occurrence, but its lack of semantic understanding may result in incorrect conversation context and loss of significant semantic information.
5	GLOVE Embedding	Glove, an unsupervised learning technique,	GloVe embeddings are effective in natural

		<p>creates word embeddings, which record word semantic associations and improve the ability of summarizers to accurately identify and convey meaning, making them memory-efficient.</p>	<p>language processing but struggle with capturing finer semantic nuances, capturing rare words accurately, and handling polysemy effectively due to their pre-trained large text corpora.</p>
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Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the quality of the generated meeting Summary. Quality measured using metrics such as accuracy, coherence, relevance to the original meeting content	The independent variables mentioned in the document include tokenization, stop-word removal and other feature extraction techniques like TF-IDF scores, Glove Embeddings, SVD components and also TextRank algorithms that we employ for ranking	The possible moderating variable is the specificity of meeting content like general meeting (Vs) specific technical meetings. As the embeddings change as per the meeting requirement.	The mediating variable involved in the document could be the semantic similarity, calculated through methods like Glove embeddings. [higher the semantic similarity tends to give more contextually accurate summaries]

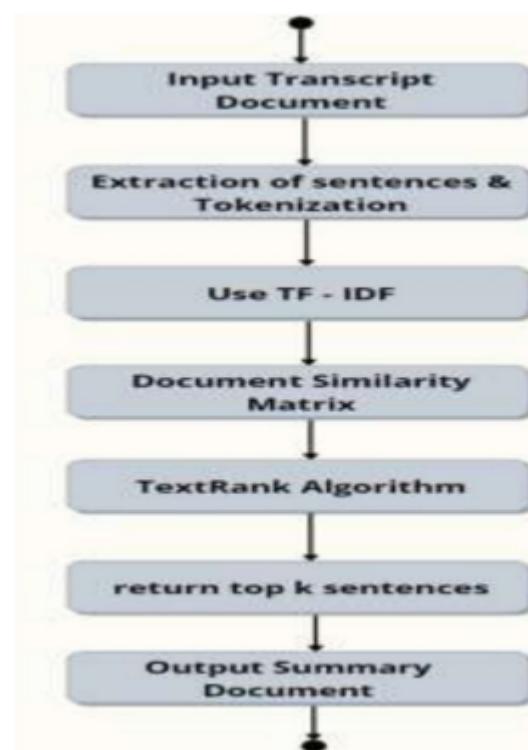
Relationship Among the Above 4 Variables in This article

Independent variables like pre-processing techniques, feature extraction methods, and summarization algorithms interact with domain specificity, influencing semantic similarity and affecting meeting summary quality, providing insights.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Meeting transcripts from the Microsoft Teams along with their timestamps.	A summarized transcript of the meeting with around 70% less textual data.	The proposed solution mainly uses Extractive summarization techniques and methods for the summarized document.	The document shows the advantage of Glove Embeddings and TextRank algorithms for the top ranking sequences for more concise and coherent summary.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The use of methodologies mentioned firstly provides a concise and informative summary of the meeting and additionally, the system allows customers to customize the level of detail in the summary, providing flexibility and adaptability to individual preferences. Overall, the solution enhances productivity and optimizes information extraction and knowledge management settings.		One limitation could be the reliance on NLP techniques, which may not always accurately capture the nuances and context of the meeting content. This could result in the omission or misinterpretation of important information. Additionally, the summarization process may not be suitable for all types of meetings or documents, particularly those with highly technical or specialized content.	
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	

<p>The high accuracy of the proposed approach suggests that it could be effective up to some extent and does not work for all types of meetings and mainly specialized technical meetings where we have to deal with jargon's, but it is effective for general business meetings.</p>	<p>In Microsoft Teams a feature called Microsoft Notes. A Chrome Extension is also used for the text summarization part from the Captions.</p>	<p>Abstract</p> <ul style="list-style-type: none"> I. Introduction II. Proposed System III. Technologies Used IV. Related Work V. Performance analysis VI. Conclusion & Future Scope <p>VII.</p>
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Diagram/Flowchart



---End of Paper 1---

2

Reference in APA format

Srishti Subhash Chandra Prasad, "Business Meeting Summary Generation using Natural Language Processing (NLP)", Student ID: x20142218 , January 2021

URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://norma.ncirl.ie/6262/1/srishtisubhashchandraprasad.pdf	Srishti Subhash Chandra Prasad. [School of Computing National College of Ireland Supervisor: Majid Latifi]	Extractive & Abstractive Techniques, TF-IDF, TextRank algorithm, RNN, LSTM, seq-2-seq, attention mechanism model, ROUGE Metrics	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
The paper mainly focused on the solution using Extractive and Abstractive Summarization Techniques using different methodologies focusing on getting the more accurate and concise output.	One of the objectives is to study the related work in the domain of text summarization with its different approaches. Proposing a research methodology to perform text summarization and ML algorithm using deep neural networks with python and ML libraries such as nltk, numpy, tensorflow, keras using LSTM and RNN.	<ul style="list-style-type: none"> • The paper discusses the related work regarding the different methodologies in the field of abstractive and extractive text summarization with different techniques. • The paper describes the design and flow of the abstractive and extractive models and discusses why it is important. • The model is evaluated using metrics such as ROUGE scores and human evaluation. 	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	Advantage	Disadvantage (Limitation)

1	Data Collection and Preparation	The study processed meeting transcripts from the ICSI corpus, consisting of 75 sessions with an average duration of 72 hours. The analysis of over 1000 lines in each transcript provided a rich, varied structured data format for better understanding.	Accurate transcriptions and missing data can significantly impact research findings, while data complexity and unique features of the ICSI corpus may limit generalizability.
2	Data Pre-Processing	Eliminating crosstalk and background noise enhances data quality by ensuring precise, targeted summaries. This process eliminates unnecessary sentences and jargon, ensuring valid language constructions.	Aggressive cleaning can lead to loss of crucial information or contextual cues, especially jargon removal, which can be challenging to balance with background noise and time.
3	Data Transformation/ Feature Extraction	Vectorization reduces text data to numerical vectors, simplifying high-dimensional areas for machine learning algorithms. TF-IDF identifies important terms for feature extraction, making data computationally economical.	Conventional TF-IDF algorithms may not capture semantic links between words, potentially causing complex meanings to disappear and fragmenting semantically related phrases, potentially impacting the summarization process.
Major Impact Factors in this Work			

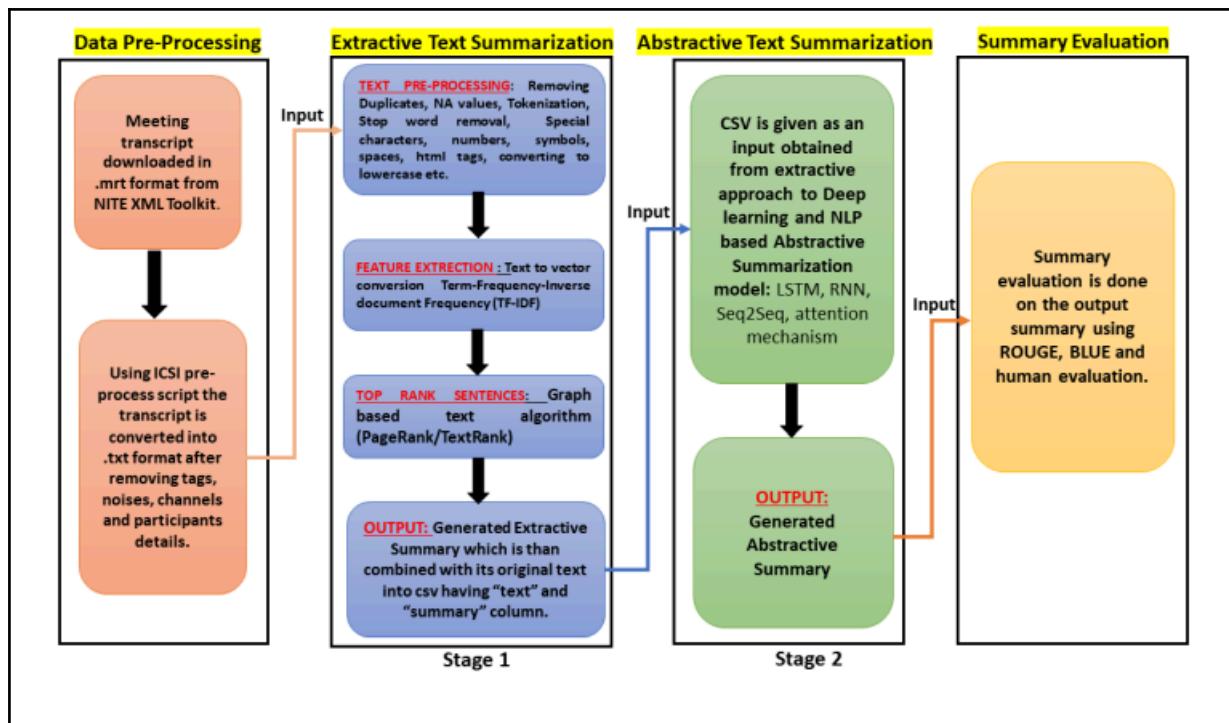
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the quality of the generated meeting Summary. Quality measured using factors like coherence, relevance, accuracy, and readability.	The paper shows various text summarization techniques, like extractive summarization using TF-IDF and TextRank algorithms, and abstractive summarization, as independent variables.	Text complexity, data quality, and user preferences moderate the effectiveness of both extractive and abstractive summarization techniques.	Extracted sentences and attention focus act as mediating variables, influencing how the abstractive summarization techniques process the i/p and summary.

Relationship Among the Above 4 Variables in This article

The analysis of independent variables, such as pre-processing techniques, feature extraction methods, RNN-LSTM, and summarization algorithms, can provide insights into the optimal combination for different meeting content types.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Meeting transcripts from the ICSI corpus	A summarized transcript of the meeting using both techniques.	The main features of the proposed work include the hybrid approach, the utilization of NLP, a well-defined workflow and design, dataset pre-processing, and evaluation with ideas for future work.	The researcher employed many methodologies, including TextRank, RNN, and LSTM with attention mechanisms, to produce succinct and comprehensible synopses from numerous extended transcripts of business meetings. With fewer redundant and clear summaries, this method seeks to reduce time and labor costs.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain	
<p>The method facilitates the efficient management of big multiple transcript files, saving time and effort while obtaining pertinent information from enormous texts. By comparing the generated summaries to reference summaries, the method attempts to provide summaries that are both human readable and have higher ROUGE metrics. This suggests that the summaries that are created are more precise and consistent with the original information.</p>	<p>The study admits that it is difficult to forecast summary findings in the absence of a sizable number of epochs and a substantial quantity of data. This restriction suggests that the performance of the solution could change based on the dataset and satisfying transcript complexity. The Abstractive technique reduces the amount of transcripts from 75 to 60 due to computing limits, which may affect the scalability of larger transcripts. It also produces its own raw input, making it more complex.</p>	
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
<p>The high accuracy of the proposed approach suggests that it could be effective up to some extent but as the research on using Neural network based solutions is still new and even complex it promises greater scope for generating summaries using this approach which leads to complete understanding of context of meeting and generate summaries.</p>	<p>In summary, the tools assessed in the proposed work include Python 3.7, IDEs such as Spyder, Jupyter Notebook, and PyCharm, Google Colab, and the NITE XML toolkit for dataset annotation and storage.</p>	<p>Abstract</p> <ul style="list-style-type: none"> I. Introduction II. Related Work III. Proposed Research Methodology IV. Design Specification V. Implementation VI. Evaluation & Results VII. Conclusion & Future Work
Diagram/Flowchart		



---End of Paper 2---

3	Reference in APA format	Authors Names and Emails	Keywords in this Reference
https://www.jetir.org/papers/JETIR2201426.pdf	Rajat Verma, Sparsh Gupta, Shubh Sharma, Tanishq Aggarwal, Mahesha A.M	Meetings, Meeting notes, online meetings, meetings minutes.	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	

<p>The paper mainly focused on the solution using Abstractive Summarization Techniques and how it helps in getting the concise output for the meeting transcript.</p>	<p>Automating the process of creating meeting minutes or notes is the aim of the suggested solution. By eliminating the need for manual note-taking, the approach seeks to free up participants to concentrate on the meeting itself.</p>	<p>The components of the solution include:</p> <ol style="list-style-type: none"> 1. UI Design: ReactJS and TailwindCSS. 2. System Design: The system utilizes speech-to-text (STT) conversion for transcribing the meetings (abstractive) 3. Database Design: SQL is used for designing the database of the system. 4. Authentication & Security: Django REST framework for user authentication and security measures. 5. ReactJS Website: The notes generated by the system are displayed using ReactJS website. The data is fetched from Django REST APIs using fetch requests.
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The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Machine learning for speech-to-text conversion	Machine learning algorithms are used to transcribe speech into human-readable text. The advantage of this step is that it allows for efficient and accurate conversion of spoken words into text.	The disadvantage is that the accuracy of the transcription may vary depending on the quality of the audio and the complexity of the speech.
2	Text Summarization	The text summarizer converts transcriptions into meeting notes, reducing lengthy discussions into concise, relevant notes using	Abstractive summarization is a method for summarizing a text based on key ideas, but it may not capture

		abstractive techniques like entity recognition and semantic analysis.	all crucial details discussed in a meeting.
3	UI Design	TailwindCSS and ReactJS are used in UI design, with ReactJS's component-based architecture allowing modularity and TailwindCSS prioritizing utility over aesthetics for aesthetically pleasing designs.	Tailwind's low-level CSS classes can negatively impact website or application performance, and modification and maintenance may require experience with these technologies.
4	System Design	The proposed system utilizes speech-to-text (STT) for abstractive text summarization and conversion, enhancing efficiency in meeting notes and making briefings more concise.	The drawback is that, depending on the intricacy of the speech and the language employed, the accuracy of STT and abstractive summary may differ.
5	Database Design	The database is designed using SQL. Managing structured data effectively and offering dependable data storage and retrieval are two benefits of utilizing SQL.	One drawback of SQL is that it could need knowledge of database administration and upkeep.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variables could include the quality and accuracy of the transcribed speech,	The independent variables include machine learning algorithms for speech-to-text	The moderating variables during a meeting may include the number of participants, the	There are no specific mediating variables mentioned in the

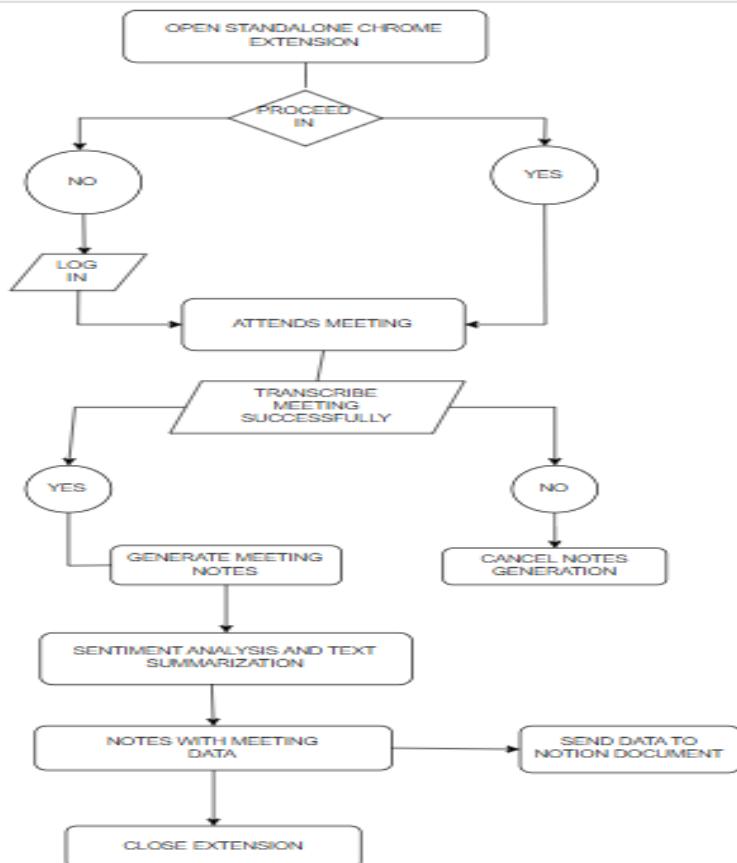
the effectiveness of the text summarization process, and the overall user satisfaction with the generated meeting notes.	conversion, text summarizer implementation, and ReactJS and TailwindCSS UI design for UI.	complexity of the discussions, and the level of background noise.	given document content.
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Relationship Among the Above 4 Variables in This article
Independent variables like meetings, participants, and speech-to-text conversion impact dependent variables like quality and accuracy. Moderating variables like participant count and text summarization parameters influence content and length.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
audio recording of the meeting with at least 2 participants.	automated meeting minutes mailed to the user, and made visible on website	The proposed solution automates meeting minutes creation, freeing participants' time for meetings, reducing manual note-taking and providing easy-to-memorize notes via email and dashboard website.	Machine learning techniques like Azure speech-to-text help reduce manual labor, increase team output, and provide concise notes for effective review and memorization in online learning environments.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The approach reduces manual note-taking during meetings, improving efficiency and team productivity. It also aids online learning by providing concise, to-the-point notes for efficient revision and memorization.		Online meetings face challenges in memory retention and potential transcription errors, necessitating continuous enhancement to ensure accurate and complete conference summaries.	

Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
Abstractive summarization techniques and machine learning tackle text summarization problems including semantic analysis and lexical relations. The project's methodology includes an abstractive text summarizer, speech-to-text conversion, and a chrome plugin. The outcomes show that the algorithm can reasonably accurately translate spoken words into text.	In summary, the tools assessed in the proposed work include Azure speech-to-text algorithms, ReactJS and TailwindCSS for UI design.	Abstract I. Introduction II. Related Work III. Proposed Work IV. Methodology V. Design of Proposed System VI. Conclusion VII. Result VIII. References

Diagram/Flowchart



---End of Paper 3---

Reference in APA format	Umadevi and Jagadesh Kannan, "Text Summarization of Spanish Documents", Publisher: IEEE, INSPEC Accession Number: 18291119, DOI: 10.1109/ICACCI.2018.8554839.	
URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/8554839	K.S Umadevi, Romansha Chopra, Nivedita Singh, Likitha Aruru	Graph, text-rank, automated summarizer, distortion, extraction
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
<p>The paper mainly focused on the solution using Text Summarization where it uses Extractive content based methodologies and performs some of the modifications to experiment and get more conciseness.</p>		<p>The main goal is to encounter the syntactic and semantic associations in a language.</p> <p>The proposed mechanized content synopsis plans to hold only key sequences in the content while skipping rest of the data</p> <p>The proposed system has two main components: the pre-processing phase and trainable summarizer.</p> <p>It mainly focuses on addressing the sentences and how to classify each sentence of that document into either a "right" or "off course" sentence, creating an extractive summary.</p>
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-Processing Phase	Pre-processing data involves opening a file, reading contents, and using natural language	The pre-processing phase can potentially lead to the loss of crucial information, making data

		processing techniques to clean and normalize text, making it easier to analyze and summarize.	accuracy a challenging task.
2	Calculation of Frequency & Normalization	Normalization measures sentence similarity using a distortion measure, aiding in identifying related sentences and aiding in computational purposes by weighting and ranking documents based on word frequency.	Frequency calculation may prioritize common words, impacting summary accuracy. Normalization's choice of similarity limit can affect summary accuracy.
3	Key word Extractive Summaries	The next step involves generating keyword extractive summaries using PageRank and an extraction-based approach, identifying important sentences and extracting key information using Weighted graphs and Damping Factor.	The disadvantage is that it may not fully capture the text's meaning and may miss crucial details due to the rotating PageRank and damping factor used.
4	Trainable Summarizer	A trainable summarizer learns summaries from academic examples, classifying sentences into "right" or "off course" for accuracy and relevance in extractive summaries.	The Part SUMY API is utilized, but it may not be suitable for texts significantly different from the training data due to its large training data requirement.
5	Evaluation	The ROUGE Metrics API is utilized to assess the efficiency of the TextRank algorithm, providing a degree of similarity for summary accuracy and transcript highlights.	ROUGE only measures n-gram overlap. So it does not take into account the semantic meaning of the summary. It is sensitive to the choice of reference summaries.

Major Impact Factors in this Work			
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the quality of summary output and it is dependent on the accuracy and relevance of the original news article.	The independent variables in the paper include methodologies used and unique content because the uniqueness influences the overall summary generated in the process.	The relationship between dependent and independent variables is not significantly influenced by any specific moderating variables, but a damping factor demonstrates some of these qualities.	Cosine similarity and sentence likeliness act as mediating variables because it explains why certain sentences/words /phrases are given preference.

Relationship Among the Above 4 Variables in This article
The analysis of the interaction between independent variables and moderating variables, such as methodologies and unique content, can provide insights into the most effective techniques and algorithms for different meeting content types.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
News article(corpus transcript between two	A short summarized transcript of the news article	The proposed system automatically summarizes large text data using an arcsine probability density function, ensuring significant information is not overlooked and evaluating its efficiency and accuracy.	The proposed system significantly contributes to natural language processing and text summarization, offering efficient and accurate summaries for news articles, documents, and text classification, with potential for future enhancement.

columbi ans	with key informatio n.				
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain			
The proposed system efficiently summarizes large text data, saving time and effort for users, and aids in identifying key information from original documents.		The solution's reliance on external resources like SUMY API may introduce limitations, impacting the accuracy and reliability of summaries, and potentially limiting their usefulness in multilingual environments.			
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper			
The proposed approach achieves high accuracy through the modified PageRank algorithm, prioritizing sentences at the beginning and end, calculating frequency, and ranking them accordingly for further processes.	SUMY API and Rogue Metrics API were used to evaluate the generated summaries by comparing them to manually summarized text.	Abstract II. Introduction III. Literature Review IV. Architecture of Proposed System V. Methodology VI. Results and Discussion VII. References			
Diagram/Flowchart					
<pre> graph TD A((Spanish Documents)) --> B[Read Text File] B --> C[Pre-Processing of Data] C --> D[Summarization Process] D --> E[Sentence Filtering] E --> F[Summarized Text] F --> G[Evaluation Measures] </pre>					

---End of Paper 4---

5					
Reference in APA format	Md Tahmid Rahman Laskar and Xue-Yong Fu, "Building Real-World Meeting Summarization Systems using Large Language Models: A Practical Perspective", Issue Date: September 2023.				
URL of the Reference	Authors Names and Emails	Keywords in this Reference			
https://www.catalyzex.com/paper/arxiv:2310.19233	Md Tahmid Rahman Laskar, Xue-Yong Fu, Cheng Chen, Shashi Bhushan TN Dialpad Canada Inc.	Text Summarization, Large Language Models (LLM's), GPT-4, GPT-3.5, PaLM-2, LLaMA-2, zero-shot performance			
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?			
The paper mainly focuses on experimenting different Large Language Models (LLM's) like GPT-4 and more with different types of datasets and tests the cost, inference and performance and suggests a model for summarization.	The objective of this research is to identify the most effective model to summarize organizational meetings that could be used in real-world applications in scenarios when in-domain labeled datasets are not available. By experimenting with several models it suggests a model by considering different parameters in mind.	The paper presents an extensive evaluation of closed-source LLMs as well as open-source LLMs in several benchmarks meeting summarization datasets. A practical perspective on the trade-offs that come with selecting a model for real-world usage based on its performance, cost, and computational requirements.			
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process					

	Process Steps	Advantage	Disadvantage (Limitation)
1	Selecting Large Language Models(LLM's)	Researchers chose 3 closed-source LLMs and 1 open-source LLM for real-world meeting summarization systems, not transformers due to domain-specific fine-tuning limitations, instead focusing on zero-shot performance.	LLMs, including ChatGPT, can 'hallucinate', producing high-quality text with factually incorrect information, despite extensive data training and complex or ambiguous text, leading to mistranslations or loss of meaning.
2	Summarization via Truncation	The approach divides a transcript into n-word chapters, with final summaries generated for each by concatenating or re-summarizing summaries, providing a comprehensive summary considering the entire transcript's context.	The process may necessitate more computational resources and still pose challenges in maintaining coherence and generating a final summary.
3	Prompt (Re-write) and Prompt (Re-summarize)	The prompts generate a summary from the chapter summaries, offering various options like concatenating or re-summarizing/re-writing them.	The effectiveness of prompts varies based on meeting context, content, and prompt type. Long summary prompts perform less than short summary prompts.
4	Models	The researcher employs four LLMs, including three closed-sources and one open-source, to benchmark their performance in meeting transcripts, delivering precise results and customizing content to	Closed-source LLMs lack public architecture and weights, making customization and fine-tuning difficult. Open-source projects may have limited

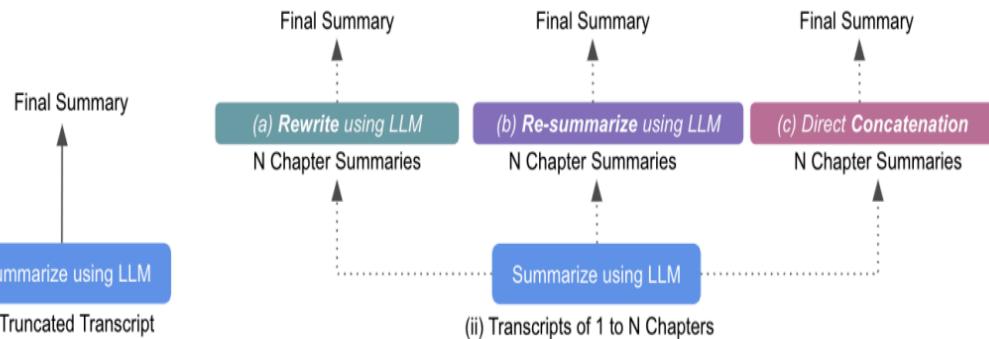
		company language and style.	resources compared to large corporations.
5	Datasets	The researcher utilized relevant datasets such as MeetingBank, QMSUM, AMI, and ICSI to develop a summarization system for real-world ASR-generated transcripts in organizational meetings.	The quality and relevance of data significantly influence model performance, potentially leading to biased or unfair models if the dataset is not representative of the specific problem or task.
6	Experiments	Researchers test various datasets and LLMs for cost effectiveness, performance. LLaMA-2-7B appears promising due to its cost effectiveness and inference speed in industrial use.	The researcher has chosen LLaMA-2-7B as their LLM, but there may be other LLMs not listed in their plate.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variables, R-1, R-2, R-L, and B-S, are performance metrics used to assess the quality and similarity of generated summaries compared to reference summaries.	The paper discusses various models and approaches used for summarization, including GPT-3.5 and GPT-4, as independent variables.	No explicit mention of moderating variables.	No explicit mention of mediating variables.

Relationship Among the Above 4 Variables in This article							
The paper examines the impact of prompts, summarization approaches, and LLM models on performance, quality, and cost-effectiveness, aiming to identify the most effective model for real-world organizational meeting summarization.							
Input and Output		Feature of This Solution	Contribution & The Value of This Work				
<table border="1"> <thead> <tr> <th>Input</th><th>Output</th></tr> </thead> <tbody> <tr> <td>dataset or the meeting transcript.</td><td>The output is the generated summary.</td></tr> </tbody> </table>		Input	Output	dataset or the meeting transcript.	The output is the generated summary.	The proposed solution evaluates various LLMs to identify the most effective LLM, considering performance, cost, and privacy concerns while balancing them.	The proposed work suggests that the LLaMA-2-7B model is more promising for real-world industrial usage, offering valuable insights for deploying LLMs in meeting summarization systems.
Input	Output						
dataset or the meeting transcript.	The output is the generated summary.						
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain					
The study suggests that large language models (LLMs) are crucial for creating real-world meeting summarization systems, as they generate summary on a broader level, rather than focusing on specific contexts.		The proposed work offers advantages but also has limitations, such as the need for expensive hardware and massive data sets, and potential bias and system hallucinations.					
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper					
A language model with good zero-shot performance can generate coherent summarizations without specific training data, based on its general language understanding capabilities.	LLM models GPT-4, GPT-3.5 and others as well as Evaluation metrics like Rouge metrics and different datasets used while experimenting the model	Abstract I. Introduction II. Related Work III. Our Methodology IV. Experiments V. Using LLMs in Real-World Systems VI. Conclusion					

Diagram/Flowchart



---End of Paper 5—

6			
Reference in APA format	Mr. Riyazahmed Jamadar, Mehul Pawar, Pavan Karke, Amogh Sonar, Yashshri Zungure, Sushant Sharavagi Assistant Professor. “AUTOMATIC SPEECH RECOGNITION: SPEECH TO TEXT CONVERTER”. Department Of Information Technology, Aissms Institute Of Information Technology, Pune,Maharashtra, India 2023.		
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://www.irjmets.com/uploadedfiles/paper/issue_5_may_2023/39369/final/fin_irjmets1684406871.pdf	Mr. Riyazahmed Jamadar, Mehul Pawar, Pavan Karke, Amogh Sonar, Yashshri Zungure, Sushant Sharavagi	Analysis, Research, CSS, HTML, Python, Speech Recognition.	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	

Model/ Tool/ Framework/etc)		
A multilingual speech-to-text conversion system., Bidirectional non stationary Kalman filter, MFCC (Mel Frequency Cepstral Coefficients), HMM (Hidden Markov Model)	The goal of this problem is to develop a speech-to-text conversion system which solves the need for converting spoken language into written text and allows for enhanced accessibility.	Preprocessing, Acoustic Modeling , Language Modeling, Decoding and Post-processing, Training and Optimization, Evaluation and Fine-tuning

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Speech signal is captured and converted into digital format using an analog-to-digital converter.	The speech signal digitally is that it allows for easy processing and analysis. improves signal quality and can be manipulated and analysed.	The background noise or other factors that can reduce the accuracy of the conversion.
2	The speech is segmented into smaller units called phonemes, which are the basic units of sound in a language.	Segmenting the speech into phonemes helps in recognizing different words.	It can be challenging for languages with complex phonetic structures.
3	These phonemes are then compared to well-known sentences, words, and phrases using a mathematical model	The speech-to-text conversion process has the advantage of providing a written representation of spoken language	It is limited by the availability of a comprehensive database.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
<ul style="list-style-type: none"> Number of words in summary accuracy 	<ul style="list-style-type: none"> Spoken words word error rate (WER) character error rate (CER) 	<ul style="list-style-type: none"> The paper does not explicitly mention a moderating variable but Voice recognition might act as it. 	<ul style="list-style-type: none"> The paper does not explicitly mention a mediating variable.

Relationship Among the Above 4 Variables in This article

- As the number of words in summary and accuracy of the solution is dependent on spoken words, word error rate, character error rate. As these variables increases the word count in the summary increases and accuracy decreases.
- Recognition of the speech from the audio file is directly related to the accuracy and the number of spoken words in speech.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
speech utterance	corresponding text representation of the speech	This can turn spoken words into written text instantly. It uses features such as MFCC (Mel-frequency cepstral coefficients) to distinguish words and achieve an overall word accuracy of 90%.	Designing a multilingual speech-to-text conversion system is a good thought, where different languages together are converted into text.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	

To achieve better accurate results is the positive impact of this solution in this project domain.	The mathematical model may have limitations in adapting to new or evolving linguistic patterns, slang, or domain-specific terms.	
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
These new tools can change what people say into written words and it is all about making communication and getting information simpler and more convenient.	Dev tools, Hidden Markov Models, Mel-frequency cepstral coefficients.	<p>Abstract</p> <p>I. THE MEETING RECOGNITION ENGINE</p> <p>II. SUMMARIZATION</p> <p>III. CONCLUSIONS AND FUTURE WORK</p> <p>IV. ACKNOWLEDGEMENTS</p> <p>V. Conclusion</p>

Diagram/Flowchart

```

graph LR
    Input((Input sound)) --> Pre[Pre-Processing]
    Pre --> Feature[Feature Extraction]
    Feature --> Class[Classification Model]
    Class --> Prediction((Prediction))
    LM((Language Model (LM))) --> Class
  
```

---End of Paper 6---

7		
Reference in APA formats	Nazim Dugan, Cornelius Glackin, Gérard Chollet, Nigel Cannings. "The Intelligent Voice ASR system for the Iberspeech 2018 Speech to Text Transcription Challenge". Intelligent Voice Ltd, London, UK.	
URL of the Reference	Authors Names and Emails	Keywords in this Reference

https://www.isca-archive.org/iberspeech_2018/dugan18_iberspeech.pdf	Nazim Dugan , Cornelius Glackin , Gérard Chollet , Nigel Cannings	DNN-HMM hybrid acoustic model, MFCCs (Mel Frequency Cepstral Coefficients), iVectors, Kaldi framework, Ground truth transcriptions, Data augmentation, Language model (LM),, Lexicon update, Feature extraction, speech recognition, forced alignment, neural network												
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?												
The Intelligent Voice ASR system for the Iberspeech Speech to Text Transcription Challenge	The goal of this solution is to develop a DNN-HMM hybrid acoustic model with MFCC's and iVectors as input features.	Automatic Speech Recognition (ASR), Deep Neural Networks, phonetic corpora, speech databases, dialogue corpora, SLT, Kaldi framework, neural network architectures.												
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process														
<table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th style="background-color: #cccccc;"></th> <th style="background-color: #cccccc;">Process Steps</th> <th style="background-color: #cccccc;">Advantage</th> <th style="background-color: #cccccc;">Disadvantage (Limitation)</th> </tr> </thead> <tbody> <tr> <td style="vertical-align: top;">1</td><td>Benchmarking the ASR model: The author used a benchmarking process to compare the produced ASR model with the base model.</td><td>This process helped in evaluating the performance of the final ASR model and other experiment results before its production.</td><td>Getting the start and end times of words right is crucial. If they're wrong, the ASR system might not learn correctly, and its accuracy will suffer.</td></tr> <tr> <td style="vertical-align: top;">2</td><td>Two-step time alignment: The author used a two-step time alignment process to solve the misalignment</td><td>The advantage of this process was that it improved the accuracy of the time alignments.</td><td>The disadvantage was that it required additional computational resources and time.</td></tr> </tbody> </table>				Process Steps	Advantage	Disadvantage (Limitation)	1	Benchmarking the ASR model: The author used a benchmarking process to compare the produced ASR model with the base model.	This process helped in evaluating the performance of the final ASR model and other experiment results before its production.	Getting the start and end times of words right is crucial. If they're wrong, the ASR system might not learn correctly, and its accuracy will suffer.	2	Two-step time alignment: The author used a two-step time alignment process to solve the misalignment	The advantage of this process was that it improved the accuracy of the time alignments.	The disadvantage was that it required additional computational resources and time.
	Process Steps	Advantage	Disadvantage (Limitation)											
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2	Two-step time alignment: The author used a two-step time alignment process to solve the misalignment	The advantage of this process was that it improved the accuracy of the time alignments.	The disadvantage was that it required additional computational resources and time.											

	issue in training and development transcripts, using a forced alignment script and the NIST sclite ASR scoring utility, a component of the Speech Recognition Scoring Toolkit.		
3	<p>Frame subsampling factor adjustment:</p> <p>During the model testing phase, the author chose a different frame subsampling factor compared to the training process. This adjustment, with a frame subsampling factor of 3 in training and 2 in testing, resulted in more accurate results when using Viterbi decoding with a language model.</p>	<p>The advantage of this adjustment was improved accuracy in the testing of audio.</p>	<p>The specific disadvantages of this process are not mentioned in the given document.</p>

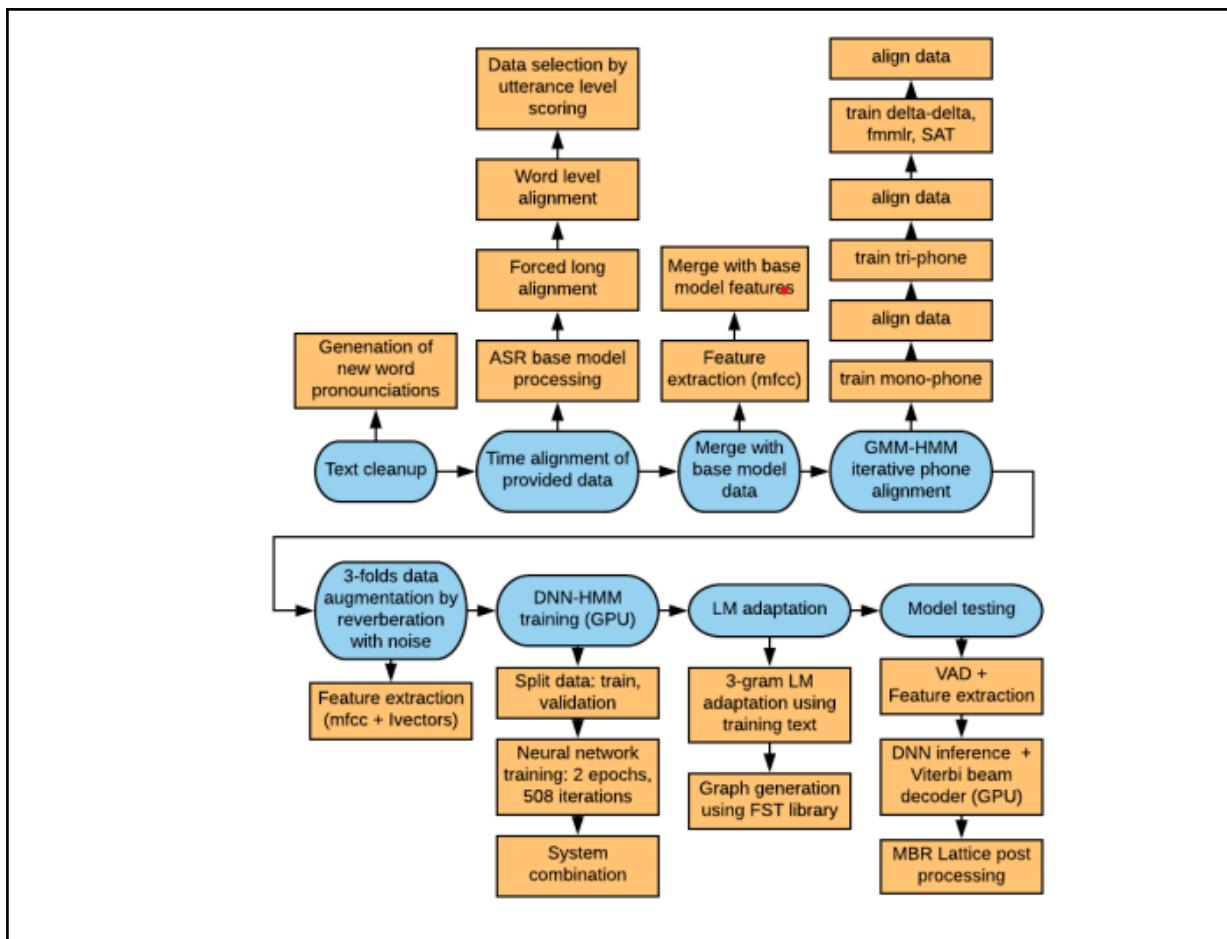
Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
<ul style="list-style-type: none"> the context of the reference paper is the Word Error Rate (WER) results obtained from the ASR system 	<ul style="list-style-type: none"> • Mel Frequency Cepstral Coefficients (MFCCs) and iVectors as input features 	<p>There is no specific mention of moderating variables. Therefore, it is not possible to identify any moderating variables from the context of the reference paper.</p>	<p>There is no specific mention of moderating variables. Therefore, it is not possible to identify any moderating variables from the context of the reference paper.</p>

Relationship Among the Above 4 Variables in This article

- The paper discusses the reduction in WER results achieved through the acoustic model building process and the usage of the provided data for training and testing the ASR system.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Audio recording	transcription of speech into text.	The model is based on a DNN-HMM hybrid architecture and uses MFCC's and iVectors as input features. The Kaldi framework is used for model development.	The contribution of this work's key innovation is a two-step process for aligning spoken words with their corresponding written text. It uses a forced alignment method and the NIST Sclite ASR scoring utility for precise word-level timing alignment.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
This was achieved through a smart combination of DNN-HMM and GMM-HMM methods, which significantly improved ASR accuracy compared to the basic model.		The negative impact in this project domain is the potential data dependency and complexity associated with the system's performance, making it resource-intensive and less adaptable to languages with limited data.	
Analyze This Work by Critical Thinking	The Tools That Assessed this Work		What is the Structure of this Paper
This demonstrates strengths in its choice of methodology and alignment procedure, the lack of quantitative results and detailed training information limits a comprehensive evaluation.	Kaldi framework, Time-delayed Deep Neural Network (TDNN)		<p>Abstract</p> <p>I. Introduction II. Data preparation III. ASR model training IV. Discussion V. Conclusion and Future work</p>
Diagram/Flowchart			



---End of Paper 7—

8			
Reference in APA format			
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://era.ed.ac.uk/bitstream/handle/1842/1040/murray-eurospeech05.pdf?sequence=1&isAllowed=y	Gabriel Murray, Steve Renals, Jean Carletta	extractive summarization, prosodic and lexical features, ICSI corpus, evaluation metrics	
The Name of the Current Solution	The Goal (Objective) of this Solution & What is		What are the components of it?

(Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	the problem that need to be solved	
Latent Semantic Analysis (LSA)	<p>Aim is to find the findings and results of the research related to automatic speech summarization.</p> <p>Compare and contrast different summarization approaches, including Maximal Marginal Relevance (MMR), Latent Semantic Analysis (LSA), and feature-based approaches.</p>	Author used extractive Summarization for meeting summary which intern determines the performance of the similarity of the summary and original meeting.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The insights into various approaches used to address the challenge of automatic speech summarization, particularly in the context of meetings including , including Maximal Marginal Relevance (MMR), Latent Semantic Analysis (LSA), and feature-based approaches.

	Process Steps	Advantage	Disadvantage (Limitation)
1	First extract a set of features from the meeting recordings, including both prosodic features (such as pitch and duration) and lexical features (such as the frequency of words).	It is a relatively simple and straightforward approach	It can produce summaries that are choppy and lack coherence.
2	Use a machine learning algorithm to select the features that are most important for summarization.	It can be used to summarize meetings quickly and efficiently.	It can miss important information that is not explicitly stated in the meeting.
3	Finally, they use a sentence scoring function to score each sentence in the meeting recording based on the selected features. The sentences with the highest	It can be used to summarize meetings that are not well-structured or that contain a lot of irrelevant information.	It can be difficult to apply to meetings that are very long or that contain a lot of technical jargon.

	scores are then selected to be included in the summary.		
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Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
<ul style="list-style-type: none"> • ROUGE Score. • Cosine Similarity. • F1 score 	<ul style="list-style-type: none"> • Weight Parameter can be varied to trade off between relevance and redundancy in the summary • redundancy that will cause a high/low score 	The selection of sentences based on singular values (topic selection criteria) directly affects the content and informativeness of the summary. Changing the dimensionality reduction method may lead to different summary lengths and contents, which can impact the quality of the summary.	The choice of the evaluation metric is important in assessing the quality of the generated summaries. Different evaluation metrics may lead to different assessments of the summary quality. It mediates the relation between similarity and summary.

Relationship Among the Above 4 Variables in This article

- Increasing the number of retained dimensions or topics in LSA is likely to result in longer summaries and decreasing the number of retained dimensions may lead to shorter summaries.
- To assess the correlation between topic selection criteria and informativeness, quality metrics such as ROUGE or F1 score can be used. These metrics can quantify how well the selected sentences cover important content from the original document.
- Giving higher importance to topics with larger singular values is likely to result in selecting sentences that contain more essential and informative content related to those topics.

Input and Output		Feature of This Solution	Contribution & The Value of This Work		
Input	Output				
An audio file of meeting is given	Summary is generated with the use of extractive summarization.(LSA)	Developing manually controllable filters such that users can find the exceptions that can be altered.	Good to have this knowledge from this paper as we review all the summarization techniques to get the accurate and more similarity output.		
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain			
Extractive summarization is easier to implement and more faithful to the source, but it can be repetitive, incoherent, or miss important information.		Since this is a performance evaluation of various techniques, not much to project on the negative side as all the things used are defined in advance.			
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper			
This work is good, as they tried automatic summary generation with high low performance evaluation and selected the best one to get an accurate one.	Switchboard and Callhome corpora, ICSI corpus	Abstract I. Introduction II. Summarization Approaches III. Experimental setup IV. Results V. Sample Summarization Output VI. Conclusion Future work			
Diagram/Flowchart					
<pre> graph LR start((start)) --> Research[Research] Research --> SA[Summarization approaches] SA --> MMR[Maximal Marginal Relevance (MMR)] SA --> LSA[Latent Semantic Analysis (LSA)] SA --> FBA[Feature-Based Approaches] </pre>					

---End of Paper 8---

Reference in APA format	Anna Nedoluzhko and Ondřej Bojar. "Towards Automatic Minuting of Meetings". Charles University, Institute of Formal and Applied Linguistics 2019.		
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://ceur-ws.org/Vol-2473/paper3.pdf	Anna Nedoluzhko, Ondřej Bojar	Automatic minuting, Dialogue transcripts, Summarization methods, Extractive summarization, Supervised learning, Graph-based methods, Pointer-generator networks	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
Towards Automatic Minuting of Meetings	The goal is to design an automatic creation of meeting minutes.	Classification of meetings, meeting minutes, available meeting datasets, dialogue summarization methods, summarize the obtained knowledge.	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	Advantage	Disadvantage (Limitation)
1	Classification of Meetings: Classification of meetings involves categorizing them based on their purpose, participants, or topics. It can be useful for organizing schedules and resources.	Helps to know the factors which may affect how the meeting is organized, and kind of agendas and minutes it needs.	It can produce summaries that are choppy and lack coherence.

2	Meeting minutes: Meeting minutes are summaries or records of discussions, decisions, and action items in a meeting.	Provides a formal record of meetings and helps in accountability and tracking action items.	It consumes more time to create detailed minutes and may not capture every nuance of discussions
3	Available Meeting Datasets: There are datasets available for training and evaluating models related to meetings and dialogue summarization	It's useful for developing and testing meeting-related models and enables research in the field.	Privacy concerns regarding recorded meetings.
4	Dialogue summarization: It is the process of making the content of a meeting into a concise summary. Here the author discusses various methods for meeting dialogue summarization, including focused-unfocused, extractive-abstractive, and supervised-unsupervised approaches.	Maintains the original context and is often more coherent. Can produce more concise summaries, human-like summarization.	May not always generate concise summaries, and coherence can still be an issue. Challenging to generate accurate and coherent summaries, and may introduce errors.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
<ul style="list-style-type: none"> Automatic minuting of meetings," can be considered the dependent variable. 	<ul style="list-style-type: none"> Types of Meetings Meeting Minutes Structure Meeting agendas Linguistic properties 	<ul style="list-style-type: none"> Meeting Content Meeting Context 	<ul style="list-style-type: none"> Methods for summarization

Relationship Among the Above 4 Variables in This article

- The nature and characteristics of different types of meetings (business, decision-making, information sharing, etc.) can influence the success of automatic minuting. A well-prepared agenda may provide a clear structure for summarization.
- The content and context of meetings, including factors like location, face-to-face vs. remote, and group size, may moderate the relationships between the independent variables and the dependent variable.
- These methods mediate the relationships between the characteristics of meetings, minutes, and linguistic properties, influencing the success of automatic minuting.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Meeting or conversation	Concise summary of the meeting	Dialogue summarization can be done through extractive or abstractive methods, and the choice of method depends on the specific use case and data available.	This information is valuable for researchers, practitioners, and developers interested in automating the process of creating meeting minutes and improving meeting management.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
Participants can quickly review and reference important points without having to go through the entire meeting transcript. This can result in increased productivity and overall time savings.		Automating the process of creating meeting minutes may result in a loss of the human touch and personalization.	
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	
Automatic minute is a wise strategy for meeting summarization and we need to have a detailed understanding of common types of meetings, of the linguistic properties and commonalities in the structure of meeting minutes, as well as of	MATRICKS, WordNet API, NLTK, spacy	Abstract I. Introduction II. Meetings and Minutes Description III. Available Datasets for Automatic Minuting	

methods for their automation.		IV. Methods for Meeting Summarization V. Discussion VI. First Steps Towards Automatic Minuting VII. Conclusion
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Diagram/Flowchart



---End of Paper 9---

10	Reference in APA format	URL of the Reference	The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)
	Yashar Mehdad, Giuseppe Carenini, Frank W. Tompa, Raymond T. NG. "Abstractive Meeting Summarization with Entailment and Fusion". Department of Computer Science, University of British Columbia ,University of Waterloo 2013.	https://aclanthology.org/W13-2117.pdf	
	Yashar Mehdad, Giuseppe Carenini, Frank W. Tompa, Raymond T. NG	Abstractive summarization, Recorded meeting summarization, Community detection, Entailment detection, Word graph, Path selection, Multidirectional entailment graph	
	The Goal (Objective) of this Solution & What is the problem that need to be solved		

Abstractive Meeting Summarization with Entailment and Fusion	The paper aims to address the limitations of existing approaches by developing a system that can generate informative and readable summaries of meeting conversations. The problem that needs to be solved in the paper is the task of recorded meeting summarization.	Community Detection, Entailment Detection, Word Graph Construction, Path Selection and Ranking, Language Generation
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The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

Performance of Detection of spam in email is evaluated based on different algorithms and constraints. Even though this author compared various results upon validating the test data and trained data using machine learning with all supervised and Lazy learning algorithms.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Community Detection: This aims to identify groups of sentences that can be clustered together to generate an abstract sentence. The CONGA algorithm is used for community detection based on the score of edges in a graph.	Helps to identify groups of related sentences, allowing for more focused summarization. Enables the generation of abstract sentences that capture the main ideas of each community.	May not accurately capture the semantic relationships between sentences if the community detection algorithm fails to identify relevant connections.
2	Entailment Detection: This component focuses on identifying the entailment relations between pairs of sentences. A logistic regression classifier is trained using various features to predict the entailment links between sentences in the document.	Identifies the entailment relations between sentences, helping to filter out redundant or irrelevant information. Enables the selection of the most informative sentences for summarization.	May struggle with complex sentence structures or ambiguous cases where the entailment relation is not clear.

3	Word Graph Construction: Once the communities and entailment relations are identified, a word graph is constructed over the sentences in each community. The word graph represents the relationships between words in the sentences.	Represents the relationships between words in the sentences, allowing for a more comprehensive understanding of the content.	Constructing the word graph can be computationally expensive, especially when dealing with a large number of sentences.
4	Path Selection and Ranking: This involves selecting the most informative path in the word graph as the abstract sentence summary. A ranking model is employed to combine various scores, such as entailment score, coverage score, and length score, to determine the best path.	Improves the overall informativeness and coherence of the generated summaries.	The ranking strategy may not always accurately capture the most relevant and informative path, leading to potential loss of important information.
5	Language Generation: The final component focuses on generating the abstractive summary sentence based on the selected path in the word graph. A language model trained on the English Gigaword corpus is used to generate grammatically correct and coherent summaries.	It enhances the readability and fluency of the generated summaries.	The generated summaries may not always capture the exact semantics or nuances of the original sentences.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

<ul style="list-style-type: none"> Metrics such as ROUGE-1 and ROUGE-2 scores, can be considered as the dependent variable. 	<ul style="list-style-type: none"> meeting summarization word graph construction community detection entailment detection sentence fusion 	<p>The characteristics of meeting transcripts, such as the formality of language, syntactic structure, and the presence of transcription errors.</p>	<p>The methods used for meeting summarization, including community detection and entailment detection, could be considered as mediating variables</p>
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Relationship Among the Above 4 Variables in This article
<ul style="list-style-type: none"> This variable depends on the different components and methods proposed in the system. They mediate the relationship between the independent variables (components and methods) and the dependent variable (effectiveness) by influencing how information is selected and fused in the summarization process. These factors may moderate the relationship between the independent variables and the effectiveness of the summarization system.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
recorded meeting	Summary of recorded meeting	<p>The solution combines various techniques i.e. word graph construction, community detection, entailment detection, path selection, and language generation, to create a comprehensive framework for abstractive summarization. These features work together to generate informative and readable summaries of meeting conversations.</p>	Got to know about various new techniques and introducing a novel approach to language generation.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	

The positive impact of the proposed solution in the project domain includes improved efficiency, contribute to more effective project management, and informed decision-making, ultimately leading to successful project outcomes.	The negative impact is that it may not possess the same level of judgment and critical thinking as human summarizers.	
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed work demonstrates innovation and addresses important challenges in meeting summarization. Balancing the benefits and drawbacks, and considering the specific requirements and context of the project, can help ensure the successful integration and utilization of the solution.	NLP tools like NLTK, spaCy, scikit-learn.	<p>Abstract</p> <p>I. Introduction</p> <p>II. Abstractive Summarization Framework</p> <p>III. Experiments and Results</p> <p>IV. Discussion</p> <p>V. Conclusion and Future Work</p> <p>VI. Automatic Minuting</p> <p>VII. Conclusion</p>
Diagram/Flowchart		
<pre> graph LR start((start)) --> CD[Community Detection] CD --> ED[Entailment Detection] ED --> WGC[Word Graph Construction] WGC --> PSR[Path Selection and Ranking] PSR --> LG[Language Generation] LG --> end((end)) </pre>		

---End of Paper 10---

11		
Reference in APA format	Aryan Jha, Sameer Temkar, Preetam Hegde, Navin Singhaniya - “Business Meeting Summary Generation Using NLP” ITM Web of Conferences 44, 03063 ICACC-2022.	
URL of the Reference	Authors Names and Emails	Keywords in this Reference

https://doi.org/10.1051/itmconf/20224403_063	Aryan Jha, Sameer Temkar, Preetam Hegde and Navin Singhaniya	Natural language processing, Text summarization, Extractive summarization, abstractive summarization.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
Natural Language Processing	The goal is to employ Business Summarization in Business Meetings to assist us summarize a recorded meeting while maintaining critical information and ensuring that the summarized meeting has the right context and meaning. Investigate various Business summarizing strategies.	Extractive summarization method involves extracting key sentences or paragraphs from the original text and compressing them into a shorter text. Sentence scoring, Intermediate representation like each sentence is a list of significant attributes such as sentence length, position in the document, the existence of certain phrases.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Speech to text conversion	The Rev-AI Speech-to-Text API is used for text conversion, ensuring precise and concise meanings for easy comprehension by everyone.	Voice recognition technology may cause misheard or misinterpreted words, and voice

			transcription may also be costly.
2	Extractive Summarization	Extractive summarization techniques generate summaries by selecting a subset of the original text's sentences. Extractive summarization also has higher accuracy, lower computational complexity.	Extractive summarization is easier to implement and more faithful to the source, but it can be repetitive, incoherent, or miss important information.
3	Summary Evaluation	ROUGE is a set of metrics for automatically generating Business Meeting summarization and machine translation, with ROUGE-1 indicating better fluency than ROUGE-2 and ROUGE-L.	ROUGE only operates on the overlaps. A score of 1 could only be obtained if both summaries have the exact same n-grams, thus making it hard to tell the model's performance from the computed scores alone.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the test accuracy metric, which is indicated using F-measure.	The independent variables mentioned in the document include sentence score. The score of a sentence in topic representation approaches demonstrates how well the sentence	The document does not explicitly mention any moderating variables. The possible moderating variable is the ROUGE, which may influence the performance of	The document does not explicitly mention any mediating variables

	explains some of the most important topics in the text.	different summaries.	
Relationship Among the Above 4 Variables in This article			
<p>The dependent variable (F-measure) is influenced by the independent variables (sentence scores and ROUGE), with sentence scoring potentially moderating the performance of ROUGE potentially mediating the accuracy score of the generated summaries. This complex interplay showcases how these variables interact in the context of generating accurate summary.</p>			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	The proposed solution uses speech to text conversion, Extractive summarization and sentence scoring features for generating summary.	The document evaluates the generated summary using: ROUGE 1 model and then correlates highly with human judgment.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The use of both Extractive summarization and ROUGE 1 features can improve the accuracy of summary generation.		The solution is an Extractive summarization method, which relies heavily on the converted text content data. Which can lead to being repetitive, incoherent, or miss important information.	
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	

The high accuracy of the proposed approach suggests that it could be effective in real-world applications. It could help businesses by saving time during these lengthy Business Meetings, it is necessary to summarize the meetings.	NLP tools like NLTK, spaCy, scikit-learn.	Abstract I. Introduction II. Organization of report III. System implementation IV. Proposed method for summarization V. Applications VI. Experimental result VII. Output VIII. Conclusion
Diagram/Flowchart		
<pre> graph LR AI[Audio Input] --> T[Text] T --> S[Sentences] S --> V[Vectors] V --> SM[Similarity Matrix] SM --> G[Graph] G --> SR[Sentence Rankings] SR --> S SR --> S </pre> <p>The flowchart illustrates the process of generating a summary from audio input. It starts with 'Audio Input' leading to 'Text', then to 'Sentences', and finally to 'Vectors'. These vectors are processed to create a 'Similarity Matrix', which is then converted into a 'Graph'. The 'Graph' leads to 'Sentence Rankings', which are used to refine the 'Sentences' and produce the final 'Summary'.</p>		

---End of Paper 11---

12	Reference in APA format	URL of the Reference	Authors Names and Emails	Keywords in this Reference
	Pallavi Lodhi, Shubhangi Kharche, Dikshita Kambri and Sumaiya Khan - "Business Meeting Summarisation System" May 22, 2022.	https://easychair.org/publications/preprint_open/hp72F	Pallavi Lodhi, Shubhangi Kharche, Dikshita Kambri and Sumaiya Khan	Meeting summarization, Natural language processing, Abstractive summarization, Audio summarization, Artificial intelligence.
The Name of the Current Solution	The Goal (Objective) of this Solution & What is			What are the components of it?

(Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	the problem that need to be solved	
Abstractive Summarization	This work demonstrates summarizing a business meeting held in regional or professional languages with the help of a machine learning model. The summarization is done using the abstractive method where words are allocated based on their frequency of occurrence in the text file.	Abstractive summarization method summarizes sentences or paragraphs from the original text based on their frequency and compresses them into a shorter text. Seq2seq model architecture(use to solve complex language like machine translation, etc.), encoder and decoder.

**The Process (Mechanism) of this Work; Means How the Problem has Solved &
Advantage & Disadvantage of Each Step in This Process**

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data collection	The data collection includes text and audio input, allowing users to provide business transcripts and record or provide audio files.	File-based files can cause contention and corruption when users access the same file, leading to issues with less audible audio data and accent variations.
2	Abstractive Summarization	Abstractive methods are allocated based on their frequency of occurrence in the text file. Abstractive summarisation technology cherry-picks the most relevant points from a data set and	Abstractive summarization focuses much on generating good results with respect to a particular sentence and too little on the corpus of text containing thousands

		creates an easily digestible summary.	of such sentences. And in this model, one of the limitation is it could only translate 1 language.
3	Error analysis	The suggested work uses GTTs library for recognising the speech audio and translating it to text and and cloud translation API to translate Hindi audio to English. These are Cloud libraries. The user can get the text summary in whichever language he or she wants. This output is available in two formats: audio and text.	As used libraries in this model are cloud libraries, if the internet connection is not stable, the GTTs library may not be able to read and record the audio. Currently the system is only summarized in Hindi and English language. If any other languages are used in the meeting, the system will not recognize the language and will cause discrepancy in the summarization.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
There are multiple dependent variables in this model, Audio Summary Quality, System Performance, User Satisfaction, Language	The independent variables mentioned in the document are Number of Training Samples, Translation API, Language used, User Input Preferences.	The document does not explicitly mention any moderating variables. The possible moderating variable is the audio summarization system, which may influence the performance of	The document does not explicitly mention any mediating variables

Translation Accuracy		different summaries.	
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Relationship Among the Above 4 Variables in This article

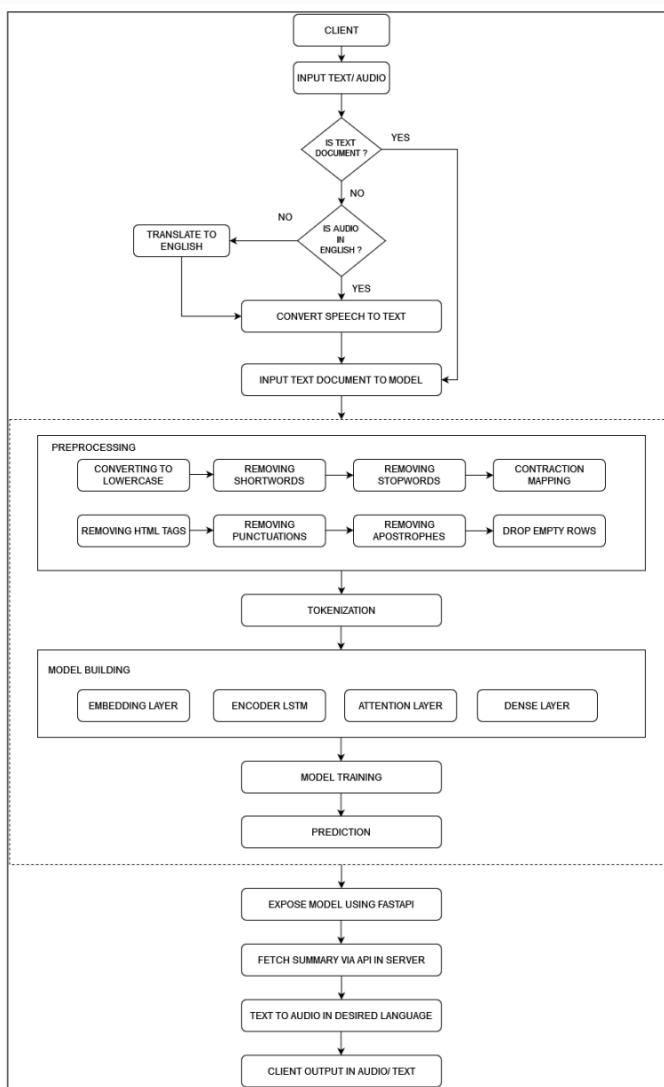
The dependent variable (language translation accuracy) is influenced by the independent variables (translation API and number of training samples), with audio summarization potentially moderating the accuracy score of the generated summaries. This complex interplay showcases how these variables interact in the context of generating accurate summary.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Hindi meeting	Summary	The proposed solution uses Google cloud translation, Abstractive summarization and tokenization features for generating summary.	The document evaluates the generated summary using Abstractive Summarization, Multilingual Support, Training Model Improvements, Addressing Real-World Needs.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The use of both Abstractive summarization and cloud API to translate a language into desired language, where these features can improve the accuracy of summary generation.		Currently the system is only summarized in Hindi and English language. If any other languages like Marathi, Gujarati are used in the meeting, the system will not recognise the language and will cause discrepancy in the summarization.	
Analyze This Work by Critical Thinking		The Tools That Assessed this Work	What is the Structure of this Paper
The high accuracy of the proposed approach suggests that it could be effective in real-world applications. It could help businesses by saving		NLP tools like NLTK, spaCy, scikit-learn.	Abstract I. INTRODUCTION II. RELATED WORK AND BACKGROUND

time during these lengthy Business Meetings, it is necessary to summarize the meetings from a language to another desired or required language.

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|-------|--|---------------------|
| | | KNOWLEDGE |
| III. | | DATA COLLECTION |
| IV. | | MODEL FRAMEWORK |
| V. | | METHODOLOGY |
| VI. | | EXPERIMENTAL SETUP |
| VII. | | RESULTS DISCUSSIONS |
| VIII. | | LIMITATIONS |
| IX. | | CONCLUSION |

Diagram/Flowchart



---End of Paper 12---

Reference in APA format	Swapnil Waghmare, Chaitanya Pathak, Raj Kshirsagar, Suyog Malkar - “Business Meeting Summarization Using Natural Language Processing(NLP)” (IJSREM) Volume: 05 Issue: 07 July – 2021.		
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://ijsrem.com/volume-05-issue-07-july-2021	Swapnil Waghmare, Chaitanya Pathak, Raj Kshirsagar, Suyog Malkar	Abstractive Summarization, AES algorithm, Natural Language Processing (NLP), Multimedia.	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
MMS (Multi-Modal Summarization)	The MMS method involves capturing speech using microphones, transcribing the speech, segmenting and aligning it with the corresponding manual report, and then generating a summary using abstractive summarization techniques.	Natural Language Processing (NLP) is used to analyze and understand the text data generated during the meeting. Speech Processing, Computer Vision, Advanced Encryption Standard (AES) Encryption.	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	Advantage	Disadvantage (Limitation)

1	Data Capture	Capturing multi-modal data, including speech, visual, and other relevant information, offers a comprehensive view of the meeting and enables more accurate summary generation.	Capturing and processing multi-modal data can be time-consuming and resource intensive.
2	Data Processing	The data is processed using technologies like natural language processing, speech processing, and computer vision, resulting in a more accurate and comprehensive summary.	The accuracy of the summary is dependent on the accuracy of the data processing technologies used.
3	Summary Generation	The summary is generated by combining the key topics and themes identified during the data processing step and paraphrasing them into a concise and readable summary. The summary is then encrypted using AES encryption to ensure its security and sent to the meeting participants via email.	Abstractive summarization techniques can be more challenging to implement and may not always accurately capture the essence of the original text.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

The dependent variable is the quality and security of the textual summary.	Mentioned independent variables are Abstractive summarization, the technologies and libraries used, including Speech Recognition, Spacy, PyCrypto, the AES encryption algorithm.	There doesn't seem to be a clear moderating variable mentioned in the PDF.	The document does not explicitly mention any mediating variables.
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Relationship Among the Above 4 Variables in This article			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
audio meeting	MM S Sum mary	The proposed solution aims to enhance the accuracy, security, and efficiency of business meeting summarization by integrating NLP, speech processing, computer vision, and AES encryption.	The proposed method utilizes abstractive summarization to provide a condensed, secure summary of business meetings, offering a more accurate, efficient, and secure method for summarizing meetings.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
The use of abstractive summarization and multi-modal sensing also improves the accuracy of the summary by capturing the main contents of the meeting.		Dependency on speech recognition, loss of context like text summarization algorithms may not always capture the full context and nuances of the original text.	

Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
By examining the methodology, evaluating the effectiveness of the summarization techniques, assessing the security measures implemented, and considering the practicality and usability of the system.	NLP tools like NLTK, spaCy, AES tool stack, scikit-learn.	Abstract I. Introduction II. Literature survey III. Implemented system IV. Result V. Comparison table VI. Conclusion VII. Reference
Diagram/Flowchart		
<pre> graph TD Start[Start Recording] -- Recording --> Record[Recorded Conversation (Audio Format)] Record -- Audio --> Transcription[Transcription Audio To Text] Transcription -- Text --> Summarization[Abstractive Summarization Method] Summarization -- Summary --> Security[Provide Security AES Algorithm Secret Key + Plain Text --> Cipher --> Cipher Text] Security -- Encrypted File --> Encrypted[Encrypted summary File] Encrypted --> Email[Send Summary to members via Email] </pre>		

---End of Paper 13---

14	
Reference in APA format	Sheetal Patil, Avinash Pawar, Siddhi Khanna, Anurag Tiwari, Somay Trivedi - "Text Summarizer using NLP (Natural Language Processing)" Volume 12, Issue 3, 2021, DOI (Journal): 10.37591/JoCTA.

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://www.researchgat... e.net/publication/365790121_Text_Summarizer_using_NLP_Natural_Language_Processing	Sheetal Patil, Avinash Pawar, Siddhi Khanna, Anurag Tiwari, Somay Trivedi	Automatic summarization, Extractive, Natural Language Processing, frequency-based
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
Frequency based approach	<p>The goal is to collect sentences and tokenize sentences into words and then calculate sentence score on the basis of TF-IDF score which is being used to select the most important sentences to retain the information and merge it to form a summary.</p>	<p>Natural Language Processing (NLP) is used to analyze and understand the text data from the input.</p> <p>Term Frequency (TF), Keyword Frequency, Stop Words Filtering, Clustering Approach like K-means Clustering.</p>
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Text Preprocessing	<p>The process involves importing libraries like NLTK and creating clean sentences by removing special characters, digits, and words, thereby standardizing and</p>	<p>It may remove important information that is not recognized as special digits, words, or characters.</p>

		simplifying text analysis.	
2	Term Frequency-Inverse Document Frequency (TF-IDF) Calculation	It helps with the calculation of TF-IDF score for each word in a paragraph. The advantages of this are that it helps to identify the most important words in the text and assign them a higher score, making it easier to select the most important sentences.	Inaccurate - It may not take into account the context of the words, which can lead to inaccurate results.
3	Sentence Scoring and Selection	Calculating the sentence score based on the TF-IDF score of the words in the sentence and selecting the most important sentences to merge into a summary. It helps to identify the most important sentences in the text and create a concise summary.	It may not capture the nuances of the text and may miss important information that is not included in the selected sentences.

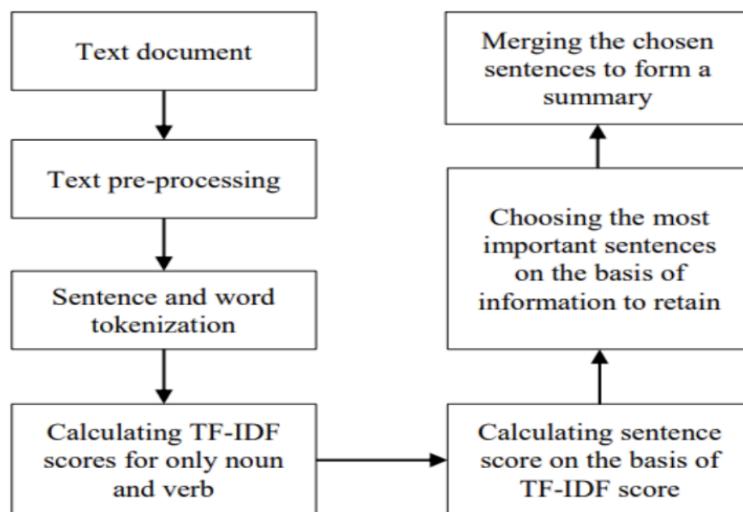
Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The possible dependent variable is the effectiveness or quality of the text summarization.	Possible independent variables are the choice of keywords, or the type of text being summarized.	The length of the input document may be a moderating variable, as longer documents may necessitate different summarization techniques	The document does not mention any mediating variables, but the TF-IDF score may mediate the relationship between word choice and

		compared to shorter ones.	summary quality.
Relationship Among the Above 4 Variables in This article			
The independent variables (the choice of text summarization technique) may influence the dependent variable (quality of summary). The mediating variable (TF-IDF score) is used to assess the importance of words in the summarization process, which affects the quality of the summary. The moderating variable (length of the input document) could moderate the relationship between the summarization technique and the quality of the summary, as longer documents may require different approaches.			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	The solution employs natural language processing techniques to analyze text, identifying key information through extractive summarization, tokenization, and ranking, and addressing information overload.	This proposal proposes a text summarization solution using natural language processing and an extractive summarizer to efficiently identify and use key information in large text volumes.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
Positive impact on the project domain by improving access to information, enhancing natural language processing tasks, and increasing text processing capacity.		Loss of Context, Sensitivity to Word Frequency which may lead to unbalanced accuracy of the generated summary, Lack of Human Judgment.	
Analyze This Work by Critical Thinking		The Tools That Assessed this Work	What is the Structure of this Paper
The article discusses the benefits of automated summarization and the significance of this PDF lies in its proposal of an		None	Abstract I. Introduction II. Literature survey III. Problem statement IV. Proposed system

effective and efficient method for text summarization, which can be particularly useful in fields such as research and development.		V. Approach VI. Conclusion VII. Future scope VIII. Reference
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Diagram/Flowchart



---End of Paper 14---

15	Reference in APA format	URL of the Reference	Authors Names and Emails	Keywords in this Reference
	Chetana Varagantham, J. Srinija Reddy , Uday Yelleni , Madhumitha Kotha , Dr P.Venkateswara Rao - “TEXT SUMMARIZATION USING NLP” JETIR May 2022, Volume 9, Issue 5.	https://www.jetir.org/papers/JETIR2205397.pdf	Chetana Varagantham, J. Srinija Reddy, Uday Yelleni, Madhumitha Kotha , Dr P.Venkateswara Rao	Machine Learning, Text Summarization, Natural Language Processing (NLP), Clustering, Tokens
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?		

Model/ Tool/ Framework/etc)		
k-means clustering approach	<p>Based on sentence scoring, the clustering technique is used to extract the final summary sentences, which are segregated into lowest and highest weighted sentences. The final output is based on the highest scored clusters, which provide meaningful and efficient summaries.</p>	Sentence segmentation, Tokenization, Stop word removal, Stemming.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing step	The process involves transforming the input document into a collection of words or phrases, and performing natural language processing tasks like sentence segmentation, tokenization, stop word removal, and stemming.	It may result in the loss of some important information.
2	Scoring step	Calculating the frequency weight age of each word in the sentence in the entire document and allocating a total score for the sentences, which helps us to find the important sentences.	It may not capture the context and meaning of the sentences accurately.

3	Clustering step	Using k-means clustering to divide the sentences into clusters based on their scores and selecting the highest scored clusters to generate the final summary which helps to group similar sentences together, reduces redundancy in the summary.	It may not capture the diversity of the input document and may result in the loss of some important information.
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Major Impact Factors in this Work

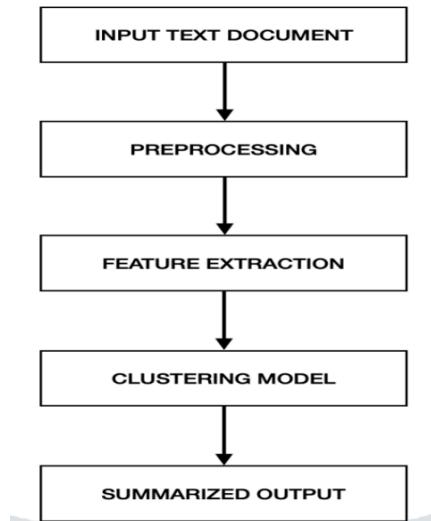
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The possible dependent variable is the effectiveness or efficiency of the text summarization.	Possible independent variables are the choice of keywords, tokenizing.	But the possible moderating variable could be Clustering.	The text does not explicitly mention a mediating variable.

Relationship Among the Above 4 Variables in This article

The independent variables (morphological elements) may influence the dependent variable (effective summarization). The moderating variable (clustering) could moderate the relationship between the summarization technique and the quality of the summary, as longer documents may require different approaches.

Input and Output	Feature of This Solution	Contribution & The Value of This Work		
<table border="1" style="width: 100%; border-collapse: collapse;"> <tr> <td style="width: 50%;">Input</td> <td style="width: 50%;">Output</td> </tr> </table>	Input	Output	The solution can automatically generate a summary of the input document without human intervention. And it can handle large volumes of	Contribution in this work proposal of a text summarization solution is the development of a framework for extractive
Input	Output			

Text Document	clustering based summary	text data and summarize them efficiently. The solution can generate summaries quickly and accurately, which can save time and effort for users.	text summarization using k-means clustering.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
This approach can help to reduce the amount of time and effort required to read and understand large volumes of text data, which can be especially useful in domains such as news articles, research papers, and legal documents.		The extractive approach used in this solution may result in the loss of context, which can affect the accuracy and relevance of the generated summary. Limited language support and Dependence on quality of input data.	
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	
The paper provides a comprehensive overview of the existing systems of text summarization, the proposed system, and the workflow involved in the process. However, it is important to consider the potential limitations of the proposed solution, such as the loss of context and dependence on the quality of input data.	None	Abstract I. Introduction II. Literature survey III. Existing system IV. Proposed system V. Workflow VI. Result VII. Conclusion VIII. Reference	
Diagram/Flowchart			



---End of Paper 15---

16			
Reference in APA format	Jaisal Shah and Neelam Jain, "Advances in Automatic Meeting Minute Generation: A Survey", IJARSCT, Volume 3, Issue 1, February 2023, DOI: https://ijarsct.co.in/Paper8328.pdf .		
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://ijarsct.co.in/Paper8328.pdf	Jaisal Shah and Neelam Jain	Automatic Meeting Minute Generation	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
The current solution for automatic meeting minute generation is called the Automated Minute Book Creation (AMBOC) system.	Aim is to find the performance Automated Minute Book Creation (AMBOC) system is to automate the process of generating meeting minutes	Supervised learning for classification which determine the Speech recognition Speaker verification and Text summarization	

The Process (Mechanism) of this Work; Means How the Problem has Solved &

Advantage & Disadvantage of Each Step in This Process

Process is used for automated method to record minutes and transcripts of a meeting with the benefit of speaker identification using deep learning and Deep neural network

	Process Steps	Advantage	Disadvantage (Limitation)
1	Mel Frequency Cepstral Coefficient (MFCC)	Human auditory system modeling: MFCCs are inspired by the human auditory system's sensitivity to different frequency bands, making them effective for capturing important features in audio signals.	One disadvantage of Mel Frequency Cepstral Coefficients (MFCCs) is that they may not capture high-frequency information as effectively as other feature extraction methods.
2	Transformers	Parallelization: Transformers can process input data in parallel, which	Large Memory Footprint: Transformers can have a large memory footprint, which may make them unsuitable for deployment on resource-constrained devices.
3	Deep Neural Networks (DNN)	Deep learning models, particularly deep neural networks, have demonstrated exceptional performance in tasks like image and speech recognition, natural language processing, and game playing.	Deep learning models are intricate and often necessitate the use of advanced expertise for their design, training, and refinement.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

Performance of the model in generating meeting minutes (e.g., accuracy percentage, adequacy score, fluency, grammatical accuracy)	The study utilized text summarization techniques, resampling techniques, machine learning classifiers, phrase segmentation, and audio/text information combination for event identification and summarization.	The study did not consider speaker recognition, and the analysis process was logically separated.	Use of auditory and perceptual signals (e.g., noise level, roughness, teaser power) to identify and summarize important events in audio data
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Relationship Among the Above 4 Variables in This article

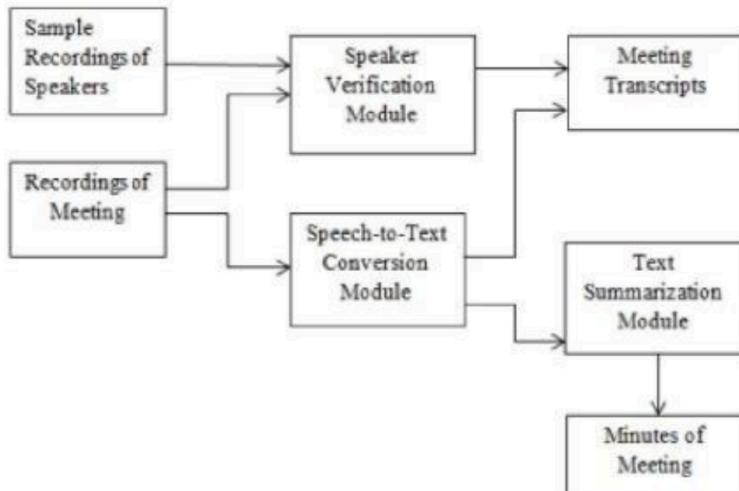
The Independent Variables directly impact the Dependent Variable, while the Moderating and Mediating Variables can influence or mediate this relationship, respectively, by affecting the process or outcomes of automatic meeting minute generation.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
speech recordings, text transcripts, and meeting data.	speaker identification, and summaries.	The proposed solution focuses on both extractive and abstractive summarization techniques.	Deep Learning techniques to extract crucial information from significant debates during meetings.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	

This allows participants to focus more on the meeting itself and actively engage in discussions.	Ability to manage picture and video files. the Base64 technique is unable to manage picture and video files.
The proposed solution improves productivity by streamlining the process of generating meeting minutes, saving time and resources, and ensuring	This limitation can hinder the comprehensive documentation of meetings that involve visual content.

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The context mainly consists of information about text summarization techniques, evaluation methods, and research studies related to audio and text summarization.	LSE (Latent Semantic Evaluation) LSA (Latent Semantic Analysis), Machine learning classifiers	Abstract I. Introduction II. Background III. Methodology IV. Main Finding V. Implementation VI. Design VII. Conclusion

Diagram/Flowchart



---End of Paper 16---

17

Reference in APA format	Neslihan Akar and Metin Turan, "A General Approach for Meeting Summarization: From Speech to Extractive Summarization", Istanbul Commerce University, 2022, Volume 9, DOI: 10.18488/76.v9i2.3038.
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URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://archive.consciencetiabeam.com/index.php/76/article/view/3038/6741	Neslihan Akar, Metin Turan	Human Factor, Sound Recording Environments, Language-Specific Problems, Interference and Noise	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
converting audio to text in meeting summarization and . It transcribes the audio stream from each meeting participant into text .	converting audio recordings of meetings into text and summarizing the obtained texts.	Speech to Text Conversion, Text Summarization, Sentence Similarity Comparison	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	Advantage	Disadvantage (Limitation)
1	Speech to Text Conversion: speech-to-text conversion (ASR) is a technology that converts spoken language into written text, despite challenges like noise, accents, and language complexity. Despite these, research continues to improve accuracy.	increased Efficiency, Accuracy	Data loss and noise recognition.

2	Text Summarization: Text summarization is the condensing of a lengthy text into a shorter version, preserving key information and enhancing reader comprehension through techniques like extraction and abstraction.	Capturing important points.	Loss of Context
3	Comparison with Human Summaries	Efficiency and Time saving.	Ambiguity and Inference

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The success rate of extractive summarization is a measure of the technique's effectiveness in producing summaries that resemble human-generated ones.	Meeting texts, speech-to-text conversion, and summarization ratios (40% and 20%) are input data for summarization processes, involving both human and machine summarizers.	Human summarizers and a dictionary are used to support the summarization process of meeting texts, ensuring equal ratios and accuracy.	Machine and human summarizers' similarity ratios and selective words determine summarization process success.

Relationship Among the Above 4 Variables in This article

Independent, Moderating, and Mediating Variables drive the summarization process, providing support and guidance, and evaluating results to impact the success rate of the extractive summarization technique.

Input and Output		Feature of This Solution	Contribution & The Value of This Work		
Input	Output				
audio input meeting		It converts the spoken words in the audio files into written text, which gives us even better results.	Contribution in this work proposal of a text summarization solution is the development of a framework for extractive text summarization using freq based approach.		
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain			
Converting audio recordings of meetings into text, the solution enables the summarization.		Hominy and misunderstanding. Loss of information.			
Analyze This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper			
Critical thinking requires examining the logical reasoning, evidence, and validity of the research findings	speech recognizer toolkit, Algorithms, summarizers.	Abstract I. Introduction II. Methodology III. Data IV. Results and Evaluation. V. conclusion			
Diagram/Flowchart					
<pre> graph LR Text[Text] --> Preprocessing[Preprocessing] Preprocessing --> Tokenization[Sentence and word tokenization] Tokenization --> Postagging[Pos-Tagging] Postagging --> TFIDF[Calculating TF-IDF] TFIDF --> SentenceScore[Calculating Sentence Score] SentenceScore --> Choose[Choosing the Most Important Sentences] Choose --> Summary[Summary] </pre>					

---End of Paper 17---

Reference in APA format	Hamza Shabbir Moiyadi, Harsh Desai, Dhairyा Pawar, Geet Agarwal, Nilesh M.Patil, "NLP Based Text Summarization Using Semantic Analysis", IJAEMS, Vol-2, Issue-10, Oct-2016, DOI: https://www.neliti.com/publications/239678 .		
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://www.neliti.com/publications/239678	Harsh Desai, Dhairyा Pawar, Geet Agarwal, Nilesh M.Patil.	text summarization techniques and classical approaches to text summarization.	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?	
Latent Semantic Analysis (LSA) Summarizer.	(LSA) Summarizer solution mentioned in the document is to summarize text documents.	Pre-processing, Singular Value Decomposition (SVD), Summary Generation.	
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
Process is used for automated method to record minutes and transcripts of a meeting with the benefit of speaker identification using deep learning and Deep neural network			
	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing	Removal of stop words. Enhanced summarization accuracy.	Initial deployment costs and potential technical challenges in maintaining sensors in remote areas.
2	Singular Value Decomposition (SVD): Singular Value Decomposition (SVD) is a text summarization	Dimensionality Reduction, Noise Reduction.	SVD might not handle missing data.

	technique that reduces dimensionality, identifying latent semantic relationships, and extracting essential features for concise summaries.		
3	Filtering.	Improved Accuracy.	
4	Sentence Selection.	sentence contain the most relevant and meaningful information.	

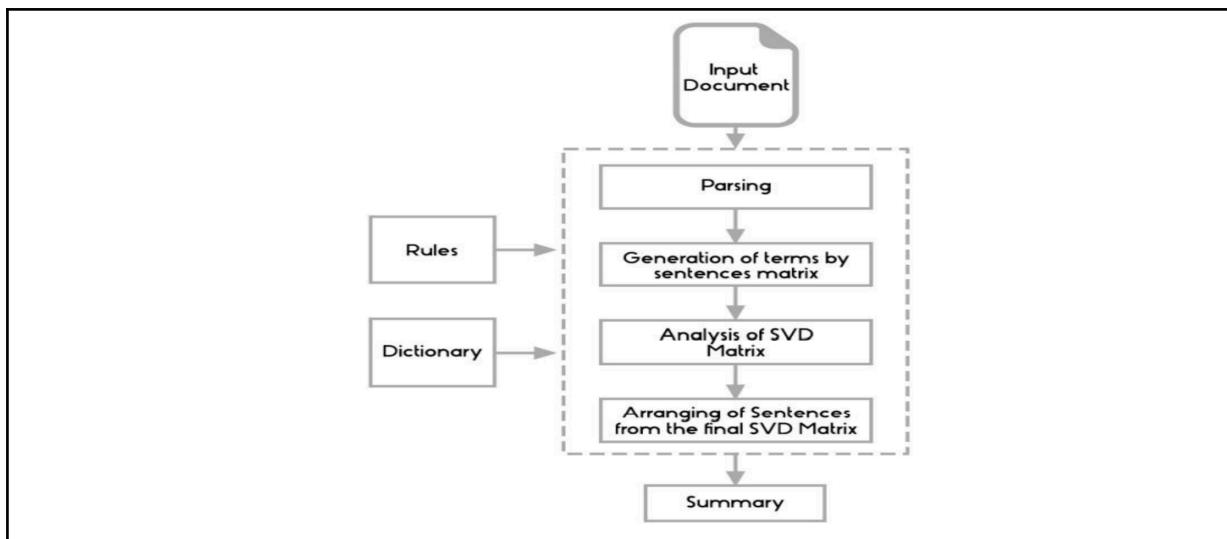
Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the quality and effectiveness of the generated document summary, measured in coherence, relevance, and comprehensiveness compared to the original document.	The system employs Latent Semantic Analysis (LSA) as the independent variable for document summarization, primarily used to extract semantic information from input documents.	Semantic rules and dictionaries from NLP libraries enhance semantic analysis and SVD phases, providing contextual information and world knowledge, but their effectiveness may vary with different domains or languages.	The SVD matrix mediates the extraction of latent semantic structures from input documents, influencing the quality of summarization and acting as an intermediary step between the input and final summary.

Relationship Among the Above 4 Variables in This article

The proposed system focuses on Latent Semantic Analysis (LSA) and Singular Value Decomposition (SVD) matrix for document summarization, with semantic rules and NLP libraries potentially influencing the process's effectiveness.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
meeting data.	techniques to select top sentences	Latent Semantic Analysis (LSA) usually summarizes and arranges the sentences.	This work is designed for the LSA in that it derives the latent semantic structure from the document, allowing for a more meaningful summary.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
Perform LSA at original text to Summarized Text.		Takes much time to generate the summary.	
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper	
Arranging of sentences from the SVD matrix	Python, NLTK (Natural Language Toolkit, Gensim (Python library).	Abstract I. Introduction II. Literature Review III. Discussion IV. Proposed System V. Conclusion & Result	
Diagram/Flowchart			



---End of Paper 18—

19		
Reference in APA format	Authors Names and Emails	Keywords in this Reference
https://www.philstat.org/index.php/MSEA/article/view/688	Vivekshel Yadav , Faraz Ahmad, Ashuvendra Singh.	Text Recognition, Document Images, OCR, Speech to Text Conversion, Multilingual Languages, K Nearest Neighbor, Text Summarization.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?

TFRSP (Text Frequency Ranking Sentence Prediction).	To combine extractive and abstractive summarization techniques using supervised and unsupervised learning algorithms.	Extractive Summarization, Abstractive Summarization, Supervised and Unsupervised Learning Algorithms.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Extractive Summarization. By scoring each and every sentence, we normalize them using cosine similarity methodology and top rank to select the important sentences.	Easier Evaluation and Faster Processing	Redundancy.
2	Abstractive Summarization: generating new sentences, unlike using the same sentences in the meeting by creating neural networks and LSTM layers.	Reduced Redundancy.	Difficulty in Ensuring Accuracy.
3	Integration Techniques.	Data Accessibility and Sharing, Cost and Time Efficiency.	

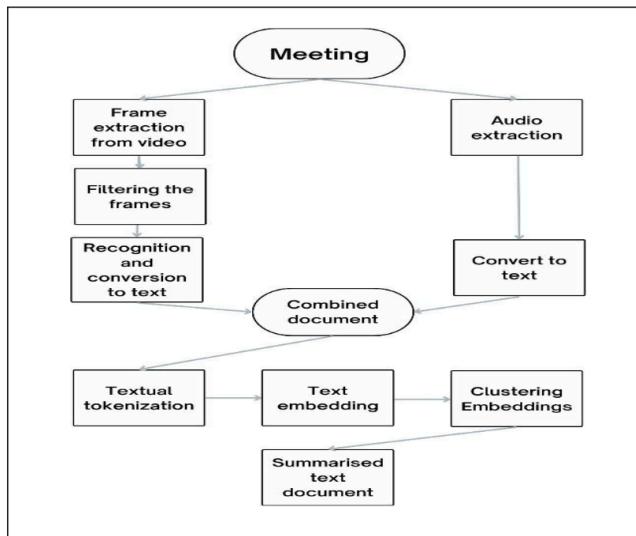
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable is the quality and effectiveness of the document	The independent variable is the use of convolutional neural networks as the primary	No Moderating variables	No mediating variables.

summarization algorithm.	method for extracting important information from documents.		
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Relationship Among the Above 4 Variables in This article			
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
meeting data	Using both techniques we generate summaries.	Reduce computational power while maintaining accuracy by integrating different models to generate a summary.	It utilizes the Text Rank (TR) method with the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm for extractive summarization.
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain	
Reduce the computational power required while maintaining the accuracy of the model. By integrating different models, TFRSP is able to generate a summary that is comparable to a summary written by a person.		Computational complexity and Reduced accuracy.	
Analyse This Work by Critical Thinking		The Tools That Assessed this Work	What is the Structure of this Paper

The context mainly discusses various methods and techniques used in handwriting and voice recognition, as well as text summarization.	Support Vector Machine(SVM), TSRFP model, KNN algorithm, Minimum Distance Classifier.	Abstract i. Introduction. ii. Literary review. iii. Methods. iv. Proposed system v. Conclusion.
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Diagram/Flowchart



---End of Paper 19---

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Reference in APA format	Authors Names and Emails	Keywords in this Reference
https://aclanthology.org/C18-1236	Jan Mandlig, Henrik Leopold	process mining, compliance checking, BPMN-Q, temporal logic, abstraction layers, automated matching, linguistic conventions, conceptual models.
The Name of the Current Solution (Technique/ Method/	The Goal (Objective) of this Solution & What is	What are the components of it?

Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	the problem that need to be solved	
NLP techniques would facilitate the automation of particular tasks in business process management.	Main goal is to execute a single process instance and to build useful conversational systems that support the execution of business processes.	Transform process model to textual descriptions. Instance Management. NLP(natural language processing).
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Textual Process Descriptions to Process Models: The system aims to automatically transform textual process descriptions into process models using tailored NLP techniques. These techniques identify actions and their inter-relations in the text to lay the foundation for generating a process model. Challenges include identifying contextual information and dealing with the ambiguity of natural language	Process models enhance communication, identify bottlenecks, and inefficiencies, leading to targeted improvements and optimizing resource allocation through visualization, simulation, and analysis.	Converting textual descriptions to models can lead to interpretation errors, oversimplification, and misalignment with actual processes, while maintaining and updating models can be time-consuming and resource-intensive.
2	Translate Process Models: The system can handle multiple definitions of the same process by comparing models created by students to text statements for grading and feedback purposes. It allows for automatic comparison, grading, and feedback provision to students learning to formalize processes	Process models enhance understanding, identify inefficiencies, facilitate simulation and analysis, and improve communication among stakeholders, facilitating better understanding, optimization of resources, and collaboration.	Converting textual descriptions to process models can introduce interpretation errors, maintenance challenges, oversimplification, and alignment issues, potentially leading to discrepancies between model and actual processes.

3	<p>Mapping Textual and Model Descriptions: The system involves a phase where issues are fixed through refactoring of the process model, using NLP techniques to enhance semantic abstraction levels.</p>	<p>Mapping textual descriptions to model representations enhances communication, thereby increasing efficiency and productivity.</p>	<p>Accurate models can be time-consuming, potentially oversimplify complex business processes, impacting analysis effectiveness and updating them with dynamic operations.</p>
4	<p>Tailored Dialogue Systems: The system uses customized dialogue systems for troubleshooting and stakeholder guidance, such as chatbot-aided troubleshooting, where artificial agents complement human operators in contact centers.</p>	<p>Personalized Customer Interaction, Enhanced, Efficient Handling of Queries, Real-time Insights and Analytics</p>	<p>Complexity and maintenance and updates issues.</p>
5	<p>Conversational Systems for Process Navigation: Conversational systems with NLP features, such as semantic understanding and context resolution, aim to assist stakeholders in navigating processes based on available descriptions.</p>	<p>Enhanced User Experience, Increased Accessibility, Improved Efficiency:</p>	<p>Limited Understanding, Data Privacy and Security Concerns</p>
6	<p>Text Annotation and Analysis: The system involves annotating textual descriptions of process models to establish relations and elicit new information for more precise descriptions. Annotations can also serve as training data to enhance automatic language analyzers for specific tasks</p>	<p>Text annotation and analysis enhance understanding, drive data-driven decision making, identify patterns and trends, and ensure compliance with regulations and standards.</p>	<p>Text data analysis is complex, resource-intensive, subjective, and raises privacy and security concerns due to its complexity, potential biases, and potential misalignment with organizational goals.</p>
<h3>Major Impact Factors in this Work</h3>			

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable in this scenario is the effectiveness of BPM practices, specifically NLP techniques, in improving processes, efficiency, and outcomes within organizations.	The study introduces NLP techniques as an independent variable to enhance BPM practices, with researchers manipulating this variable to observe its impact on the dependent variable.	The complexity of business processes may moderate the relationship between NLP techniques and BPM effectiveness, as complex processes may require different levels of integration or yield varying results.	The accuracy and completeness of NLP-generated process models may influence the relationship between NLP techniques and BPM effectiveness, potentially leading to improved outcomes.

Relationship Among the Above 4 Variables in This article

The study suggests that the effectiveness of Business Process Management (BPM) is influenced by NLP techniques, potentially influenced by process complexity and the quality of generated process models.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output		
Conversion between formal process descriptions and text.	Applications that consider both the process perspective and its enhancement	Integration of natural language processing (NLP) features and textual and graphical process descriptions.	Aligning textual descriptions of processes with graphical representations and improve the understanding and analysis of business processes by bridging the gap between textual and graphical descriptions.

	through NLP.	
Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain
Improving the understanding and analysis of business processes.		Lack of domain adaptation and Missing tasks or relations.
Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
NLP can contribute to improving the understanding, analysis, and refinement of business processes.	Business Process Model and Notation (BPMN). Integer Programming NLP(natural processing).	Abstract i. Introduction ii. Background iii. Expanding BPM Capabilities through NLP. iv. Application. v. Conclusion.
Diagram/Flowchart		

---End of Paper 20---

2.1 COMPARISON TABLE

Author	Year	Approach	Description
Vishnuprasad, Paul Martin, Salman Nazeer, Prof. Vydehi	2023	Extractive text Summarization with help of Document Similarity Matrix	The study employs an extractive approach, in which the best-scoring sequences are chosen and those sentences are included in the output summary structure after being verified by glove embedding.
Srishti Subhash Chandra Prasad	2021	A combination of Extractive and Abstractive Summarization approaches.	The abstractive portion of the solution, which employs LSTM cells and an attention mechanism to assess the phrases and provide an output after following the general extractive summarization, is the main emphasis of the study.
Rajat Verma Sparsh Gupta, Shubh Sharma, Tanishq Aggarwal	2022	The paper focuses on the Abstractive based approach	The goal of the paper is to summarize the meeting, not to create notes. To do this, it goes through a rigorous process that includes sentiment analysis and lexical analysis to determine the underlying meaning, which is then used to create summary notes.
Umadevi,	2018	Uses a modified version of Text	The primary technique used in the solution by the author for sentence weighing is based on a page rank graph, along with

Romansha Chopra, Nivedita Singh, Likitha Aruru, Jagadesh		Rank algorithm	some modifications made to the way weights are assigned to words and phrases in order to rank the sequences and provide summaries at the top.
Xue- Yong Fu, Cheng Chen	2023	Uses Large Language models evaluation.	The goal of the study is to select the original LLM by carefully weighing the cost-effectiveness and performance of each LLM when applied to various datasets.
Mr. Riyazahmed Jamadar, Mehul Pawar, Pavan karke, Amogh Sonar, Yashshri Zuungure.	2023	Automatic Speech Recognition (ASR) System.	They proposed a model that captures the relationship between the acoustic features of the speech signal and the corresponding textual representation.
Nazim Dugan, Cornelius Glackin, Gerad Chollet, Nigel Cannings.	2018	Acoustic model building	When a new training data is combined with the training data of the basic model, their method suggests a two-step temporal alignment approach and word level thresholding with WER values which produces a satisfactory functioning audio model.
Gabriel Murray,	2012	Latent Semantic Analysis	This involves analyzing relationships between terms and documents as per the patterns of

Jean Carletta		(LAS)	co-occurrence in large datasets.
Anna Nedoluzhko and Ondřej Bojar	2019	Decision-Focused Meeting Summarization, Extractive and Abstractive Summarization Strategies and Supervised and Unsupervised Summarization Methods	The main approach is to lay the foundations for research into automatic minuting of meetings by analyzing various sources and gathering knowledge about common types of meetings, linguistic properties of meeting minutes, available meeting corpora and datasets, and methods for automatic minuting.
Yashar Mehdad, Raymond T. NG	2013	Abstractive Summarization method	This organizes the sentences within the input into groups and constructs an entailment graph across these sentence clusters, facilitating the identification of relevant sentences.
Aryan Jha, Preetam Hegde, Navin	2022	Text Rank Algorithm	Page Rank method gives ranking for web pages in search results. The Text Rank algorithm is based on this method which creates an adjacent matrix $m \times m$. Cosine similarity is used for comparing two sentences.
Pallavi Lodhi, Dikshita Kambri	2022	Abstractive Summarization method	The system uses a NodeJS server that is connected with a machine

			learning model by a python connector.
Swapnil Waghmare, Raj Kshirsagar	2021	MMS (Multi-Modal Summarization)	The MMS method involves capturing speech using microphones, transcribing the speech, segmenting and aligning it with the corresponding manual report.
Sheetal Patil, Avinash Pawar, Siddhi Khanna, Anurag Tiwari, Somay Trivedi	2022	Frequency based approach	To collect sentences and tokenize sentences into words and then calculating sentence score based on TF-IDF score values which is used to select the most important sentences and combine them to form a summary.
Chetana Varagantham, Dr P.Venkateswara Rao	2022	K-means clustering approach	Based on sentence scoring, the clustering technique is used to extract the final summary sentences, which are segregated into lowest and highest weighted sentences.
Jaisal Shah and Neelam Jain	2023	MFCC(Mel Frequency Cepstral Coefficient)	With the help of Deep Learning Neural Networks and MFCC model the minute meetings are evaluated for summary or relevant information retrieval.
Neslihan Akar and Metin Turan	2022	Extractive summarization	This approach mainly prefers a subset of sentence or word that

			contains main points is pulled from the long text and merged or combined to make a summary
Hamza Shabbir Moiyadi, Geet Agarwal, Nilesh M.Patil,	2016	Semantic analysis	This analyzes the grammatical format of sentences, arranging words in order, phrases, and clauses, and usually determining the relationship between independent terms and context in text summarization.
Viveksheel Yadav, Faraz Ahmad and Ashuvendra Singh	2022	Deep Neural Network(DNN) in NLP	The process involves using a combination of extractive and abstractive methods, and techniques like SVM are used to form a decision boundary between the sentence planes where the boundary fits in the neural network that is created.
Han van der Aa, Henrik Leopold	2018	Latent Semantic Analysis in BPM model.	Using both the BPMN model and semantic analysis, the system analyzes the underlying meanings between the sentences to form summaries using some NLP techniques like LSA and others.

TABLE 1. COMPARISON TABLE OF DIFFERENT APPROACHES OF MEETING SUMMARIZERS.

2.2 WORK EVALUATION TABLE

	Work Goal	System's Components	System's Mechanism	Features /Characteristics	Performance	Advantages	Limitations /Disadvantages	Platform	Results
Vishnuprasad , Paul Martin, Salam an Nazee r, Prof. Vydehi Year – 2023	The system aims to enhance productivity by efficiently extracting crucial information, enhancing understanding and decision-making based on meeting content.	The system uses natural language processing, TF-IDF, and PageRank algorithms to process a meeting transcript, extract key sentences, rank them, and create an output summary.	The system aims to enhance productivity by efficiently extracting crucial information, enhancing understanding and decision-making based on meeting content.	The model outperforms previous work on ROUGE-1, ROUGE-2, and METEOR scores in scientific paper datasets, especially when applied to longer documents.	The proposed approach, while highly accurate, may not be suitable for all meetings, particularly specialized technical ones with jargon, but is effective for general business meetings.	Improved Performance, Enhanced Information Extraction and flexibility to future techniques to be used to increase efficiency.	Lack of Multilingual Support, Limited Evaluation Metrics, More dependent on NLP methodologies, No comparison with existing system.	Specifically designed for Microsoft teams meetings and uses Google Chrome extensons for captioning the audio and the data is presented on the website.	The proposed work on Meeting Summarizer utilizes Natural Language Processing (NLP) and other techniques to enhance understanding and decision-making based on the meeting content.

Srishti Subhash Chandra Prasad Year – 2021	The proposed system aims to create an automatic text summarization model for business meeting applications, utilizing Rouge Metric abstractive and extractive techniques to produce concise and readable summaries.	Extractive step and Abstractive step and also outlines the important aspect s like automatic text summarization and Rouge Metric abstractive and extractive techniques to produce concise and readable summaries.	The proposed work employs a hybrid text summarization approach, combining abstractive and extractive techniques like TextRank, RNN, and LSTM, specifically for handling large transcript files for business meetings.	The proposed work utilizes a hybrid approach, NLP, and a well-defined workflow, enhancing the development of a robust text summarization system for business meetings.	The proposed approach, while highly accurate, may not be suitable for all meetings, particularly specialized technical ones with jargon, but is effective for general business meetings.	The hybrid approach offers improved ROUGE metric scores, efficient handling of large transcript files, approximate model selection, time and effort savings, and flexibility for future improvements.	Restricted to Short Text, Difficulty in Handling Disruptions, Lack of Training Data, Length Constraints of Meeting summaries.	Python 3.7 as platform for implementation and other IDEs, including Jupyter, PyCharm and Google Colab was used for faster execution	The system's output summaries were evaluated through experiments, reference summaries, actual summaries, ROUGE scores, and human readability and understanding ability.
Rajat Verma , Spars	The proposed work aims	The proposed work comprises	The proposed work uses a	Automated meeting notes are	The document reveals a 60%	Time-saving, Increased	Dependency on Spec	The proposed work employ	The transcriptions from a meetin

h Gupta , Shubh Shar ma, Tanish q Aggar wal. Year – 2022	to create an automated meeting minute s generator, allowing individuals to focus on meetings instead of taking notes by transcri bed speech into text.	ses UI Design , Syste m Design , and Database Design , aimed at autom ating meetin g minute s genera tion and provid ing a user-fr iendly interfa ce for manag ing notes.	chrom e extensi on and text summarizer to transcr ibe and edit user-g enerat ed meetin g notes, allowi ng users to focus on the meetin g and genera te autom ated notes.	genera ted, sent via email, and accessi ble via the dashbo ard websit e, provid ing time-s aving conve nience.	accuracy rate for speech -to-tex t conver sion, utilizin g an abstrac tive text summ arizati on algorit hm to produc e gramm aticall y correct and engagi ng summ aries based on the transcr ibed text's key ideas.	Productivity, Improved team collaboration , enhanc ed flexibi lity.	h-to-te xt accuracy, Lack of Conte xtual unders standin g, and potenti al privac y concer ns.	ys variou s platfor ms includi ng React JS for UI design and Tailwi ndCSS for backen d data captur e, along with Django REST frame work and chrom e extensi ons.	g with two participants were accura tely conver ted to text, with notes genera ted using a text summ arizer for a shorte ned versio n.
Umad evi.K. S, Roma nsha Chopr a, Nivedi ta Singh, Likith	The aim is to summarize the original text, focusing on key ideas,	Pre-pr ocessi ng the data, Keyw ord Extrac tive summ aries, Graph	The propos ed text summ arizati on algorit hm uses an extract ion-ba	The TextRa nk algorit hm modifi cation is crucial for genera ting	The modifi ed Text Rank algorit hm, as indicated by a higher Rogue	Autom ated Text Summ arizati on, Efficie nt Proces sing, Weight	Depen dency on ML approa ch, Langu age depen dency, Limite d	Python Librar y, SUM Y API, Rogue Metric API.	The algorit hm, applie d to Colom bian presid ents' talks, demon strated

a Arrur u, R. Jagadeesh Kann an Year – 2018	removi ng redund ant inform ation, and examini ng syntact ic and semant ic associ ations in a langua ge.	Constr uction and Text Ranki ng , Norma lizatio n and Distort ion Measu re.	sed approa ch, assigni ng weight s to senten ces based on positio n and keywo rd presen ce, and compa ring genera ted summ aries using the SUM Y API.	concis e summ aries of top rankin g sequen ces, while graph-based rankin g algorit hms are also import ant charac teristic s.	Score, has been found to be more efficie nt than the normal versio n.	ed Graph Repres entatio n, Langu age Proces sing Applic ations	availa bility of Refere nce summ aries,		high efficie ncy in genera ting accura te and releva nt summ aries, with high simila rity to referen ce summ aries from SUM Y online resour ce.
Md Tahmi d Rahm an Laska r, Xue-Y ong Fu, Cheng Chen, Shashi Bhush an TN Year – 2023	The propos ed work aims to study how to effecti vely build meetin g summ arizati on system s for real-w orld usage	The study evalua tes both closed -sourc e and open-s ource LLMs, and propos es two approa ches to tack le the long input sequen	The system emplo ys two approa ches: Summ arizati on via Trunca tion, which uses the first n words of the transcri pt, and Summ	The propos ed solutio n evalua tes variou s LLMs to identif y the most effecti ve LLM, consid ering perfor mance,	The paper compa res perfor mance metric s like ROUG E scores, F1 scores, and perple xity, and discus ses trade-o ffs that	Handli ng Real- world data that transfo rmer based model fails to handle and trade-o ffs that come while selecti	The paper's limitat ions includ e its focus on acad emic dataset s and a limi ted numbe r of open-s ource LLMs, despite the system	-	The study evalua tes and com pares variou s open-s ource and closed -sourc e LLMs using variou s param eters, demon

	using large language models (LLMs).	ce length issue in LLMs: Summarization via Truncation and Summarization via Chapterization.	arizati on via Chapte rizatio n, which genera tes summ aries of every n words.	cost, and privac y concer ns while balanc ing them.	betwee n perfor mance, cost, and computa tional require ments for real-w orld usage.	ng a model/	's potenti al for real-w orld usage.		stratin g zero-s hot perfor mance.
Mr. Riyaz ahmed Jamar dar, Mehul Pawar , Pavan Karke , Amogh Sonar, Yashshri Zungure, Sushant Shara vagi Year- 2023	The goal of this problem is to develop a speech -to-text conversion system which solves the need for converting spoken language into written text and allows for enhanc	The system used a multilingual speech -to-text conversion system ., Bidirectional nonstationary Kalman filter, MFCC (Mel Frequency Cepstral Coefficients) , HMM	The mechanism to design a multilingual speech -to-text conversion system .., Bidirectional nonstationary Kalman filter, where different languages together are converted	The system features are Preprocessing, Acoustic Model ing, Language Modeling, Decoding and Post-processing, Training and Optimization, Evaluation and accuracy.	The performance of the speech -to-text system can be evaluated using different metrics such as word error rate (WER), character error rate (CER), and accuracy. The	Segmenting the speech into phone mes helps in recognizing different words. The speech -to-text conversion process has the advantage of providing a written	The background noise or other factors that can reduce the accuracy of the conver sion.	It can be challe nging for languages with compl ex phonetic	The results show that the accuracy of the generated summary is 90%.

	ed accessibility.	(Hidden Markov Model).	into text.	Fine-tuning	system can be fine-tuned based on the evaluation results to improve its performance.	representation of spoken language.	structures.		
Nazim Dugan , Corne lius Glackin , Gérard Cholle t , Nigel Cannings Year- 2018	The goal of the work is to develop an Intelligent Voice ASR system for the IberSpeech 2018 Speech to Text Transcription Challenge.	The system developed by the Empathetic team consists of a DNN-HMM hybrid acoustic model with MFCC's and iVectorizers as input features.	The system uses a two-step alignment procedure to clean up and realign the provided ground truth transcripts options. It also utilizes word lattice results from a previous ASR system for	The system uses a factor 3 times data augmentation by reverberation and realignment using a noise corpus to increase the training data. It also incorporates new pronunciation additions and language model	This demonstrates strengths in its choice of methodology and alignment using a noise corpus to increase the training data. It also incorporates new pronunciation additions and language model	This process helps in evaluating the performance of the final ASR model and the other experiments before its production. The advantage of this adjustment was	Getting the start and end times of words right is crucial. If they're wrong, the ASR system might not learn correctly, and its accuracy will suffer.	No information about the platform is provided in the source s.	This was achieved through a smart combination of DNN-HMM and GMM-HMM methods, which significantly improved ASR accuracy compared to the basic model.

			realign ment.	adapta tion	ve evalua tion.	impro ved accura cy in the testing of audio.			
Gabri el Murr ay, Steve Renal s, and Jean Carlet ta Year- 2012	The study compares various automat- ic speech summari- zation metho- ds using the ICSI Meetings corpus, focusing on extract- ive summari- zation techniques and their performance in	The system employs feature- based metho- ds, includ- ing prosod- ic and lexical feature s with MMR and LSA summari- zation metho- ds, maxim- al margin- al relevance (MMR) and latent semant- ic analysi- s (LSA) techniques, for summa- rizati- on.	The system employs prosodic and lexical feature s to analyze the speech data, utiliz- ing unique prosodic informa- tion like F0 mean, energy , duration, and TF-IDF- based lexical feature s.	The system employs feature- based metho- ds to evalua- te using the ROUGE data, utilizin- g unique prosodic informa- tion like F0 mean, energy , duration, and TF-IDF- based lexical feature s.	The system's perfor- mance is evalua- ted using the ROUG E softwa- re, which compa- res the extract- ive summari- es. Howev- er, specifi- c perfor- mance metri- cs or results are not men- tioned in the provid-	It is a rela- tively simple and straight- forward approa- ch.	It can pro- duce summa- ries that are choppy and lack coher- ence.	This work is good, as they tried autom- atic summa- ry genera- tion with high perfom- ance evalua- tion and select- ed the best one to get an accura- te one.	The results of the summa- rization are com- pared using the ROUGE softwa- re, but specifi- c results or metric s are not mentio- ned in the provided source s.

	ASR output compared to manual transcripts.	software.	incorporates MMR and LSA techniques for summarization	ed sources.				
Anna Nedoluzhko, Ondřej Bojar Year-2019	The goal is to design an automatic creation of meeting minutes, the use of available datasets, dialogue summarization methods, and the summarization of the gathered knowledge.	The paper outlines the classification of meetings, the use of available datasets, dialogue summarization methods, and the summarization of the gathered knowledge.	The authors propose a classification system for meetings, the use of available datasets, dialogues, and the choice of summarization methods, and aiming to design an automatic meeting system for structured knowledge.	Dialogue summarization can be done through extractingive or abstractive methods, and the choice of summarization methods, and depending on the specific use case and data available.	Understanding communication types of meetings, influencing linguistic properties, abstract structures, and the choice of summarization methods, and the specific use case and data available.	This tool aids in understanding the factors influencing meeting organization, agenda, and minutes, while also providing a formal record for accountability and tracking meeting summaries, and coherence may still be a concern.	Creating detailed minute summaries can be time-consuming, may not capture all discussions' nuances, may also not always yield concise summaries, and coherence may still be a concern.	The platform of the project is not mentioned. This information is beneficial for researchers, practitioners, and developers interested in automating meeting minutes creation and improving meeting management. Provides a formal record

									of meetings and helps in accountability and tracking action items
Yasha r Mehd ad, Giuse ppe Caren ini, Frank W. Tomp a, Raym ond T. NG YEAR- 2013	The paper aims to develop a system for generating informative and readable summaries of recorded meetings, conversations, addressing the limitations.	The main components of the system are Comm unity group algorit hm to group similar senten ces, Entail ment Detect ion, Word Graph Constr uction, Path Selecti on and word graphs , rank the best path, and genera tion. The system uses the CONG A word algorit hm to group similar senten ces, Entail ment Detect ion, Word Graph Constr uction, Path Selecti on and word graphs , rank the best path, and genera tion.	The solution employs CONG A word graph constr uction, Comm unity group algorit hm to group similar senten ces, Entail ment Detect ion, Word Graph Constr uction, Path Selecti on and word graphs , rank the best path, and genera tion.	The proposed solution improves project perfor mance by increasing efficie ncy, impro ving path selecti on, and word langua ge genera tion to create a compr ehensi on.	The proposed solution relatio ns, filters out irrelev ant inform ation, and selects key senten ces for summ arizati on. Repres ents , and enabli ng genera tion to create a compr ehensi on-maki ng,	Identif ies entail ment relatio ns, filters out irrelev ant inform ation, and selects key senten ces for summ arizati on. Repres ents , and enabli ng genera tion to create a compr ehensi on-maki ng,	The comm unity detecti on algorit hm may miss semant ic relatio nships, strugg le with compl ex or ambigu ous senten ces structu res, and can be compu tationa lly expens es.	This paper doesn't provide the platform on which it is executed.	The project 's results demonstrate its potential to significantly advance the field of meeting summarization, thereby enhancing its overall success and

	ions of existing approaches.		te a summary sentence.	ve frame work for abstractive summarization, generating informative and readable summaries of meeting conversations	ultimately leading to successful project outcomes.	ve content understanding.	ive for large sentences.		impact .
Aryan Jha, Sameer Temkar, and Preeta Hegde , Navin Singhaniya Year-2022	The goal of the research was to develop a method for gene rating sum maries for busi ness	Techniques and algori thms used in text summarization, includ ing Text Rank, ROU GE1.	The system likely involves processing meetings transc ripts or recordings for the users to recall important information	The system provided has a higher accuracy and saves time for the users to recall important information	The performance of the system has been evaluated through ROUGE1.	The system provides an alternativ e technology for summarization	-	The platform provided for the research was ICAC.	Gives a precise and concise meaning that is not only understandable to everyone but also covers all of the recorded file's

	meetings which provides an overview of text summarization techniques and applications.	important sentences or phrases and generate a summary using NLP techniques such as Text Rank.	n during a business meeting.	ated summary or translation to a set of reference summaries	ings which makes time efficient with higher accuracy.			important points.	
Pallavi Lodhi, Shubhangi Kharche, Dikshita Kambri and Sumaiya Khan Year-2022	The Business Meeting Summarization System is a tool designed to efficiently summarize significant business meetings using abstract	The system comprises a client-side application and a server-side application, with the client-side application using a machine learning mode 1 for	The system converts user input into text using a Speech-to-Text library and uses a machine learning mode 1 for	The system provided has a selection of regional language and saves time for the users to recall important	Audio summarization accurately provides structured and diverse content from trends to topics, based on analysis,	The system offers a cost-effective and accurate alternative for summarizing generation during business meetings,	-	The platform used for the research was easy chair proprietor.	The speech input is converted to a text document with good accuracy. Abstractive summarization is used in

	tive summ arizati on.	provi ding a web interf ace for user input.	abstr active sum mariz ation, provi ding both text and audio outpu t for futur e use.	rtant infor mati on duri ng a busi ness meet ing.	sis of input file conte nt.	utiliz ing regio nal langu age select ion for effici ent time mana gement.			the mod el by pre- proc essin g, toke nizat ion.
H. Ueno, M. Kaneda, and M. Tsukino Year-2002	The project aims to develop technologies to prevent drowsiness at the wheel and create an accident avoidance system, detecting and resetting drivers to prevent	The drowsiness detection system uses image processing to analyze driver's face images and detect drowsiness based on eye openness, detects eyeballs and faces, controls processing, and uses an infrared lamp	The system uses image processing to analyze driver's face images and detect drowsiness based on eye openness, and closeness, assessing alertness levels.	The noncontact method offers highly accurate and reliable drowsiness detection without any interference or annoyance.	The performance of the system has been evaluated through driving tests, accurately tracking changes in the alertness level over time.	The noncontact approach to detecting drowsiness is highly accurate and reliable, ensuring no annoyance or interference.	-	-	Tests conducted under drowsy conditions in the lab and on a real vehicle demonstrated highly accurate and reliable detection of drowsiness using a noncontact approach.

	t drowsiness.	for facilitating detection.							
Jing Tao, Hon gbo Wa ng, Xin yu Zha ng, Xiao yu Li, Hua wei Yan g. Year - 2017	The goal of the work is to build an object detection system for images in traffic scenes that is fast, accurate, and robust.	THE SYSTEM USES COMP RISES YOL O, OY OLO , R-F CN, AND A PRE-P ROCE SSING PROC EDUR E FOR CHAL LENG ING IMAG ES IN THE NIGH T.	THE SYSTEM USES YOLO FOR LOCATI ON AND OY CLASSIF ICATION , REPLAC ING FULLY- AND CONNEC TED LAYERS WITH AN AVERAG E POOL LAYER AND OPTIMIZ ING LOSS FUNCTI ON, PRODUC ING FASTER OYOL O AND OUTPER FORMIN G R-CN N	THE SYSTEM USES YOLO FORMS AND R- FCN IN TERMS OF SPEED, ACCUR ACY, AND ROBUST NESS, OUTPER FORMIN G YOLO R-FC N WHICH OTHER OBJECT DETECT ION ALGORI THMS, AND ENHAN CING ACCUR ACY FOR CHALLE NGING IMAGES IN THE NIGHT.	The system achieves an mAP of 86.4 on the testing set, and more than 6% improvement in mAP on the testing set. It	THE SYSTEM BOASTS SPEED, ACCUR ACY, AND ROBUST NESS, OUTPER FORMIN G YOLO R-FC N WHICH OTHER OBJECT DETECT ION ALGORI THMS, AND ENHAN CING ACCUR ACY FOR CHALLE NGING IMAGES IN THE NIGHT.	-	-	The system achieves a process speed of 44ms per image, an mAP of 86.4 on the testing set, and more than 6% improvement in mAP on the testing set. It
Jua n Du,	The paper introd	The syst em	The YOLO model	YOLO v2, an impro	-	YOL O achi	YOL O is a simpl	-	YOLO achiev es a

Year - 2018	uces the You Only Look Once (YOLO) approach, aiming to enhance object detection speed while maintaining high accuracy and generalization ability.	com pon ents incl ude Con volu tion al Neu ral Net wor k(CNN) fam ily, spec ifica lly Fast er R-C NN mod el, and the YO LO mod el.	revolut ionizes object detecti on by proces sing the entire image simultaneou sly, achiev ing high efficie ncy and speed, unlike traditi onal CNN family approa ches.	ved versio n of Faster R-CN N, offers a tradeof f between speed and accura cy, with strong genera lizatio n ability.		eves a Mea n Aver age Preci sion (mA P) of 78.6, surp assin g the perf orma nce of Fast er R-CN N	e, effici ent objec t detect ion meth od that outpe rform s Faste r R-CN N in speed and accur acy, and has stron g gener alizat ion abilit entire imag es.		Frame Per Secon d (FPS) of 155 and a Mean Average Precision (mAP) of 78.6, surpassing the performance of Faster R-
Jaisal Shah and Neelam Jain Year- 2023	Aim to find the perfor mance Auto mated Minut e Book Creati on (AM)	Speci h recog nition Speaker verifi cation and Text summ arizati on	Audio file is transc ribed to text and summ arize the text to get a conci	The propo sed soluti on focus es on both extra ctive and abstr active sum	-	Paral leliza tion High Perfo rmance in Deep learn ing mod els	Compl exity:- Deep learning models are compl ex and often requir e expert ise to design	The platf orm used for abstr activ e sum mari zatio n tech niqu es.	speake r identif ication , and summ arized meetin g transcr ipts.

	BOC) system is to automate the process of generating meeting minutes.		se and succinct summaries.	marization techniques.			, train, and fine-tune effectively		
Neslihan Akar Metin Turan Year-2022	converting audio recordings of meetings into text and summarizing the obtained texts.	Speech-to-Text Conversion. Text Summarization. Sentence Similarity Comparison.	Speech-to-text conversion, text summarization, and sentence similarity comparison are crucial technologies in natural language processing, improving	It converts the spoken word s in the audio files into written text. which gives us even better results.	Increased efficiency. Accuracy. Capturing important points. Efficiency and Time-saving	Data loss and noise recognition.	The platform used for the research was easy chair preprint.	The speech input is converted to a text document with good accuracy. Abstractive summarization is used in the model by pre-processing,	

			communication, comprehension, and information management in applications like virtual assistants and educational tools.					tokenization.
Harsh Desai , Dhairya Pawar , Geet Agrawal , Nilesh M.P. patil. Year- 2016	(LSA) Summarizer solution mentioned in the document is to summarize text documents .	Pre-processing, Singular Value Decomposition (SVD), Summary Generation.	Pre-processing, Singular Value Decomposition (SVD), and summary generation are essential steps in text analysis and summ	Latent Semantic Analysis (LSA) usually summarizes	Em oval of stop words. Enhanced summarization accuracy Imensionality	SVD might not handle missing data-	This work designed for the LSA that it derives the latent semantic structure from the document, allowing for	system uses LSA to identify semantically important sentences and arranges them in a way

			arization, preparing data, identifying key features, and extracting significant information.	riz es an d arr an ge the se nte nc es.		Red ucti on. Noi se Red ucti on. Imp rove d Acc urac y		a more meaningful summary.	that the summary.
Vive ksheei Yada v, Fara z Ahm ad, Ashu vend ra Sing h. Year- 2022	To combine extra ctive and abstr active sum mariz ation techn iques using super vised and unsu pervised learni ng algori thms.	Extr activ e Sum mari zatio n. Abst racti ve Sum mari zatio n. Supe rvise d and Uns uper vise d Lear ning Algo rith ms.	Extr activ e Sum mari zatio n. Abst racti ve Sum mari zatio n. Supe rvise d meth ods and to extra ct key sente nces from text, usin g supe rvise d and	reduc e comp utatio nal powe r while maint ainin g accur acy by integr ating differ ent mode ls to gener ate a sum mary.	Easie r Evalu ation and Faste r Proce ssing. Data Acce ssibili ty and Shari ng. Cost and Time Effici ency. Redu ced Redu ndanc y.	Redun dancy-	It utilizes the Text Rank (TR) method with the Term Frequency-In verse Document Frequency (TF-IDF) algorithm for extractive summarization.	integr ates both extractive and abstractive resulting in a more comprehensive and accurate summary of the meeting.	

Jam Men dling Henr il Leop old. Year- 2016	Main goal is to execution of a single process instance and to build useful conversational systems that support the execution of business processes.	Transfor m proc ess mod el to text ual desc riptions. Inst anc e Ma nag eme nt. NL P(n atur al lang uag e proc essi ng).	Instanc e man age men t in (NL P) invo lves cont rolli ng spec ific ling uisti c NL P(n atur al lang uag e proc essi ng).	Integr ation of natur al langu age proce ssing (NLP) featur es and textu al and graph ical proce ss descri ptions.	Auto matic refact oring. Sema ntic searc h and mergi ng of proce ss mode ls. Proce ss archit ectur e. Adap tabilit y and Flexi bility. Com plian ce and Gove rnanc	Time- consum ing.	Integra tion of natural langu age proces sing (NLP) feature s and textual and graphi cal proces s descri ptions. -	Conve rsion betwee n formal proces ses descri ptions and text.

			ghts fro m text ual data whil e adh erin g to the proc ess mod el's con strai nts.		e.		
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TABLE 2.WORK EVALUATION TABLE.

2.3 DISADVANTAGES OF EXISTING SYSTEM

Meeting summarizers, while offering several benefits, also come with their own set of disadvantages. Here are some of the common disadvantages associated with existing systems on meeting summarizers:

- Many existing systems may struggle to comprehend the nuanced context of meetings. This can result in inaccurate or incomplete summaries that fail to capture the essence of the discussion.
- Meetings often involve multiple speakers talking over each other, interrupting, or engaging in side conversations. Existing summarizers may find it challenging to accurately attribute statements to the correct speaker, leading to confusion in the summary.

- Meeting summarizers typically analyze audio recordings or transcripts of discussions, raising concerns about privacy and data security. Users may be hesitant to use these systems if they feel uncomfortable with the idea of their conversations being recorded and analyzed.
- Like any AI system, meeting summarizers can be susceptible to bias and inaccuracies, especially if they are trained on biased or limited datasets. This can lead to skewed or misleading summaries that do not accurately reflect the content of the meeting.
- Meetings in specialized fields often involve technical jargon and industry-specific acronyms. Existing summarizers may struggle to accurately interpret and summarize discussions that contain such terminology, resulting in incomplete or misunderstood summaries.
- Meeting summarizers may not be easily customizable or adaptable to the specific needs and preferences of different users or organizations. Lack of flexibility in tailoring the summarization process can limit the utility of these systems in diverse settings.

CHAPTER 3

PROPOSED SYSTEM

3.1 PROPOSED SYSTEM

In our proposed system, we seamlessly integrate both extractive and abstractive summarization techniques, leveraging the strengths of each approach. While the extractive method selects and condenses existing phrases, the abstractive-based technique allows for the generation of novel expressions, enriching the summary with diverse language patterns. At the core of our system lies the sophisticated Encoder-Decoder layered architecture, a robust framework adept at handling both encoding and decoding tasks. Preceding this architecture, a series of preprocessing steps including TF-IDF analysis and TextRank algorithms are employed to identify the most salient sequences within the input transcripts. This ensures that the subsequent summarization process is built upon the foundation of the top-ranked segments, enhancing the coherence and relevance of the generated summaries. Furthermore, we harness the power of LSTM (Long Short-Term Memory) memory cells within the Encoder-Decoder framework. LSTM cells excel at capturing intricate long-term dependencies within the data, enabling our system to grasp the nuanced relationships embedded within the input text. Through rigorous experimentation with various training and testing ratios, we meticulously fine-tune our model to achieve the optimal balance between comprehensiveness and conciseness in the generated summaries. This iterative approach allows us to identify the ideal configuration where the model produces succinct yet informative outputs, catering to the diverse summarization needs across different contexts and domains.

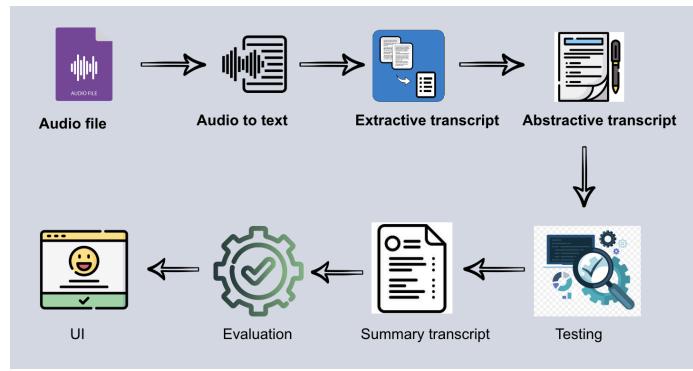


Figure 2: Proposed System Architecture

3.2 OBJECTIVES OF PROPOSED SYSTEM

- Creating a user-friendly application.
- Generate concise summaries to save time for the busy people.
- Identify and highlight key insights from the meeting discussions.
- Provides clear and relevant information for decision-makers.
- Makes it easier for the participants to remember and apply the key takeaways.

3.3 ADVANTAGES OF PROPOSED SYSTEM

The proposed system has the following advantages:

- Seamlessly integrates extractive and abstractive summarization techniques
- Leverages Encoder-Decoder architecture for robust summarization
- Utilizes preprocessing steps like TF-IDF and TextRank for identifying salient sequences

- Employs LSTM memory cells for capturing long-term relationships in the data
- Fine-tunes model through experimentation for optimal summarization balance
- Produces succinct yet informative summaries tailored to diverse contexts
- Enhances summary coherence by incorporating top-ranked segments from input transcripts
- Improves summarization quality through iterative refinement processes
- Facilitates the creation of concise summaries without sacrificing information richness

3.4 SYSTEM REQUIREMENTS

The system requirements for the development and deployment of the project as an application are specified in this section. There are no specific, end-user requirements as the intended application is cross-platform and is supposed to work on devices of all form-factors and configurations.

3.4.1 SOFTWARE REQUIREMENTS

Below are the software requirements for application development:

1. Operating System - Windows, macOS or Linux distributions are suitable for development
2. Development Environments: Python virtual environments are suitable for machine learning tasks, along with libraries like Tensorflow, PyTorch or Hugging Face's Transformers for natural language processing (NLP) tasks.
3. Editor for HTML, CSS and JavaScript- VS Code, or Notepad++

4. Google Chrome, Firefox, Microsoft Edge or Brave Browser with Extension Support.
5. Version Control - utilize version control systems like Git to manage project code and collaborate with team members effectively.
6. IDE (integrated Development Environment): Use an IDE like PyCharm, Jupyter Notebook, or VSCode for code development, debugging, and visualization of results.
7. Dependencies and Libraries: Install necessary Python packages and libraries such as NumPy, pandas, scikit-learn, NLTK (Natural Language Toolkit), and spaCy for data preprocessing, feature extraction, and NLP tasks.
8. GPU Support (Optional): While training deep learning models, having access to a GPU can significantly accelerate training times. NVIDIA GPUs with CUDA support are commonly used for such tasks.

3.4.2 HARDWARE REQUIREMENTS

Hardware requirements for application development are as follows:

1. CPU- intel i5 or higher
2. RAM – 8 GB or higher
3. Storage - adequate storage to store model checkpoints, etc. A solid SSD is recommended.

3.4.3 IMPLEMENTATION TECHNOLOGIES

Speaker Diarization:

Speaker diarization is a crucial technique in speech processing, tasked with segmenting audio recordings into speaker-specific segments without necessarily identifying individuals. It involves detecting speech regions, extracting speaker embeddings, and clustering them to

group similar speakers. This process finds applications in tasks such as transcribing multi-speaker recordings and analyzing speaker-based content in media. Accurate diarization algorithms are essential for improving the efficiency of speech processing systems, particularly in scenarios with multiple speakers interacting.

Audio-to-Text Transcription:

Audio-to-text transcription using Whisper revolutionizes speech recognition in environments where sound is barely audible or in noisy conditions. Whisper employs advanced algorithms to decipher speech from faint audio signals, overcoming challenges like background noise or low volume. By analyzing subtle acoustic cues, Whisper accurately transcribes whispered speech, ensuring high-quality text output even in adverse conditions. This technology finds applications in scenarios where discretion or privacy is paramount, such as surveillance, confidential meetings, or medical consultations. Whisper's ability to transcribe whispered speech with precision opens up new possibilities for efficient and confidential communication in various domains.

Natural Language Processing (NLP):

The transformative field of Natural Language Processing (NLP) plays a crucial role in understanding human language intricacies, as demonstrated in meeting summarization projects. By employing syntactic and semantic analysis, NLP deciphers sentence structures and lexical relations, enabling a nuanced comprehension of language nuances. This capability is particularly essential in business meeting summarization, where grasping subtle variations in speaking styles is vital. NLP's significance extends beyond linguistic analysis; it is indispensable in the summarization process, aiding in pre-processing tasks by removing unnecessary elements for cleaner transcript processing.

Extractive Summarization:

Extractive summarization involves selecting important sentences directly from the source text to create a summary. The system assesses sentences based on criteria like keyword frequency and semantic similarity, assigning scores for importance. These scores determine the ranking of sentences, with the highest-scoring ones forming the summary. Unlike abstractive summarization, extractive summarization doesn't require generating new text, making it simpler to implement. However, it may result in summaries that are less coherent as it relies on stitching together existing text fragments.

TF-IDF:

TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer is a popular technique used in natural language processing to convert text documents into numerical vectors. It is often used as a pre-processing step before applying machine learning algorithms to text data.

$$\begin{aligned} \text{TF}(t, d) &= \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Number of terms in document } d} \\ \text{IDF}(t, D) &= \log \left(\frac{\text{Number of documents containing term } t}{\text{Total number of documents in the corpus } D} \right) \\ \text{TF-IDF}(t, d, D) &= \text{TF}(t, d) \times \text{IDF}(t, D) \end{aligned}$$

Figure 3: TF-IDF formula

TF-IDF vectorization is useful for text classification, clustering, and information retrieval tasks, as it captures the importance of terms in individual documents relative to their importance in the entire corpus.

Abstractive Summarization:

Abstractive summarization in natural language processing aims to condense lengthy texts by generating new sentences that encapsulate key points. Unlike extractive summarization, it involves paraphrasing and understanding the text's meaning, which is more challenging for machines. The process begins with analyzing the input text to identify main ideas, relationships, and key entities. The system then constructs a high-level conceptual representation, capturing essential information. This representation serves as the basis for generating a concise and coherent summary, sometimes requiring the fusion of information from various parts of the text. Despite its complexity, abstractive summarization can yield more human-like summaries by considering context, meaning, and nuances, resulting in grammatically correct and concise summaries compared to extractive techniques.

RNN-LSTM:

Recurrent Neural Networks (RNNs) are specialized for sequential data tasks like natural language processing (NLP), with Long Short-Term Memory (LSTM) networks excelling at capturing long-term dependencies. LSTMs, a type of RNN, process data step by step, retaining a hidden state summarizing the sequence thus far. Unlike basic RNNs, LSTMs boast a sophisticated architecture featuring memory cells with three gates: forget, input, and output. The forget gate removes irrelevant information, the input gate stores new information, and the output gate determines the cell's output. LSTMs utilize backpropagation through time (BPTT) for training, considering the sequential data's nature. Widely applied in NLP tasks like language modeling and translation, LSTMs excel in capturing extensive dependencies within sequential data, making them invaluable in various applications.

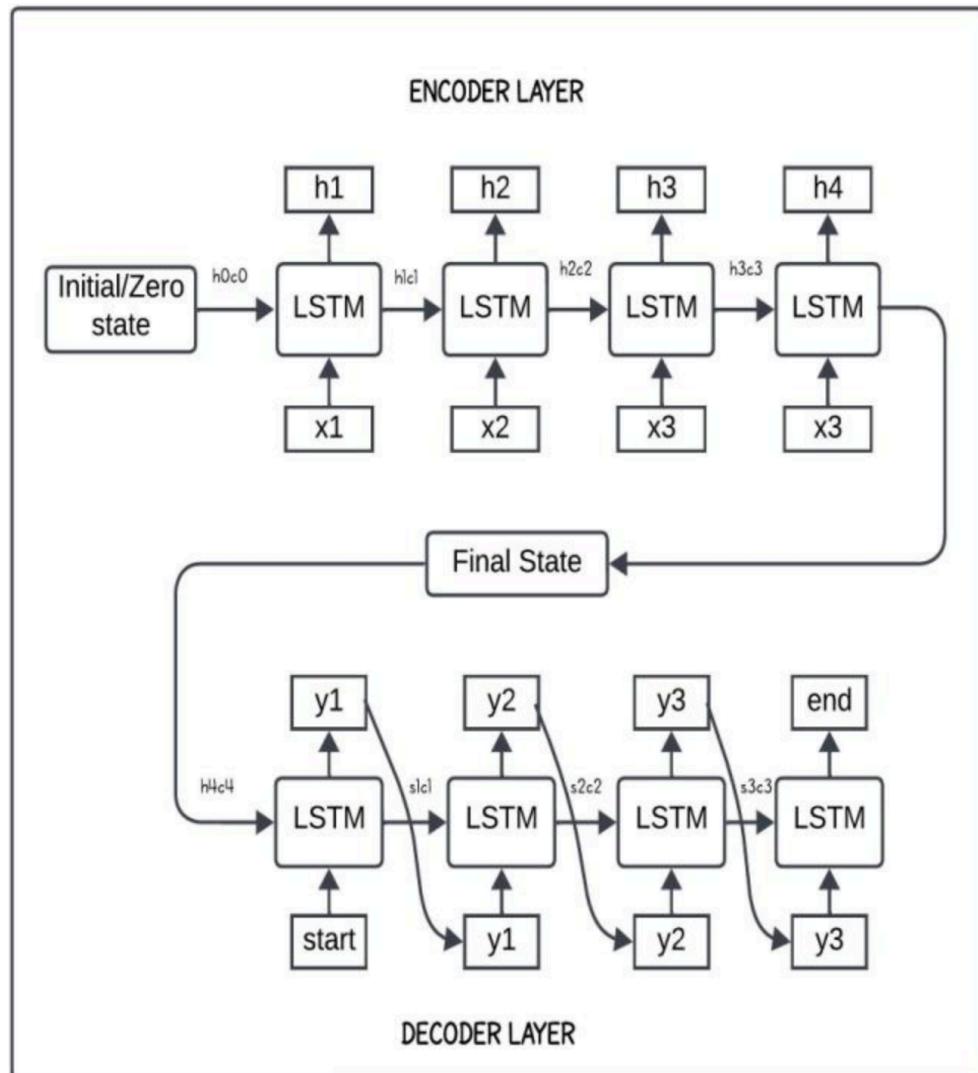


Figure 4: Encoder-Decoder Architecture

CHAPTER 4

SYSTEM DESIGN

4.1 PROPOSED SYSTEM ARCHITECTURE

The proposed system involves combining extractive and abstractive summarization techniques. First, the audio file is transcribed to get the text transcript, from which we are able to perform speaker diarization to identify individual utterances and segregate them using the Pyanote and Whisper libraries. Unlike the extractive method, the abstractive-based technique facilitates the creation of new phrases. The encoder-decoder layered system was employed after the succession of processes such as TF-IDF and text rank to construct the top-ranked sequences existing in the input transcripts. LSTM memory cells are excellent at capturing long-term relationships in the data. We experimented with training and testing ratios to find the ideal fit where the model gives succinct outputs.

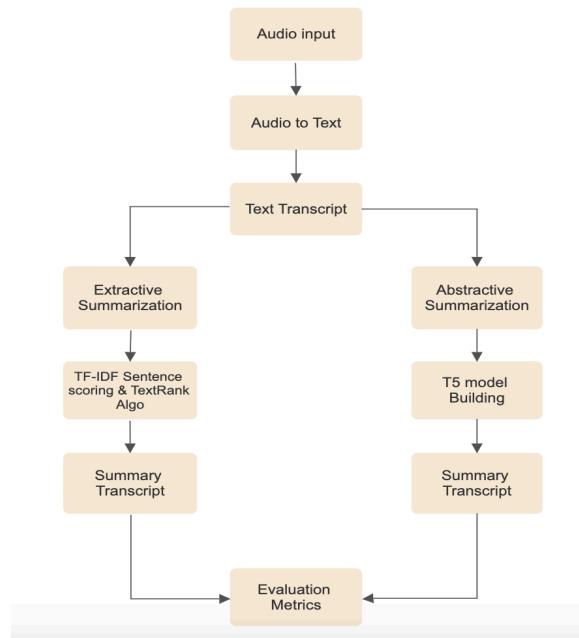


Figure 5: Proposed System Flowchart

4.2 APPLICATION MODULES

The application overall involves several main modules, which cater to the two main functions of this application, i.e., to transcribe the audio file and to generate summary.

4.2.1 Transcribe the audio file:

4.2.1.1 Speaker Diarization Module:

Our application uses the pyannote speaker-diarization pipeline to distinguish and identify different speakers speaking in the audio file. The process involves segmenting audio into speaker turns and exporting them to a wav file where it makes use of an external recognition library for transcription. Overall, the code orchestrates the entire process of speaker diarization, audio segmentation, caption generation, and retrieval.

4.2.1.2 Audio Recognition Module:

For our audio recognition we use the Whisper library to convert the audio file into text format. A base module is utilized in this process. We remove timestamps, IDs, and other information from the output produced so that it is only text that we need for our objectives.

4.2.3 Top-Ranking Summarization Module:

The extractive summary step begins after the first phase is finished, using a text transcript captured from the audio file as the input. It passes through several stages given below.

- Cleaning and preparing the text:-We may take care of punctuation and stop words by using spacy libraries. It eliminates punctuation and stopwords from the transcript, which are frequent terms like "the" and "and."
- Calculating Web Frequency:- We keep track of terms and their frequencies in a dictionary and add to the count whenever a word appears more than once.

- Normalizing Word Scores:- We calculate the importance score for each word by first determining the highest word frequency in the transcript. We then normalize the word frequency by dividing it by the maximum frequency.
- Sentence Scoring:- phrase scoring involves creating a dictionary to hold the scores of the sentences. Then, we iterate through the transcript, checking each phrase to see if each word has a normalized frequency score. If it does, we increment the score.
- Selecting Top Sentences:- We set a starting percentage barrier, say 0.3. We locate and choose the sentences from the sentence score dictionary that have the highest scores using the n largest function.
- Summary Creation:- To create a summary, the list of phrases with the highest scores is combined into a single string.

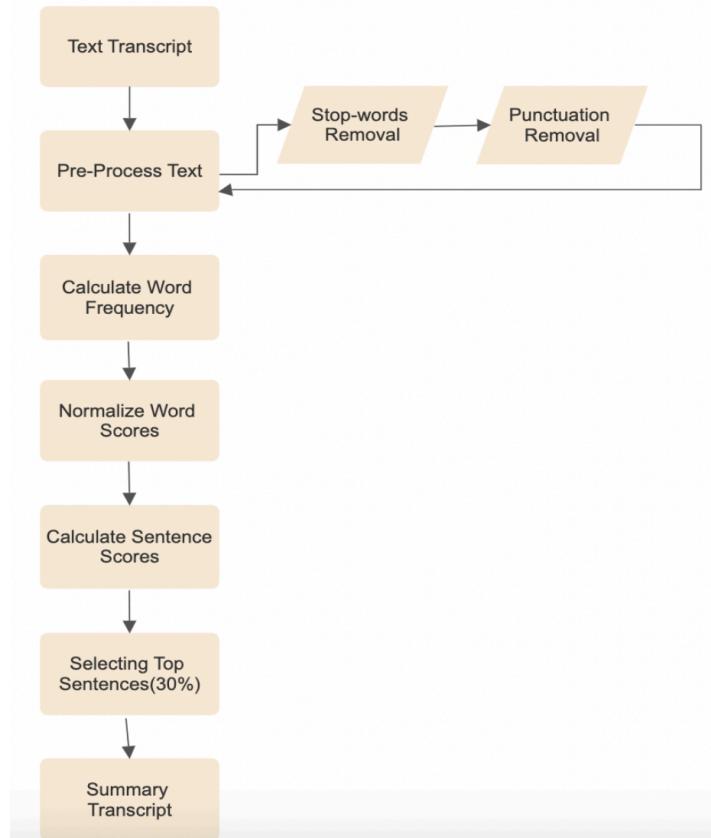


Figure 6: Flowchart of Extractive Summarization

4.2.4 Abstractive Summarization Module:

Implementing abstractive summarization with the Hugging Face Transformers library on the T5 model. To overcome computational constraints, the approach takes a lengthy input text and divides it into manageable parts. It then creates summaries for each chunk separately. The T5 tokenizer and model are loaded from the "t5-small" pre-trained model within the function. The input text is divided into pieces, with chunk length defining the maximum length of each chunk. The tokenizer passes the text to the model to create a summary for each chunk, encoding it with a summarizing prefix ("summarize:"). The tokenizer is used to decode the created summary, and then all of the summaries from the various chunks are combined to create the final summary.

To get the headline or theme of the meeting, train and infer a summarization model using the SimpleT5 library. Initially, the dataset is loaded from a CSV file, which contains headlines and corresponding text. The dataset is then preprocessed to rename columns and add a task-specific prefix ("summarize:") to the source text, as required by T5 models. After splitting the dataset into training and testing sets, the SimpleT5 model is initialized and trained on a subset of the data. The training process involves specifying parameters such as maximum token lengths, batch size, and number of epochs. After training, the trained model is saved in the outputs folder. Subsequently, the trained model is loaded for inference, and a sample text is provided for summarization. The model predicts a summary for the given text.

4.3 UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized fashionable-cause modeling language in the subject of object-oriented software engineering. In its modern shape, UML comprises two essential components: a Meta-model and a notation. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and

documenting the artifacts of software program machines, in addition to for commercial enterprise modeling and other non-software systems. The UML uses more often than not graphical notations to express the design of software program projects.

4.3.1 Use-Case Diagram:

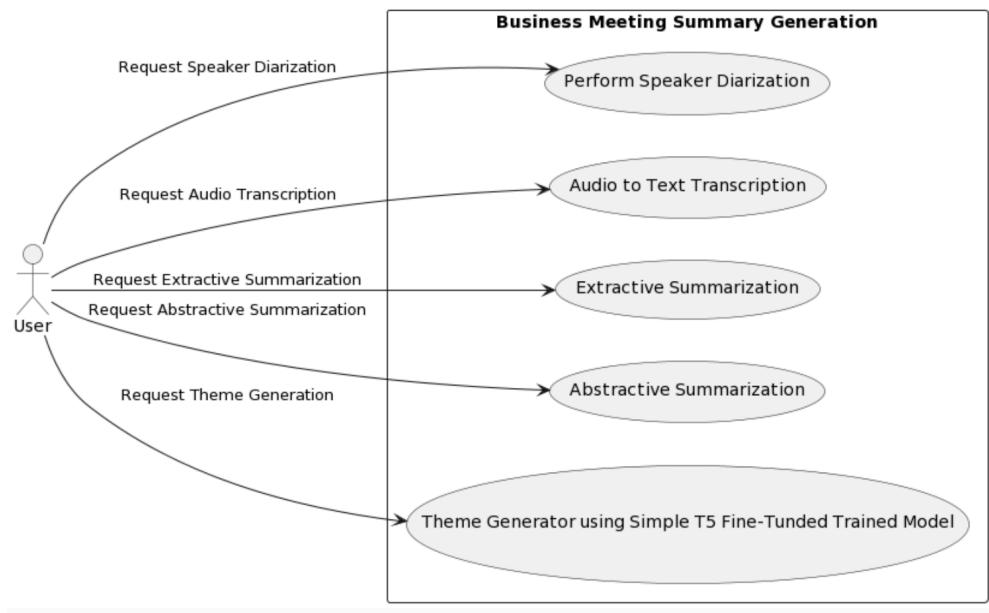


Figure 7: Use case diagram of proposed system

A use case diagram is a behavioral diagram in the Unified Modeling Language (UML) that depicts the interactions between the system and its actors (users or external systems). It helps to visualize the system's functionalities from the user's perspective.

The use case diagram shown in the figure 7 illustrates the various interactions between the actors(User) and the system's functionalities related to Audio transcription and text summarization

The interaction starts with the user actor. The user can submit an audio file to the system, which then stores user information and directs to individual pipelines like speaker diarization and audio transcription pipeline followed by extractive and abstractive summarization pipelines to generate summaries for the audio file provided and displayed onto the dashboard.

4.3.2 Class Diagram:

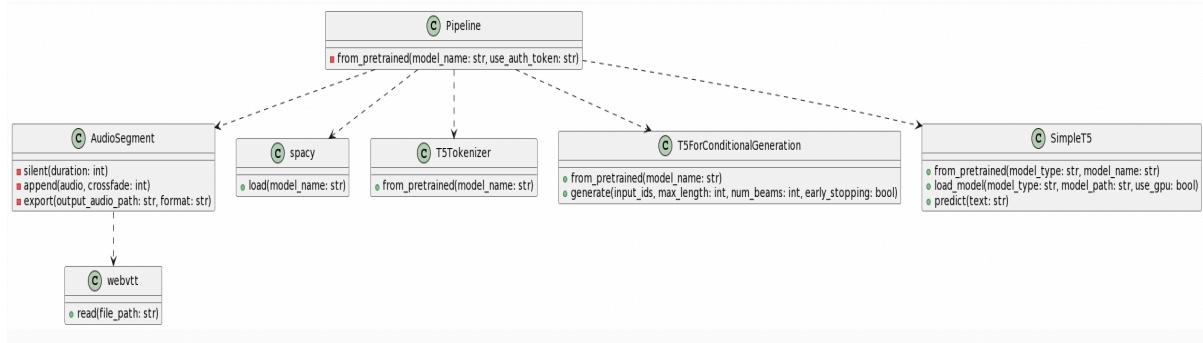


Figure 8: Class diagram of proposed system

In software engineering, a class diagram within the Unified Modeling Language (UML) is a static shape diagram that delineates the architecture of a machine. It achieves this by illustrating the training within the gadget, inclusive of their attributes, operations (or techniques), and the connections between those classes. This diagram elucidates the distribution of statistics among lessons and clarifies which elegance is responsible for housing unique records.

The figure 8 represents a depicted class diagram that outlines a comprehensive system for text and audio processing. At its core, the **Pipeline** class serves as the orchestrator, coordinating tasks between various components. **PreprocessText** handles text preprocessing duties, including stop word removal and punctuation cleansing. **AudioSegment** manages audio manipulation tasks, while **SpaCy** facilitates natural language processing operations. **T5ForConditionalGeneration** interacts with the **T5** model for text generation tasks, while **SimpleT5** provides an interface to leverage the same model efficiently. Together, these classes form a robust framework capable of transcribing audio, preprocessing text, and generating summaries or other textual outputs using advanced language models.

4.3.3 Sequence Diagram:

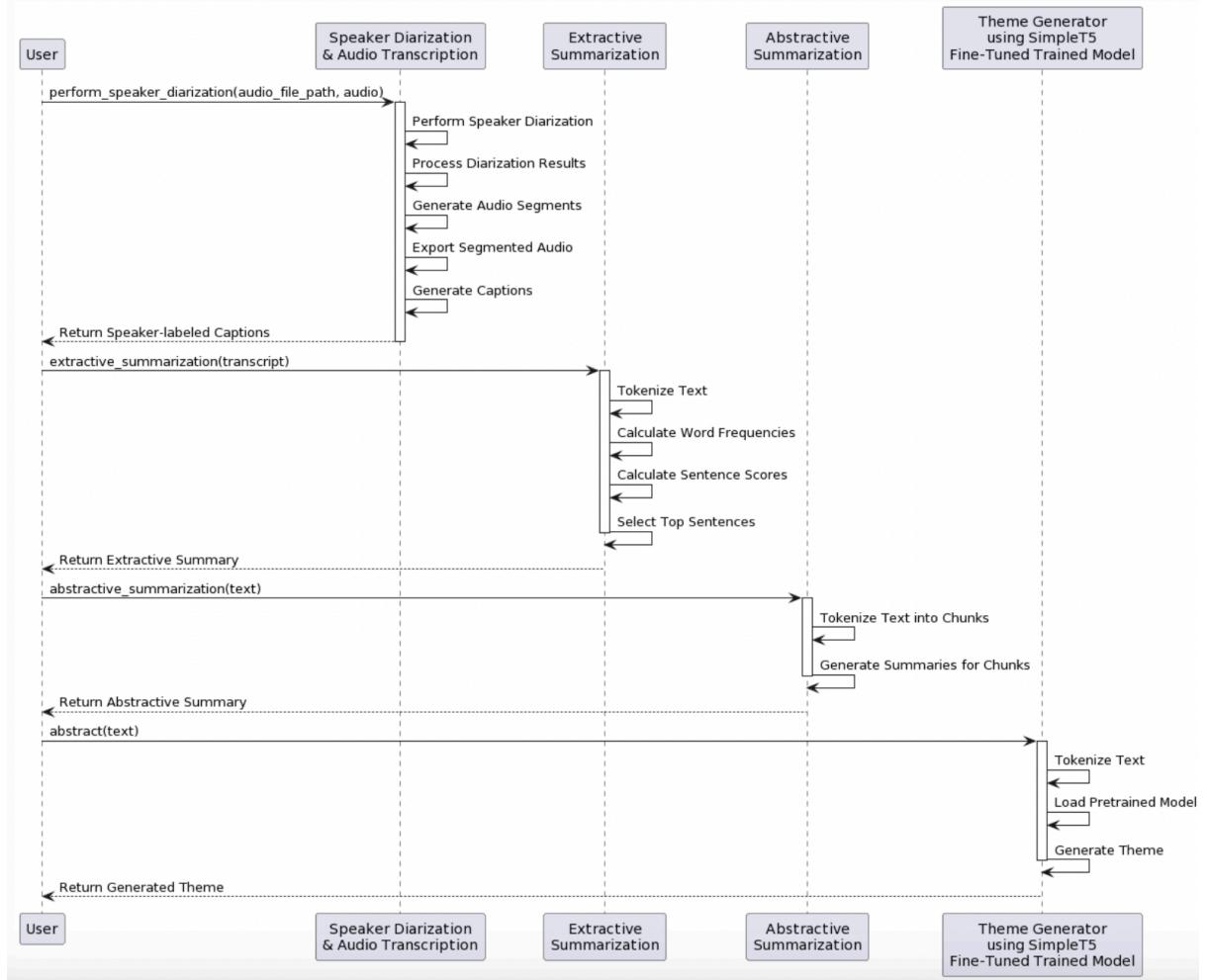


Figure 9: Sequence diagram of proposed system

The figure 9 represents a sequence diagram illustrates the intricate flow of interactions within the meeting summary generation system. Initiated by the User, the system seamlessly executes Speaker Diarization and Audio Transcription, generating Speaker-labeled Captions. Subsequently, the system calls upon distinct methods for various summarization techniques: extractive summarization, abstractive summarization, and theme generation. Through these processes, the system meticulously crafts Extractive and Abstractive Summaries alongside a thematic representation. Ultimately, these generated outputs are relayed back to the User, encapsulating a comprehensive process from audio input to synthesized meeting insights.

4.3.4 Activity Diagram:

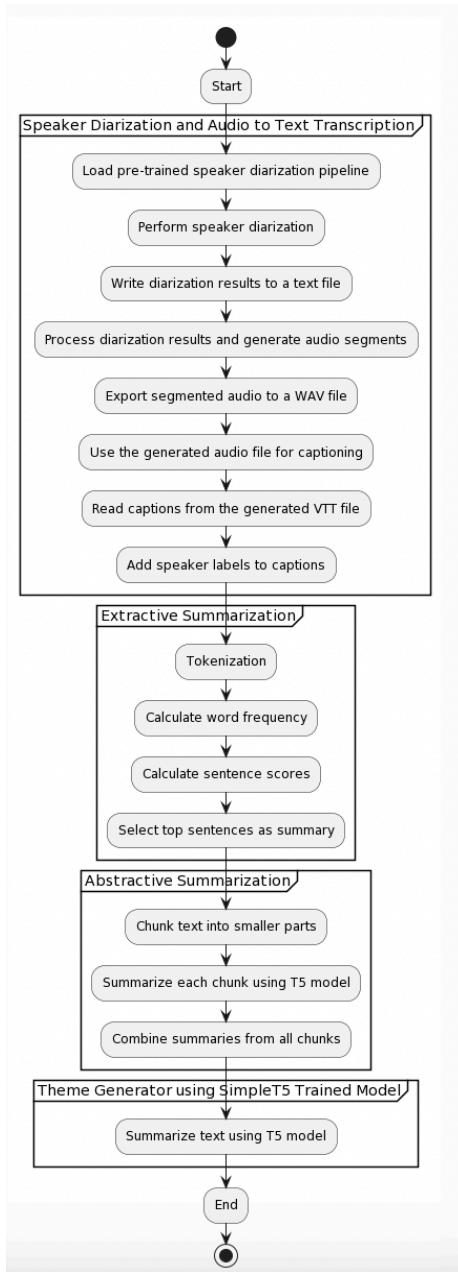


Figure 10: Activity diagram of proposed system

Activity diagram is a graphical representation used to illustrate the flow of activities or actions within a system, process, or workflow. It depicts the sequence of tasks, decisions, and actions involved in completing a specific process. They provide a clear visualization of the workflow, making it easier to understand, analyze, and communicate complex processes within a system.

The figure 9 represents an depicted activity diagram that offers a detailed portrayal of the meeting summary generation system's workflow. Initiated by the user, the system seamlessly executes Speaker Diarization and Audio Transcription, leading to the creation of Speaker-labeled Captions. These captions then diverge into two distinct paths: the Extractive Summarization Path, where the transcript undergoes direct summarization, and the Abstractive Summarization Path, which involves chunking, summarizing, and subsequent combination for abstractive synthesis. Concurrently, Theme Generation occurs utilizing a SimpleT5 model. Finally, the system merges outputs from both paths, furnishing the user with Extractive and Abstractive Summaries, alongside thematic insights, thus presenting a comprehensive summary of the meeting's proceedings.

CHAPTER 5

IMPLEMENTATION

5.1 BRIEF EXPLANATION OF IMPLEMENTATION

The proposed system implementation encompasses multiple modules aimed at achieving two primary objectives: audio transcription and summary generation. For audio transcription, the system employs the pyannote speaker-diarization pipeline, enabling the segmentation of audio into distinct speaker turns for identification purposes. Additionally, the system utilizes the Whisper library to convert audio files into text format, ensuring that only the essential information is retained for further processing.

In the context of summary generation, the system begins with a top-ranking summarization module, which involves several stages. These stages include cleaning and preparing the text by removing punctuation and stopwords using spacy libraries. Furthermore, the system calculates word frequency to identify important terms and scores sentences based on the normalized frequency of their constituent words. Finally, it selects the top-scoring sentences to form a concise summary, catering to scenarios where extractive summarization is preferred.

Moreover, the system incorporates an abstractive summarization module, leveraging Hugging Face Transformers and the T5 model. This module divides the input text into manageable chunks for processing, allowing for efficient abstractive summarization. Additionally, the system employs SimpleT5 for training and inference, utilizing a dataset containing headlines and corresponding text. Through training and inference, the model predicts summaries for given text inputs, providing a comprehensive approach to generating summaries.

Overall, the implementation combines speaker diarization, audio recognition, and summarization techniques to accurately transcribe audio files and generate summaries

effectively. This approach caters to a wide range of use cases, including meeting transcription and content summarization, with the aim of enhancing efficiency and productivity in various domains.

5.2 SOURCE CODE

index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8" />
    <meta name="viewport" content="width=device-width,
initial-scale=1.0" />
    <title>Business Meeting Summary Generation</title>
    <link rel="stylesheet"
href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/6.3.0/css/
all.min.css">
    <link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Kumbh+Sans&display=sw
ap" rel="stylesheet">
<link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Kumbh+Sans:wght@700&d
isplay=swap" rel="stylesheet">
</head>
<body>
    <!-- Navbar Section -->
    <nav class="navbar">
        <div class="navbar__container">
            <a href="#home" id="navbar__logo"><i class="fa-solid
fa-square-poll-horizontal"></i> BMSG</a>
            <div class="navbar__toggle" id="mobile-menu">
                <span class="bar"></span>
                <span class="bar"></span>
                <span class="bar"></span>
            </div>
            <ul class="navbar__menu">
                <li class="navbar__item">
                    <a href="#home" class="navbar__links"
id="home=page">Home</a>
```

```

        </li>
        <li class="navbar__item">
            <a href="#services" class="navbar__links"
id="services-page">Services</a>
        </li>
        <li class="navbar__item">
            <a href="#about" class="navbar__links"
id="about-page">About</a>
        </li>
        <li class="navbar__btn"><a href="#sign-up" class="button"
id="signup">Sign Up</a></li>
    </ul>
</div>
</nav>

<!-- Main Section -->
<div class="main" id="home">
    <div class="main__container">
        <div class="main__content">
            <h1>BUSINESS MEETING</h1>
            <h2>SUMMARY GENERATION</h2>
            <p>Unlock the hidden potential of your meetings.</p>
            <button class="main__btn"><a href="#signup">Get
Started</a></button>
        </div>
        <div class="main__img--container">
            
        </div>
    </div>
</div>

<!-- Services Section -->
<div class="services" id="services">
    <h1>Our Services</h1>
    <div class="services__container">
        <div class="services__card">
            <h2>Audio to text</h2>
            <p>Get Clear and Accurate Transcripts.</p>
            <button class="card__btn"><a href="aud2text">Get
Started</a></button>
        </div>
        <div class="services__card">
            <h2>Summarize the audio file</h2>
            <p>From rambling riffs to insightful briefs.</p>
            <button class="card__btn"><a href="aud2sum">Get
Started</a></button>
        </div>
        <div class="services__card">

```

```

<h2>Meeting Agenda</h2>
<p>A straightforward indication of the covered topic.</p>
<button class="card__btn"><a href="#">Get Started</a></button>
</div>
</div>
</div>

<!-- About Section -->
<div class="main" id="about">
    <div class="main__container">
        <div class="main__img--container">
            <div class="main__img--card"><i class="fas fa-layer-group"></i></div>
        </div>
        <div class="main__content">
            <h1>What do we do?</h1>
            <!-- <h2>Turn your meetings into actionable outcomes with AI-powered summaries.</h2> -->
            <ul>
                <li>Automating summary creation</li>
                <li>Get clear, concise summaries.</li>
                <li>Saving you time and effort</li>
                <li>Improving meeting efficiency</li>
            </ul>
            <!-- <button class="main__btn"><a href="#">Schedule Call</a></button> -->
        </div>
    </div>
</div>

<!-- Footer Section -->
<div class="footer__container">
    <div class="footer__links">
    </div>
    <section class="social__media">
        <div class="social__media--wrap">
            <div class="footer__logo">
                <a href="#" id="footer__logo"><i class="fa-solid fa-square-poll-horizontal"></i>BMSG</a>
            </div>
            <p class="website__rights">© BMSG 2024. All rights reserved</p>
            <div class="social__icons">
                <a
                    class="social__icon--link"
                    href="/"
                    target="_blank"
                >

```

```

        aria-label="Facebook"
    >
        <i class="fab fa-facebook"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="Instagram"
    >
        <i class="fab fa-instagram"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="Twitter"
    >
        <i class="fab fa-twitter"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="LinkedIn"
    >
        <i class="fab fa-linkedin"></i>
    </a>
</div>
</div>
<script src="app.js"></script>
</body>
</html>
```

styles.css

```

* {
    box-sizing: border-box;
    margin: 0;
    padding: 0;
    font-family: 'Kumbh Sans', sans-serif;
}
.navbar {
    background: #131313;
    height: 80px;
    display: flex;
```

```
justify-content: center;
align-items: center;
font-size: 1.2rem;
position: sticky;
top: 0;
z-index: 999;
}
.navbar__container {
display: flex;
justify-content: space-between;
height: 80px;
z-index: 1;
width: 100%;
max-width: 1300px;
margin-right: auto;
margin-left: auto;
padding-right: 50px;
padding-left: 50px;
}
#navbar__logo {
background-color: #ff8177;
background-image: linear-gradient(to top, #ff0844 0%, #ffb199 100%);
background-size: 100%;
-webkit-background-clip: text;
-moz-background-clip: text;
-webkit-text-fill-color: transparent;
-moz-text-fill-color: transparent;
display: flex;
align-items: center;
cursor: pointer;
text-decoration: none;
font-size: 2rem;
}
.fa-gem {
margin-right: 0.5rem;
}
.navbar__menu {
display: flex;
align-items: center;
list-style: none;
text-align: center;
}
.navbar__item {
height: 80px;
}
.navbar__links {
color: #fff;
display: flex;
```

```
    align-items: center;
    justify-content: center;
    text-decoration: none;
    padding: 0 1rem;
    height: 100%;
}
.navbar__btn {
    display: flex;
    justify-content: center;
    align-items: center;
    padding: 0 1rem;
    width: 100%;
}
.button {
    display: flex;
    justify-content: center;
    align-items: center;
    text-decoration: none;
    padding: 10px 20px;
    height: 100%;
    width: 100%;
    border: none;
    outline: none;
    border-radius: 4px;
    background: #f77062;
    color: #fff;
}
.button:hover {
    background: #4837ff;
    transition: all 0.3s ease;
}
.navbar__links:hover {
    color: #f77062;
    transition: all 0.3s ease;
}
@media screen and (max-width: 960px) {
    .navbar__container {
        display: flex;
        justify-content: space-between;
        height: 80px;
        z-index: 1;
        width: 100%;
        max-width: 1300px;
        padding: 0;
    }
    .navbar__menu {
        display: grid;
        grid-template-columns: auto;
        margin: 0;
    }
}
```

```
width: 100%;  
position: absolute;  
top: -1000px;  
opacity: 1;  
transition: all 0.5s ease;  
/* height: 50vh; */  
z-index: -1;  
}  
.navbar__menu.active {  
background: #131313;  
top: 100%;  
opacity: 1;  
transition: all 0.5s ease;  
z-index: 99;  
height: 50vh;  
font-size: 1.6rem;  
}  
#navbar__logo {  
padding-left: 25px;  
}  
.navbar__toggle .bar {  
width: 25px;  
height: 3px;  
margin: 5px auto;  
transition: all 0.3s ease-in-out;  
background: #fff;  
}  
.navbar__item {  
width: 100%;  
}  
.navbar__links {  
text-align: center;  
padding: 2rem;  
width: 100%;  
display: table;  
}  
.navbar__btn {  
padding-bottom: 2rem;  
}  
.button {  
display: flex;  
justify-content: center;  
align-items: center;  
width: 80%;  
height: 80px;  
margin: 0;  
}  
#mobile-menu {  
position: absolute;
```

```
    top: 20%;
    right: 5%;
    transform: translate(5%, 20%);
}
.navbar__toggle .bar {
    display: block;
    cursor: pointer;
}
#mobile-menu.is-active .bar:nth-child(2) {
    opacity: 0;
}
#mobile-menu.is-active .bar:nth-child(1) {
    transform: translateY(8px) rotate(45deg);
}
#mobile-menu.is-active .bar:nth-child(3) {
    transform: translateY(-8px) rotate(-45deg);
}
/*
Main Content CSS */
.main {
    background-color: #141414;
}
.main__container {
    display: grid;
    grid-template-columns: 1fr 1fr;
    align-items: center;
    justify-self: center;
    margin: 0 auto;
    height: 90vh;
    background-color: #131313;
    z-index: 1;
    width: 100%;
    max-width: 1300px;
    padding-right: 50px;
    padding-left: 50px;
}
.main__content h1 {
    font-size: 4rem;
    background-color: #ff8177;
    background-image: linear-gradient(to top, #ff0844 0%, #ffb199 100%);
    background-size: 100%;
    -webkit-background-clip: text;
    -moz-background-clip: text;
    -webkit-text-fill-color: transparent;
    -moz-text-fill-color: transparent;
}
.main__content h2 {
    font-size: 4rem;
```

```
margin-top: 10px;
background-color: #ff8177;
background-image: linear-gradient(-20deg, #b721ff 0%, #21d4fd
100%);
background-size: 100%;
-webkit-background-clip: text;
-moz-background-clip: text;
-webkit-text-fill-color: transparent;
-moz-text-fill-color: transparent;
}
.main_content p {
margin-top: 1rem;
font-size: 2rem;
font-weight: 700;
color: #fff;
}
.main_content ul {
margin-top: 1rem;
font-size: 2rem;
font-weight: 700;
color: #fff;
list-style-type: none;
margin: 0;
padding: 20px 0;
}
.main_btn {
font-size: 1rem;
background-image: linear-gradient(to top, #f77062 0%, #fe5196
100%);
padding: 14px 32px;
border: none;
border-radius: 4px;
color: #fff;
margin-top: 2rem;
cursor: pointer;
position: relative;
transition: all 0.35s;
outline: none;
}
.main_btn a {
position: relative;
z-index: 2;
color: #fff;
text-decoration: none;
}
.main_btn:after {
position: absolute;
content: '';
top: 0;
```

```
    left: 0;
    width: 0;
    height: 100%;
    background: #4837ff;
    transition: all 0.35s;
    border-radius: 4px;
}
.main_btn:hover {
    color: #fff;
}
.main_btn:hover:after {
    width: 100%;
}
.main_img--container {
    text-align: center;
}
#main_img {
    height: 80%;
    width: 80%;
}
/* Mobile Responsive */
@media screen and (max-width: 768px) {
    .main_container {
        display: grid;
        grid-template-columns: auto;
        align-items: center;
        justify-self: center;
        width: 100%;
        margin: 0 auto;
        height: 90vh;
    }
    .main_content {
        text-align: center;
        margin-bottom: 4rem;
    }
    .main_content h1 {
        font-size: 2.5rem;
        margin-top: 2rem;
    }
    .main_content h2 {
        font-size: 3rem;
    }
    .main_content p {
        margin-top: 1rem;
        font-size: 1.5rem;
    }
}
@media screen and (max-width: 480px) {
    .main_content h1 {
```

```
    font-size: 2rem;
    margin-top: 3rem;
}
.main__content h2 {
    font-size: 2rem;
}
.main__content p {
    margin-top: 2rem;
    font-size: 1.5rem;
}
.main__btn {
    padding: 12px 36px;
    margin: 2.5rem 0;
}
}
a{
    text-decoration: none;
    color: #fff;
}
/* Services Section */
.services {
    background: #141414;
    display: flex;
    flex-direction: column;
    align-items: center;
    /* height: 100vh; */
}
.services h1 {
    background-color: #ff8177;
    background-image: linear-gradient(
        to right,
        #ff8177 0%,
        #ff867a 0%,
        #ff8c7f 21%,
        #f99185 52%,
        #cf556c 78%,
        #b12a5b 100%
    );
    background-size: 100%;
    -webkit-background-clip: text;
    -moz-background-clip: text;
    -webkit-text-fill-color: transparent;
    -moz-text-fill-color: transparent;
    margin-bottom: 5rem;
    font-size: 2.5rem;
}
.services__container {
    display: flex;
    justify-content: center;
```

```
    flex-wrap: wrap;
}
.services_card {
  margin: 1rem;
  height: 500px;
  width: 420px;
  border-radius: 4px;
  background-image: linear-gradient(
    to bottom,
    rgba(0, 0, 0, 0) 0%,
    rgba(17, 17, 17, 0.6) 100%
  ),
  url('static/images/pic2.jpg');
  background-size: cover;
  position: relative;
  color: #fff;
}
/* .services_card:before {
  opacity: 0.2;
} */
.services_card:nth-child(2) {
  background-image: linear-gradient(
    to bottom,
    rgba(0, 0, 0, 0) 0%,
    rgba(17, 17, 17, 0.7) 100%
  ),
  url('static/images/pic3.jpg');
}
.services_card:nth-child(3) {
  background-image: linear-gradient(
    to bottom,
    rgba(0, 0, 0, 0) 0%,
    rgba(17, 17, 17, 0.8) 100%
  ),
  url('static/images/pic4.jpg');
}
.services_card h2 {
  position: absolute;
  top: 350px;
  left: 30px;
}
.services_card p {
  position: absolute;
  top: 400px;
  left: 30px;
}
.services_card button {
  color: #fff;
  padding: 10px 20px;
```

```
border: none;
outline: none;
border-radius: 4px;
background: #f77062;
position: absolute;
top: 440px;
left: 30px;
font-size: 1rem;
}
.services__card button:hover {
  cursor: pointer;
}
.services__card:hover {
  transform: scale(1.075);
  transition: 0.2s ease-in;
  cursor: pointer;
}
@media screen and (max-width: 960px) {
  /* .services {
    height: 1600px;
  } */
  .services h1 {
    font-size: 2rem;
    margin-top: 12rem;
  }
}
@media screen and (max-width: 480px) {
  .services {
    height: 1400px;
  }
  .services h1 {
    font-size: 1.2rem;
  }
  .services__card {
    width: 300px;
  }
}
/* Footer CSS */
.footer__container {
  background-color: #141414;
  padding: 5rem 0;
  display: flex;
  flex-direction: column;
  justify-content: center;
  align-items: center;
}
#footer__logo {
  color: #fff;
  display: flex;
```

```
    align-items: center;
    cursor: pointer;
    text-decoration: none;
    font-size: 2rem;
}
/* Social Icons */
.social__icon--link {
    color: #fff;
    font-size: 24px;
}
.social__media {
    max-width: 1000px;
    width: 100%;
}
.social__media--wrap {
    display: flex;
    justify-content: space-between;
    align-items: center;
    width: 90%;
    max-width: 1000px;
    margin: 40px auto 0 auto;
}
.social__icons {
    display: flex;
    justify-content: space-between;
    align-items: center;
    width: 240px;
}
.social__logo {
    color: #fff;
    justify-self: start;
    margin-left: 20px;
    cursor: pointer;
    text-decoration: none;
    font-size: 2rem;
    display: flex;
    align-items: center;
    margin-bottom: 16px;
}
.website__rights {
    color: #fff;
}
@media screen and (max-width: 820px) {
    .footer__links {
        padding-top: 2rem;
    }
    #footer__logo {
        margin-bottom: 2rem;
    }
}
```

```

.website_rights {
  margin-bottom: 2rem;
}
.footer_link-wrapper {
  flex-direction: row;
}
.social_media--wrap {
  flex-direction: column;
}
}

```

service.html

```

<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width,
initial-scale=1.0">
  <title>BMSG - Audio File to Summary</title>
  <link rel="stylesheet"
href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/6.3.0/css/
all.min.css">
    <link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Kumbh+Sans&display=sw
ap" rel="stylesheet">
<link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Kumbh+Sans:wght@700&d
isplay=swap" rel="stylesheet">
</head>
<body>
  <!-- Navbar Section -->
  <nav class="navbar">
    <div class="navbar_container">
      <a href="/" id="navbar_logo"><i class="fa-solid
fa-square-poll-horizontal"></i>BMSG</a>
      <div class="navbar_toggle" id="mobile-menu">
        <span class="bar"></span>
        <span class="bar"></span>
        <span class="bar"></span>
      </div>
      <ul class="navbar_menu">
        <li class="navbar_item">
          <a href="/" class="navbar_links">Home</a>
        </li>
      </ul>
    </div>
  </nav>
</body>

```

```

        <li class="navbar__item">
            <a href="/aud2text" class="navbar__links">Aud2Text</a>
        </li>
        <li class="navbar__item">
            <a href="/headline" class="navbar__links">Theme</a>
        </li>
        <li class="navbar__btn"><a href="/" class="button">Sign
Up</a></li>
    </ul>
</div>
</nav>
<!-- Main Section -->
<div class="main">
    <div class="main__container">
        <div class="main__content">
            <h1>Summarize the audio file</h1>
            <p>From rambling riffs to insightful briefs.</p>
            <h3>Upload Your Audio file</h3>
            <form action="/aud2sum" method="POST"
enctype="multipart/form-data">
                <div class="form-group">
                    <input type="file" name="file" id="input-file"
class="input_file" />
                </div>
                <button type="submit"
class="submit__btn">Summarize</button>
            </form>
        </div>
        <div class="main__img--container">
            
        </div>
        <div class="summary">
            {% if summary %}
            <h2>Summary:</h2>
            <p class="main__summary">{{ summary }}</p>
            {% endif %}
        </div>
    </div>
</div>
<!-- Footer Section -->
<div class="footer__container">
    <div class="footer__links">
    </div>
    <section class="social__media">
        <div class="social__media--wrap">
            <div class="footer__logo">
                <a href="/" id="footer__logo"><i class="fa-solid
fa-square-poll-horizontal"></i>BMSG</a>
            </div>

```

```

<p class="website__rights">© BMSG 2024. All rights reserved</p>
<div class="social__icons">
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="Facebook"
    >
        <i class="fab fa-facebook"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="Instagram"
    >
        <i class="fab fa-instagram"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="Twitter"
    >
        <i class="fab fa-twitter"></i>
    </a>
    <a
        class="social__icon--link"
        href="/"
        target="_blank"
        aria-label="LinkedIn"
    >
        <i class="fab fa-linkedin"></i>
    </a>
</div>
</div>
<script src="app.js"></script>
</body>
</html>

```

service-style.css

```

* {
    box-sizing: border-box;
    margin: 0;
    padding: 0;
}

```

```
    font-family: 'Kumbh Sans', sans-serif;
}
.navbar {
    background: #131313;
    height: 80px;
    display: flex;
    justify-content: center;
    align-items: center;
    font-size: 1.2rem;
    position: sticky;
    top: 0;
    z-index: 999;
}
.navbar__container {
    display: flex;
    justify-content: space-between;
    height: 80px;
    z-index: 1;
    width: 100%;
    max-width: 1300px;
    margin-right: auto;
    margin-left: auto;
    padding-right: 50px;
    padding-left: 50px;
}
#navbar__logo {
    background-color: #ff8177;
    background-image: linear-gradient(to top, #ff0844 0%, #ffb199 100%);
    background-size: 100%;
    -webkit-background-clip: text;
    -moz-background-clip: text;
    -webkit-text-fill-color: transparent;
    -moz-text-fill-color: transparent;
    display: flex;
    align-items: center;
    cursor: pointer;
    text-decoration: none;
    font-size: 2rem;
}
.fa-gem {
    margin-right: 0.5rem;
}
.navbar__menu {
    display: flex;
    align-items: center;
    list-style: none;
    text-align: center;
}
```

```
.navbar__item {
  height: 80px;
}
.navbar__links {
  color: #fff;
  display: flex;
  align-items: center;
  justify-content: center;
  text-decoration: none;
  padding: 0 1rem;
  height: 100%;
}
.navbar__btn {
  display: flex;
  justify-content: center;
  align-items: center;
  padding: 0 1rem;
  width: 100%;
}
.button {
  display: flex;
  justify-content: center;
  align-items: center;
  text-decoration: none;
  padding: 10px 20px;
  height: 100%;
  width: 100%;
  border: none;
  outline: none;
  border-radius: 4px;
  background: #f77062;
  color: #fff;
}
.button:hover {
  background: #4837ff;
  transition: all 0.3s ease;
}
.navbar__links:hover {
  color: #f77062;
  transition: all 0.3s ease;
}
@media screen and (max-width: 960px) {
  .navbar__container {
    display: flex;
    justify-content: space-between;
    height: 80px;
    z-index: 1;
    width: 100%;
    max-width: 1300px;
  }
}
```

```
    padding: 0;
}
.navbar__menu {
  display: grid;
  grid-template-columns: auto;
  margin: 0;
  width: 100%;
  position: absolute;
  top: -1000px;
  opacity: 1;
  transition: all 0.5s ease;
  height: 50vh;
  z-index: -1;
}
.navbar__menu.active {
  background: #131313;
  top: 100%;
  opacity: 1;
  transition: all 0.5s ease;
  z-index: 99;
  height: 50vh;
  font-size: 1.6rem;
}
#navbar__logo {
  padding-left: 25px;
}
.navbar__toggle .bar {
  width: 25px;
  height: 3px;
  margin: 5px auto;
  transition: all 0.3s ease-in-out;
  background: #fff;
}
.navbar__item {
  width: 100%;
}
.navbar__links {
  text-align: center;
  padding: 2rem;
  width: 100%;
  display: table;
}
.navbar__btn {
  padding-bottom: 2rem;
}
.button {
  display: flex;
  justify-content: center;
  align-items: center;
```

```
    width: 80%;  
    height: 80px;  
    margin: 0;  
}  
#mobile-menu {  
    position: absolute;  
    top: 20%;  
    right: 5%;  
    transform: translate(5%, 20%);  
}  
.navbar__toggle .bar {  
    display: block;  
    cursor: pointer;  
}  
#mobile-menu.is-active .bar:nth-child(2) {  
    opacity: 0;  
}  
#mobile-menu.is-active .bar:nth-child(1) {  
    transform: translateY(8px) rotate(45deg);  
}  
#mobile-menu.is-active .bar:nth-child(3) {  
    transform: translateY(-8px) rotate(-45deg);  
}  
}  
/* Main Content CSS */  
.main {  
background-color: #141414;  
}  
.main__container {  
display: grid;  
grid-template-columns: 1fr 1fr;  
align-items: center;  
justify-self: center;  
margin: 0 auto;  
height: 90vh;  
background-color: #131313;  
z-index: 1;  
width: 100%;  
max-width: 1300px;  
padding-right: 50px;  
padding-left: 50px;  
}  
.main__content h1 {  
font-size: 4rem;  
background-color: #ff8177;  
background-image: linear-gradient(to top, #ff0844 0%, #ffb199  
100%);  
background-size: 100%;  
-webkit-background-clip: text;
```

```
-moz-background-clip: text;
-webkit-text-fill-color: transparent;
-moz-text-fill-color: transparent;
}
.main__content p {
margin-top: 1rem;
font-size: 1.5rem;
font-weight: 700;
color: #fff;
}
.main__content h3 {
font-size: 2.3rem;
margin-top: 10px;
background-color: #ff8177;
background-image: linear-gradient(-20deg, #b721ff 0%, #21d4fd
100%);
background-size: 100%;
-webkit-background-clip: text;
-moz-background-clip: text;
-webkit-text-fill-color: transparent;
-moz-text-fill-color: transparent;
}
.form-group {
margin-top: 1rem;
font-size: 1.5rem;
font-weight: 700;
color: #fff;
}
.submit__btn {
font-size: 1rem;
background-image: linear-gradient(to top, #f77062 0%, #fe5196
100%);
padding: 14px 32px;
border: none;
border-radius: 4px;
color: #fff;
margin-top: 2rem;
cursor: pointer;
position: relative;
transition: all 0.35s;
outline: none;
}
.submit__btn {
position: relative;
z-index: 2;
color: #fff;
text-decoration: none;
}
.submit__btn:after {
```

```
position: absolute;
content: '';
top: 0;
left: 0;
width: 0;
height: 100%;
background: #4837ff;
transition: all 0.35s;
border-radius: 4px;
}
.submit__btn:hover {
color: #fff;
}
.submit__btn:hover:after {
width: 100%;
}
#input-file {
position: relative;
z-index: 2;
color: #fff;
text-decoration: none;
font-size: 1rem;
background:rgb(63, 63, 63);
padding: 14px 32px;
border: none;
border-radius: 4px;
margin-top: 2rem;
cursor: pointer;
transition: all 0.35s;
outline: none;
}
input[type=file]::file-selector-button {
font-size: 1rem;
background-image: linear-gradient(to top, #f77062 0%, #fe5196
100%);
padding: 10px 25px;
border: none;
border-radius: 4px;
color: #fff;
cursor: pointer;
position: relative;
transition: all 0.35s;
outline: none;
}
.main__img--container {
display: flex;
}
#main__img {
height: 80%;
```

```
width: 80%;  
}  
/* Mobile Responsive */  
@media screen and (max-width: 768px) {  
.main__container {  
    display: grid;  
    grid-template-columns: auto;  
    align-items: center;  
    justify-self: center;  
    width: 100%;  
    margin: 0 auto;  
    height: 90vh;  
}  
.main__content {  
    text-align: center;  
    margin-bottom: 4rem;  
}  
.main__content h1 {  
    font-size: 2.5rem;  
    margin-top: 2rem;  
}  
.main__content h2 {  
    font-size: 3rem;  
}  
.main__content p {  
    margin-top: 1rem;  
    font-size: 1.5rem;  
}  
}  
}@media screen and (max-width: 480px) {  
.main__content h1 {  
    font-size: 2rem;  
    margin-top: 3rem;  
}  
.main__content h2 {  
    font-size: 2rem;  
}  
.main__content p {  
    margin-top: 2rem;  
    font-size: 1.5rem;  
}  
.main__btn {  
    padding: 12px 36px;  
    margin: 2.5rem 0;  
}  
}  
a{  
text-decoration: none;  
color: #fff;
```

```
}

.summary h2{
font-size: 2rem;
background-color: #ff8177;
background-image: linear-gradient(to top, #ff0844 0%, #ffb199
100%);
background-size: 100%;
-webkit-background-clip: text;
-moz-background-clip: text;
-webkit-text-fill-color: transparent;
-moz-text-fill-color: transparent;
padding: 14px 0;
}

.main__summary {
padding: 0.5rem;
width: 81vw;
height: 330px;
background-color: #4c4b4b;
color: #fff;
border-radius: 12px;
overflow: scroll;
}

/* Footer CSS */
.footer__container {
background-color: #141414;
padding: 5rem 0;
display: flex;
flex-direction: column;
justify-content: center;
align-items: center;
}
#footer__logo {
color: #fff;
display: flex;
align-items: center;
cursor: pointer;
text-decoration: none;
font-size: 2rem;
}
/* Social Icons */
.social__icon--link {
color: #fff;
font-size: 24px;
}
.social__media {
max-width: 1000px;
width: 100%;
}
.social__media--wrap {
```

```
        display: flex;
        justify-content: space-between;
        align-items: center;
        width: 90%;
        max-width: 1000px;
        margin: 40px auto 0 auto;
    }
    .social__icons {
        display: flex;
        justify-content: space-between;
        align-items: center;
        width: 240px;
    }
    .social__logo {
        color: #fff;
        justify-self: start;
        margin-left: 20px;
        cursor: pointer;
        text-decoration: none;
        font-size: 2rem;
        display: flex;
        align-items: center;
        margin-bottom: 16px;
    }
    .website__rights {
        color: #fff;
    }
    @media screen and (max-width: 820px) {
        .footer__links {
            padding-top: 2rem;
        }
        #footer__logo {
            margin-bottom: 2rem;
        }
        .website__rights {
            margin-bottom: 2rem;
        }
        .footer__link--wrapper {
            flex-direction: row;
        }
        .social__media--wrap {
            flex-direction: column;
        }
    }
}
```

loading.css

```
.transcript h2{
    font-size: 2rem;
    background-color: #ff8177;
    background-image: linear-gradient(to top, #ff0844 0%, #ffb199
100%);
    background-size: 100%;
    -webkit-background-clip: text;
    -moz-background-clip: text;
    -webkit-text-fill-color: transparent;
    -moz-text-fill-color: transparent;
    padding: 14px 0;
}
.main_transcript {
    padding: 0.5rem;
    width: 82vw;
    height: 330px;
    background-color: #4c4b4b;
    color: #fff;
    border-radius: 12px;
    overflow: scroll;
}
```

main.py[Flask application]

```
from flask import Flask, render_template, request
from werkzeug.utils import secure_filename
import os
import total
from pydub import AudioSegment
from total import process_audio
from total import extractive_summarization
from total import abstractive_summarization
from total import abstract
from total import perform_speaker_diarization

app = Flask(__name__, template_folder="templates")

app.config['UPLOAD_FOLDER'] =
'/Users/dheerajreddy/Desktop/sample-copy/audio_folder'
ALLOWED_EXTENSIONS = {'mp3', 'wav'}

# Function to check if a file has an allowed extension
def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in ALLOWED_EXTENSIONS
```

```

# Define a route for the main page

@app.route('/')
def index():
    return render_template('index.html')

# Define a route to handle file upload
@app.route('/aud2text', methods=['POST', 'GET'])
def aud2text():
    if request.method == 'POST':
        file = request.files['file']
        if file.filename == '':
            return 'No selected file'

        if file and allowed_file(file.filename):
            # Save the uploaded file
            file_path =
os.path.join(app.config['UPLOAD_FOLDER'],
secure_filename(file.filename))
            file.save(file_path)

            # Load the audio data
            audio = AudioSegment.from_file(file_path)

            # Perform speaker diarization
            result =
total.perform_speaker_diarization(file_path, audio)

            # Remove the uploaded file
            os.remove(file_path)
            return render_template('aud2text.html',
result=result)
        else:
            return 'Invalid file format'

    return render_template('aud2text.html')

@app.route('/aud2sum', methods=['POST', 'GET'])

def aud2sum():
    if request.method == 'POST':
        file = request.files['file']

```

```

        # If user does not select file, browser also submits an
        empty part without filename
        if file.filename == '':
            return 'No selected file'

        if file and allowed_file(file.filename):
            file_path =
os.path.join(app.config['UPLOAD_FOLDER'],
secure_filename(file.filename))
            file.save(file_path)
            # Process the uploaded audio file to text
            audio_text = total.process_audio(file_path)
            # Generate abstractive summarization of the text
            summary =
total.extractive_summarization(audio_text)
            os.remove(file_path)
            return render_template('aud2sum.html',
summary=summary)
        else:
            return 'Invalid file format'

    return render_template('aud2sum.html')

@app.route('/headline', methods=['POST','GET'])

def headline():
    # Check if the POST request has the file part
    if request.method == 'POST':
        file = request.files['file']

        # If user does not select file, browser also submits an
        empty part without filename
        if file.filename == '':
            return 'No selected file'

        if file and allowed_file(file.filename):
            file_path =
os.path.join(app.config['UPLOAD_FOLDER'],
secure_filename(file.filename))
            file.save(file_path)
            # Process the uploaded audio file to text
            audio_text = total.process_audio(file_path)
            # Generate abstractive summarization of the text
            theme = total.abstract(audio_text)

```

```

        summary =
total.abstractive_summarization(audio_text,
max_chunk_length=1500, max_summary_length=300)
        os.remove(file_path)
        return render_template('headline.html',
theme=theme, summary=summary)
    else:
        return 'Invalid file format'

return render_template('headline.html')

if __name__ == '__main__':
    app.run(debug=True)

```

Speaker-Diarization.py & Audio-to-Text-Transcription.py

```

import whisper
import torch
from pyannote.audio import Pipeline
from pydub import AudioSegment
import subprocess

def perform_speaker_diarization(audio_file_path, audio,
output_audio_path='dz.wav', output_vtt_path='dz.vtt'):
    # Load the pre-trained speaker diarization pipeline
    pipeline =
Pipeline.from_pretrained("pyannote/speaker-diarization-3.1",
use_auth_token="authentication_token")

    # Perform speaker diarization
    dz = pipeline({'uri': 'blabal', 'audio': audio_file_path})

    # Write diarization results to a text file
    with open("diarization.txt", "w") as text_file:
        text_file.write(str(dz))

    # Function to convert time string to milliseconds
    def millisec(timeStr):
        spl = timeStr.split(":")
        s = (int)((int(spl[0]) * 60 * 60 + int(spl[1]) * 60 +
float(spl[2])) * 1000)
        return s

    # Process diarization results and generate audio segments

```

```

    spacer = AudioSegment.silent(duration=100) # adjust the
duration as needed
    sounds = spacer
    segments = []

dz = open('diarization.txt').read().splitlines()
for l in dz:
    start, end =
tuple(re.findall(r'[0-9]+:[0-9]+:[0-9]+\.[0-9]+', string=l))
    start = int(millisecond(start)) # milliseconds
    end = int(millisecond(end)) # milliseconds

    segments.append(len(sounds))
    sounds = sounds.append(audio[start:end], crossfade=0)
    sounds = sounds.append(spacer, crossfade=0)

# Export segmented audio to a WAV file
sounds.export(output_audio_path, format="wav")

# Use the generated audio file for captioning
subprocess.run(['whisper', output_audio_path, '--language',
'en', '--model', 'base'])

# Read captions from the generated VTT file
captions = [[(int)(millisecond(caption.start)),
(int)(millisecond(caption.end)), caption.text] for caption in
webvtt.read('dz.vtt')]

# Add speaker labels to captions
speaker_labels = []
spacermilli = 100 # Define spacermilli value (adjust as needed)
for i in range(len(segments)):
    idx = 0
    for idx in range(len(captions)):
        if captions[idx][0] >= (segments[i] - spacermilli):
            break;

        while (idx < (len(captions))) and ((i == len(segments) - 1)
or (captions[idx][1] < segments[i+1])):
            c = captions[idx]

            start = segments[i] + (c[0] - segments[i])

            if start < 0:
                start = 0
            idx += 1

            start = start / 1000.0

```

```

        startStr =
'{0:02d}:{1:02d}:{2:02.2f}'.format((int)(start // 3600),
                                         (int)(start %
3600 // 60),
                                         start % 60)
        speaker_label = "[Speaker1]" if i % 2 == 0 else
"[Speaker2]"
        speaker_labels.append(f"{startStr} {speaker_label}
{c[2]})")

# Return the captions with speaker labels
return speaker_labels

```

Extractive-Summarization.py

```

import spacy
import ssl
from spacy.lang.en.stop_words import STOP_WORDS
from string import punctuation
from heapq import nlargest

def extractive_summarization(transcript):
    stopwords = list(STOP_WORDS)
    nlp = spacy.load('en_core_web_sm')
    doc = nlp(transcript)

    tokens = [token.text for token in doc]

    word_freq = {}
    for word in doc:
        if word.text.lower() not in stopwords and word.text.lower()
not in punctuation:
            if word.text not in word_freq.keys():
                word_freq[word.text] = 1
            else:
                word_freq[word.text] += 1

    max_freq = max(word_freq.values())

    for word in word_freq.keys():
        word_freq[word] = word_freq[word]/max_freq

    sent_tokens = [sent for sent in doc.sents]

    sent_scores = {}
    for sent in sent_tokens:
        for word in sent:

```

```

        if word.text in word_freq.keys():
            if sent not in sent_scores.keys():
                sent_scores[sent] = word_freq[word.text]
            else:
                sent_scores[sent] += word_freq[word.text]

    select_len = int(len(sent_tokens) * 0.3)
    summary = nlargest(select_len, sent_scores, key=sent_scores.get)
    final_summary = [word.text for word in summary]
    summary = ' '.join(final_summary)

    return summary

```

Abstractive-Summarization.py

```

import torch
from simpleT5 import SimpleT5
from transformers import T5ForConditionalGeneration, T5Tokenizer

def abstractive_summarization(text, max_chunk_length=1500,
max_summary_length=300):
    model_name = "t5-small"
    tokenizer = T5Tokenizer.from_pretrained(model_name)
    model = T5ForConditionalGeneration.from_pretrained(model_name)

    chunks = [text[i:i+max_chunk_length] for i in range(0,
len(text), max_chunk_length)]
    summaries = []
    for chunk in chunks:
        input_ids = tokenizer.encode("summarize: " + chunk,
return_tensors="pt", max_length=512, truncation=True)
        output = model.generate(input_ids,
max_length=max_summary_length, num_beams=4, early_stopping=True)
        summary = tokenizer.decode(output[0],
skip_special_tokens=True)
        summaries.append(summary)

    final_summary = " ".join(summaries)

    return final_summary

def abstract(text):
    text = "summarize: " + text
    model = SimpleT5()
    model.from_pretrained(model_type="t5", model_name="t5-base")

model.load_model("t5","outputs/simpleT5-epoch-2-train-loss-0.9274-val-loss-1.4256", use_gpu=False)

```

```

    res = model.predict(text)
    result = res[0]

    return result

```

Fine-Tuning.py & Model-Training.py

```

!pip install numpy
!pip install pandas
!pip install scikit-learn

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g.
pd.read_csv)
from sklearn.model_selection import train_test_split

# Taking news-summary.csv dataset as input and Fine-Tuning Training
the Model

import os
for dirname, _, filenames in os.walk('ABS_T5/news'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

df =
pd.read_csv("/Users/dheerajreddy/pytorch-test/ABS_T5/news/news_summary.csv", encoding='latin-1', usecols=['headlines', 'text'])

# simpleT5 expects dataframe to have 2 columns: "source_text" and
"target_text"
df = df.rename(columns={"headlines":"target_text",
"text":"source_text"})
f = df[['source_text', 'target_text']]

train_df, test_df = train_test_split(df, test_size=0.3)
train_df.shape, test_df.shape

from simpleT5 import SimpleT5

model = SimpleT5()
model.from_pretrained(model_type="t5", model_name="t5-base")

```

CHAPTER 6

RESULTS

Our proposed system is connected to a front-end application where the user can upload an audio file (mp3 or wav) and get their desired outputs following the simple project workflow.

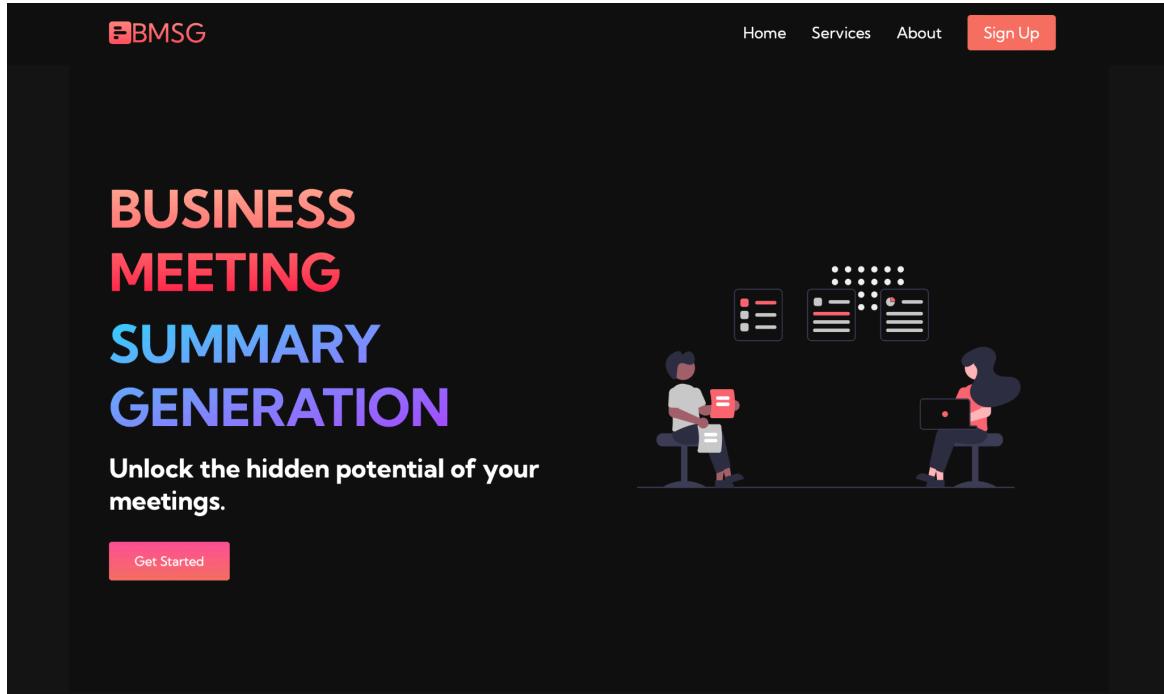


Figure 11: User Interface(1)

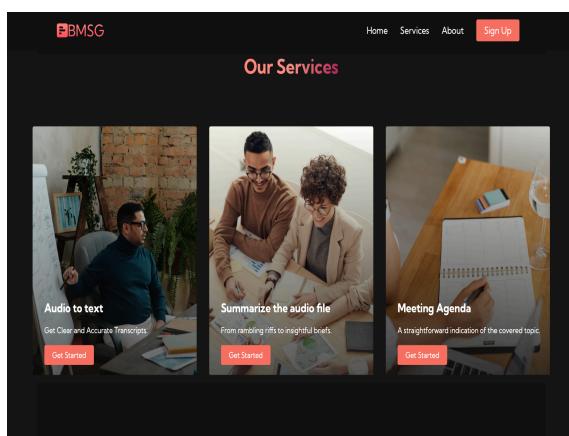


Figure 12: User Interface(2)

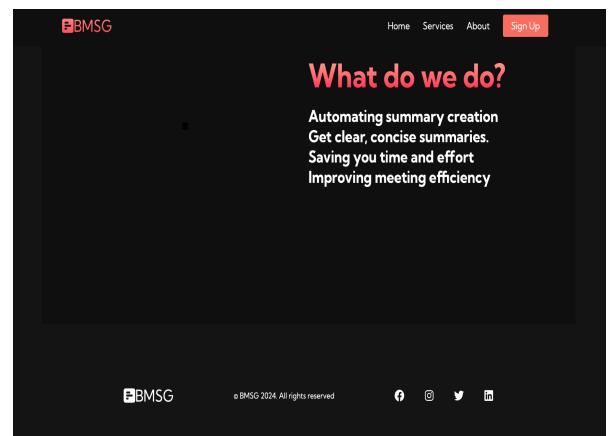


Figure 13: User Interface(3)

We have divided our project into three major services.

1. Audio to Text Transcription
2. Extractive Summary
3. Theme of the Summary & Abstractive Summary

Service 1:

In the first service we are able to identify individual speakers and transcribe the audio to text.

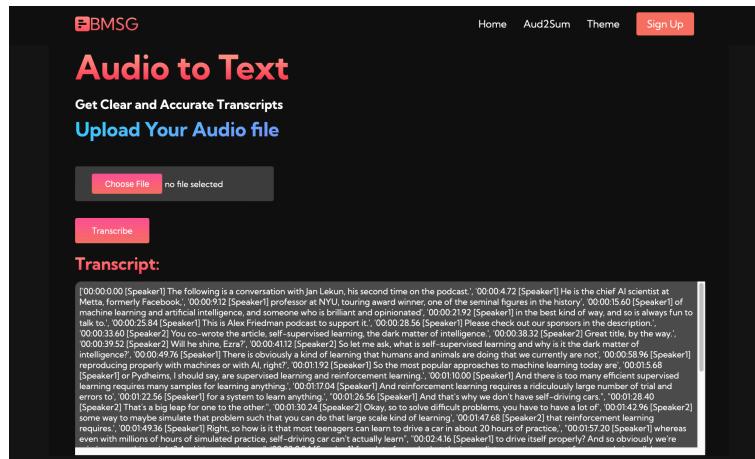


Figure 14: Generated Text Transcript

Service 2:

In the second service we are able to generate a summary that consists of sentences which are most important according to their frequency scores.

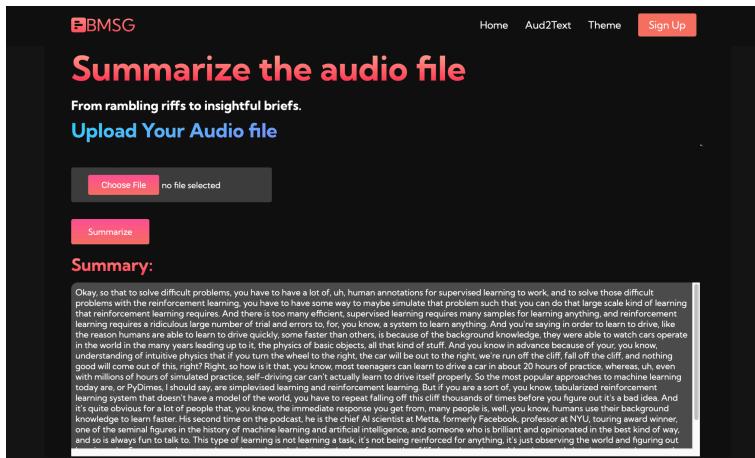


Figure 15: Top Ranked Sentences Summary

Service 3:

In the third service we are able to generate a theme of the summary that best suits the audio file and also generate a short summary.

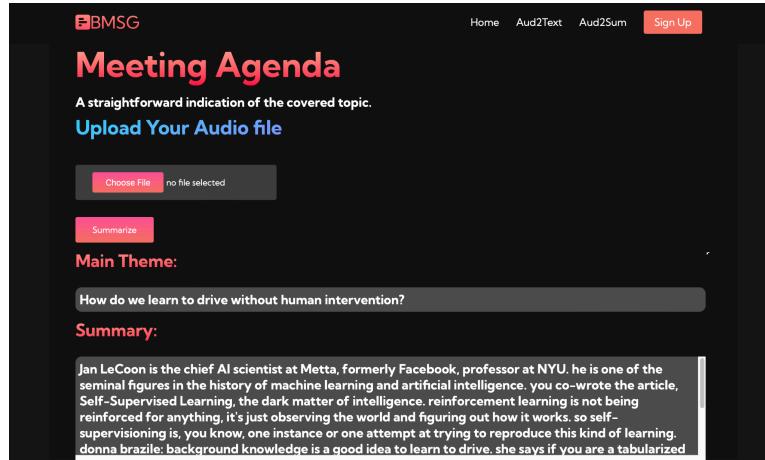


Figure 16: Theme of the Audio File & Short Summary

Result Analysis:

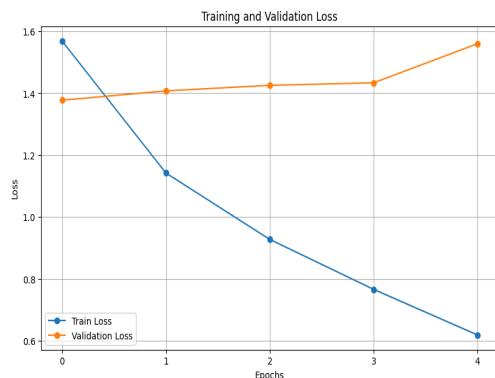


Figure 17: Training and Validation Loss

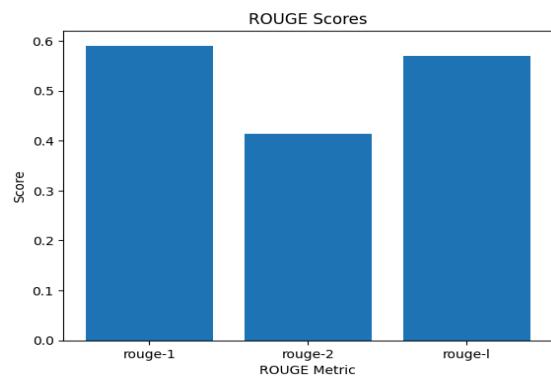


Figure 18: T5 Model: Precision-Recall Curve

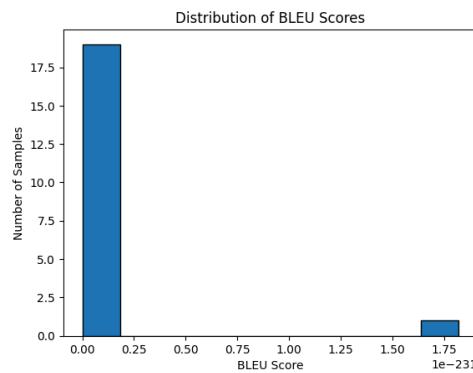


Figure 19: T5 Summarization Model: BLEU Curve

CHAPTER 7

CONCLUSION

After a thorough examination of various methodologies of content summarizing and textual understanding, our research has demonstrated how technology can revolutionize summary generation in the field of business meetings. Our system provides users with various advantages, like a better understanding of context, more trust, and informed decisions. Many industry sectors are interested in exploring this research to form effective solutions because of its promising and efficient results that help in the progress of the company or an individual. In general, it is a type of trial-and-error experiment to reach a point of generalization. In the current working environment, we can see a variety of new features that further help in the progress of decision-making. One of them includes real-time processing and tailored summary generation according to specific types of meetings to produce concise and information-driven summaries

FUTURE ENHANCEMENTS AND DISCUSSIONS

Our work showcases the benefits of natural language processing (NLP) and involves integrating advanced NLP techniques like transformer models for better coherence and context understanding. Multi-modal summarization, real-time summarization, and user customization can offer more comprehensive and tailored summaries. Integration with knowledge graphs, feedback mechanisms, and robust security measures are essential considerations. Discussions should focus on user experience, scalability, integration, quality assurance, ethical considerations, training and support, and quantifying business value. These enhancements aim to improve efficiency, decision-making, and collaboration in organizations.