Survey Paper: Business Meeting Summary Generation

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***Abstract*—** In today's fast-paced corporate world, business meetings are a crucial component of decision-making, teamwork, and progress measurement. This article explains the potential of meeting summarizers. The study presents various approaches and an NLP-based solution to provide succinct and logical summaries in order to meet this pressing requirement. Over the years, Extractive Summarization gained a lot of steam until a new method known as Abstractive Summarization emerged. In this review work, we thoroughly examine the methods of several summarization approaches and provide descriptions and comparisons of them using comparison tables.

Keywords— Text Summarization, NLP, Sentiment Analysis, Text Rank Algorithm, TF-IDF, LSTM, HMM's, LSA, K-Means Clustering.

I. INTRODUCTION

In the fast-paced world of contemporary business, effective communication and information dissemination are crucial elements for success. Business meetings serve as vital platforms for collaboration, decision-making, and strategy formulation. However, the wealth of information exchanged during these meetings often poses a challenge for professionals to efficiently distill and retain key insights. Recognizing the growing significance of addressing this challenge, the field of business meeting summary generation has emerged as a focal point for research and development. Business meetings can last for a long time, and it can be challenging to capture the crucial details of any given discussion. It has been shown that traditional note-taking techniques are less beneficial.

When the foundations of NLP were developed in the 1950s, text summarization entered the picture. Many techniques have been used in the process of discovering the best way to show key information from the corpus pool. Extractive Summarization and Abstractive Summarization are the two primary approaches that served as the foundation for all summarization-based models. Because the neural network baselines had not yet been established, extractive summarization was more popular for a longer time than the abstractive way.

To create a summary report, extractive summarization involves a number of processes, starting with standard pre-processing and ending with sophisticated feature extraction, word embedding, and Vectorization tools. Pre-processing is the most important step in any summarization model. It involves removing all superfluous and irrelevant characteristics from a dataset, such as stop words, special characters, jargon, repeated characters, background noise, etc., to make the dataset clean, facilitate analysis, and allow for additional steps to be taken for better transcript processing.

Following the pre-processing stages, adhere to the Extractive or Abstractive methodology's procedures. The widely utilized Vectorization or Feature Extractive approach in Extractive Summarization is called TF-IDF [1], and using this method we can determine a word's significance inside a meeting transcript document. IDF stands for Inverse Document Frequency that indicates how frequently or seldom is a specific word or phrase happening in a given group of documents. TF stands for Term Frequency, which counts the number of times a phrase/word occurs in the text transcript. It is computed by multiplying a word or phrase's inverse document frequency by its term frequency. The more the term, the more common or likely it is to appear.

The two primary strategies listed above are applied to all summary problems, and they are followed by a top-ranking method such as the Text Rank algorithm from Page Rank, which generates summaries by placing words, phrases, and sentences with better scores at the top. The primary issue with the extractive-based technique is that it just replicates the most important lines from the transcript for the summaries rather than coming up with original sentences. In order to address this issue, we discovered Abstractive Summarization, in which the system generates new phrases by comprehending the underlying syntactic and semantic meanings of the input sentences. In order to implement this strategy, we mostly employ RNNs [2] and other neural networks, in which words and phrases are represented as nodes and the semantic meaning between sentences is represented by edges. In order to minimize cycle times and computational expenditures, longer dependencies are often processed using the LSTM cells.

This survey paper deeply focuses on understanding the various static techniques, methodologies, and advancements in the field of business meeting summarizations. By understanding the diverse works of vivid scholars, researchers, and professionals we get to understand the baseline of meeting summarizers and the potential the future offers in this domain.

There are no summarizations without Natural Language Processing (NLP) because delving into the character-wise understandings of a sentence structure makes use of many concepts like syntactic analysis, semantic analysis, and lexical relations and that of matter understandings of phonology and annotations are also equally important. When dealing especially with textual sequences, the way of speaking also matters. A man can speak the same sentence in two different ways and have two different meanings. Semantic Understanding that is sentimental values that are hidden in the sentences also affects the meanings of the sentence. Therefore NLP and other Machine Learning concepts and techniques play a vital role in the field of Summarization.

When it comes to the difference between Abstractive and Extractive Summarization [21] paradigms, Extractive methods while processing only give the sentences that have the utmost importance in the input whereas the abstractive constructs new phrases and words. The domain of Business Meeting Summarization is abundantly growing. To catch the working dynamics and requirements of the people new techniques and approaches need to be explored and provide succulent results..

II. LITERATURE SURVEY

Vishnuprasad [1] has suggested a system takes a more Extractive Summarization-based methodology [21]. By creating a document similarity matrix [29] by down sampling unusual words and identifying relevant sentences with a higher probability score, the system uses TF-IDF [26] technique to assign scores to the words and phrases in a given input sentence. Text Rank is then used to identify the top ranked sequences that correspond to a threshold value, which sets a sentence limit for generating the summary output sequences.

Subhash [2] has suggested combining extractive and abstractive summarization techniques in their study. Unlike the extractive method, the abstractive-based technique facilitates the creation of new phrases. The RNN-LSTM [28] system was presented by the study employing a succession of processes such as TF-IDF [1] and Text Rank [1] to construct the top-ranked sequences existing in the input transcripts. LSTM memory cells are excellent at capturing long-term relationships in the data. When producing the summary result, the attention mechanism was used to further assist by concentrating on particular segments of the input sequence. They experimented with training and testing ratios to find the ideal fit where the model might provide summaries that are broadly applicable in order to produce an accurate and succinct output.

Rajat Verma [3] explained that although extractive summarizing has been a popular method, the author recommended utilizing an abstractive-based technique. The fundamental issue with extractive summary is that it only duplicates the top-ranked sequences [30] rather than creating new sentences. Machine learning technologies are used to convert voice to text at the beginning of the process, and a text summarizer is then used to further handle the text once it has been transcribed. The speaker employed abstractive methodology after converting speech to text because it was flexible enough to comprehend word embeddings in sentences, lexical relations, and semantic structure. This allowed for a clear analysis of sentence ordering and semantic structure, which in turn produced computer-generated new summary output sequences.

Umadevi [4] modified the original extractive-based procedures adaptively while introducing a new method. Sentence grading in relation to context relevance is the primary focus of the paper. The procedure comes after a distinct pre-processing stage in which superfluous subjects are removed to concentrate on the information that has interpretive significance. This method selects the higher weighted sentences with a change by using top ranking. The change clarifies the hypothesis that sentences at the start and conclusion of paragraphs have more meaning, giving them better ratings when the Page Rank algorithm is used to evaluate them. This procedure aids in producing a summary that is more succinct.

Xue-Yong Fu [5] suggested using Large Language Models in the research, which sets it apart from all previous summarization models. Despite the potential to provide state-of-the-art performance, the research primarily focused on LLMs rather than any abstractive or extractive solutions since these techniques need network-specific tweaking, which is impractical in real-world circumstances (zero-shot performance). Different LLMs [26] use their own methods for comprehending the prompts and presenting the findings in a variety of ways. In order to achieve a balance between cost-effectiveness and performance, the paper uses a large number of LLMs [27] and experiments with them. The kind of datasets like ICSI and many more are also important because it affects how well the general information is showcased and how well it can be evaluated in order to produce succinct summaries using the LLMs.

Mehul Pawar [6] suggested using Speech-to-text (STT) which employs voice recognition and complicated machine learning models to transform audio into editable text, utilizing linguistic algorithms and Unicode characters. This STT model involves: data collection, preprocessing, acoustic modeling, language modeling, decoding and post-processing. Different datasets and preprocessing techniques are essential for effective usage, ensuring adaptability to various speakers and languages. Acoustic modeling uses Hidden Markov Models (HMMs) and deep neural networks to summarize the connections between audible features and their corresponding text representation. Evaluation measures used are word error rate (WER) and character error rate (CER) which highlight the accuracy, adaptability to various speakers.

Nazim Dugan [7] has proposed using a DNN-HMM [6] [23] hybrid model with MFCCs and iVectors in the Kaldi framework. Data preparation involves cleaning and realignment of ground truth transcriptions in the model. A procedure is implemented in which utilizing word lattice results from a preceding ASR system. The training dataset, totaling 1057 hours, includes data augmentation and language model adaptation. The testing data shows a word error rate of 23.9. The primary challenge is the inaccurate time alignments in the provided data. The system's performance has been benchmarked against a base model.

Gabriel Murray [8] paper investigates speech summarization in multiparty meetings, focusing on the underexplored domain. Using the ICSI meetings corpus, the authors employ Maximal Marginal Relevance (MMR) [24], Latent Semantic Analysis (LSA), and feature-based methods for extractive summarization. LSA consistently outperforms other methods in speech summarization. The study shows that in future the expansion of prosodic databases and extrinsic evaluation methods are used to access summarization utility.

Anna Nedoluzhko [9] paper explores the diverse landscape of the meetings, minute's formats, examining types and available datasets for automatic minuting. Meetings are either business or decision-making, each with specific agendas and minutes. This shows the linguistic features of the meeting minutes, focuses clarity, recommending plain English. The mentioned summarization methods are decision-faced meeting, supervised and unsupervised methods and Extractive and abstractive methods. The AMI meeting corpus and other resources state the need for expanding datasets beyond domains. Author specifies an extensive corpus for automating the minuting, including recordings, ASR transcripts.

Yashar Mehdad [10] introduced an innovative framework for abstractive meeting summarization. This approach involves clustering sentences into communities, constructing an entailment graph for sentence selection, and collecting chosen sentences using a word graph model. The method outperforms previous models in terms of informativeness, generating longer and grammatically competitive sentences. The ranking model considers readability, content coverage, and conceptual connections to produce a summary sentence, with re-ranking for paths containing at least one verb. Comparative evaluations against various baselines, including MMR-centroid [24] and Text Rank, demonstrate the superior performance of the proposed approach.

Aryan Jha [11] proposed work will convert almost every recorded meeting, interviews, etc. and other audio streams into text documents. The generated meeting summaries are automatically summarized while preserving important information content and overall context. For system implementation they have used the Text Rank algorithm approach. The Text Rank algorithm is implemented on the basis of Page Rank [29], a popular algorithm which ranks web pages in search engines. It also explains different methods of business summarization: Extractive Summarization and Abstractive Summarization. They have also used a speech to text API converter for better conversion of speech to text from a specific recorded audio file.

Pallavi Lodhi [12] demonstrated a system summarizing a business meeting by using a machine learning tool, held in the local language or a professional language. The meeting summarization is done by using an abstractive method [22] which is based on the frequency of occurrence in the given text file. With the help of the Python connector, the Node-JS server application is connected by a machine-learning model. To avoid the existing barriers, the proposed model takes an audio file of English or Hindi language from the user end and summarizes it by using ML techniques which helps to enhance the succession and provide the desired language output. For translation, they used Google Cloud Translation API.

Swapnil Waghmare [13] and others discussed various techniques and methods for text summarization, including NLP-based summarization, statistical novel methods, and Abstractive and Extractive methods [30]. It also seeks for various uses of AES encryption to improve the security of summary files. Additionally, the article discusses an MMS method that combines NLP, speech processing, computer vision, and AES encryption to improve the quality and security of multi-modal data. The method aims to bridge and lessen the semantic gaps between different types of data.

Sheetal Patil [14] introduced the concept of text summarization as a way of opting for important points from a document, and explains that abstracting a large document manually is challenging and time-consuming. The paper mainly focused on the frequency-based approach, calculating the sentence score by using the Term Frequency-Inverse Document Frequency [25] score for text summarization which selects the highest-scored sentences and merges them as a summary.

Chetana Varagantham [15] presented a framework for summarizing large amounts of information quickly and efficiently, using both morphological elements and semantic data. They have also discussed the overview of text summarization techniques and methodologies, including both Abstractive and Extractive summarization methods [30]. The result of the proposed framework is a summarized output of the input document, which is obtained through k-means clustering. In k-means clustering after sentence segmentation, the tokenization process will be done followed by the clustering technique for effective text summarization.

Jaishal Shah [16] proposed a system which is ultimately used for automation in meeting minute generation. The main aim is to save time during business meetings. This approach extracts crucial information, and the author's main ideology is to use significant debates by implementing deep learning techniques. The general process of automated meeting minute generation is to record a minute and transcript the meeting information for speaker identification. In this process, speakers use MFCC (Mel Frequency Cepstral Coefficient), mainly used to convert audio files to plain text, using AI technology and Deep Neural Networks (DNN) to summarize the meeting text transcript into minutes.

Neslihan Akar [17] introduced an easier way to access information in meetings, following two phases: speech-to-text and then extractive summarization. This paper is focused on extracting the inferential content that is most important and is discussed in meetings and lectures. A meeting generally consists of more than one person, and to recognize the audio of each individual and segment them, we use a speech-to-text translator via a Python library function called Kaldi Recognizer. High-frequency sounds have noise present in them, which is removed, and the clean speech is translated to text. The TF-IDF method is used to select the top modeling sequences in the text. Extractive summaries have a factor named the thresholding factor, which determines how many sentences are in the output summary. Thereafter, these summaries are compared with human-generated summaries for quality and content assessment.

Hamza Shabbir Moiyadi [18] demonstrated that the system implemented by him and his co-workers use NLP, where text summarization via semantic analysis is implemented. Evaluation is done by latent semantic analysis, which summarizes documents from user inputs. The input document mainly required parsing or pro-processing, with the removal of unneeded words. SVD analysis stages drive the latent semantic structure of the transcript representation matrix. After the summarization process, the system arranges the sentences generated from SVD analysis in semantic order in such a way that the summary encompasses all the concepts related to the original, non-summarized text.

Viveksheel Yadav [19] paper describes various techniques for meeting summarization. It has a diversified strategy for the summarizing of meetings; it brings abstractive and extractive methods. The hybridized text summarizer model is applied in a conference video call. Here, the audio is converted into text, and text embedding is processed in the tokenization and clustering processes. In the ongoing process, we finally get a summarized text document. Various techniques are applied; one of them includes the use of support vector machines (SVM), whose purpose is speech classification, and deep neural networks (DNN) [23] [6], whose identification of handwriting is done accurately. Numerous different approaches are used in a summary meeting. When an abstractive and extractive system is combined, the overall summary is improved and signified.

Joseph Carmona [20] mainly uses NLP techniques in his approach. The process starts with a textual description, where the process outlines the sequence of activities that act as inputs to the system. NLP processing techniques analyze the structure of content in the text, progressing towards semantic understanding to identify the verbs, nouns, and relationships between the sentence structures. The system uses a BPMN model, depending on the representation of the data. The system highlights the growing potential of NLP in the field of automating business solutions, in this case meeting summary generation.

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 approach.	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, Romansha Chopra, Nivedita Singh, Likitha Aruru, Jagadesh	2018	Uses a modified version of Text Rank algorithm	The primary technique used in the solution by the author for sentence weighing is based on a page rank graph, along with 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.
Md Tahmid Rahman Laskar, 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,		Acoustic	When a new training data is combined with the training data of

Cornelius Glackin, Gerad Chollet, Nigel Cannings.	2018	model building	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, Steve Renals, Jean Carletta	2012	Latent Semantc Analysis (LAS)	This involves analyzing relationships between terms and documents as per the patterns of co-occurrence in large datasets.
Anna Nedoluzhko and Ondˇrej 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, Giuseppe Carenini,Frank W. Tompa,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, Sameer Temkar, Preetam Hegde and Navin Singhaniya	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 x m. Cosine similarity is used for comparing two sentences.
Pallavi Lodhi, Shubhangi Kharche, Dikshita Kambri and Sumaiya Khan	2022	Abstractive Summarization	The system uses a NodeJS server that is connected with a machine learning model by a python connector.
Swapnil Waghmare, Chaitanya Pathak, Raj Kshirsagar, Suyog Malkar	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 tokenizing 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, J. Srinija Reddy , Uday Yelleni , Madhumitha Kotha , 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, Harsh Desai, Dhairya Pawar, 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, Josep Carmona, Henrik Leopold, Jan Mendling	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. COMPARIOSN TABLE OF DIFFERENT APPROACHES OF MEETING SUMMARIZERS.

III. PROBLEM FORMULATION

In today’s fast-paced and dynamic business environment, time is very precious. Professionals often have limited time and lengthy meetings and are inefficient. Meetings generate a significant amount of data, making it challenging for humans to absorb and retain crucial details.

People attending meetings can only stay focused for a limited amount of time and they fail to remember key details discussed during the meeting. In order to solve these challenges Business Meeting Summarization is introduced. It saves time for busy professionals by condensing important information and helps to remember key details.

In order to summarize the business meeting the following objectives need to be met:

1. Generate concise summaries by saving time for the busy professionals.
2. Identify and highlight key insights from the meeting discussions.
3. Use of NLP techniques that can be used to ensure a deep understanding of meetings [P3].
4. A system that tailors summaries to meet the specific informational needs and preferences of the user [P4].
5. Develop a system that balances the accuracy and speed of generated summaries.

IV. PROPOSED SOLUTION

To effectively extract the critical decisions, strategy planning, and key information that were discussed in the meetings would be the main goal of the proposed system. Solving the challenges posed by the meeting transcripts requires a comprehension approach that makes use of different technologies and methodologies. The generated summary output should be relevant, concise, and accurate. To achieve this we divide our problem domain into five main stages so that the system can meet its objectives.

STEP 1: DATA COLLECTION & SPEECH TRANSCRIBING

In the first phase of our proposed system, the user logs into our Google extension and starts recording the meeting, and the audio is then transcribed to text using Automatic Speech Recognizers like Rev API, and IBM Watson recognizers. The speech-to-text transcription process involves converting spoken language from audio into written text. It includes encoding the audio, generating embeddings, decoding them into text using recurrent neural networks or similar architectures, and producing the final transcription.

STEP 2: DATA PRE-PROCESSING

After completing the first phase then comes the pre-processing stage where the irrelevant data from the text document is removed for easy processing like stop-word removal, special character elimination, noise reduction, etc.

STEP 3: EXTRACTIVE SUMMARIZATION

After the data is cleaned, we start with our Extractive Summarization process where various techniques like TF-IDF, Text Rank, and Lex Rank are used for assigning weights to each and every word/phrase in the document according to its frequency of use and its similarity index then from them we rule out the sentences according to its highest weight values. This process involves various machine learning techniques and resources like NLTK (Natural Language Tool Kit) and scikit-learn environments.

STEP 4: ABSTRACTIVE SUMMARIZATION

This approach involves constructing sequence-to-sequence models and RNN-LSTM architectures where the words are represented as nodes and edges represent the semantic value between two nodes. The encoder network processes the meeting content and the decoder generates the abstractive summary. Attention mechanisms and other techniques of reinforcement-based learning are implemented while constructing the networks.

STEP 5: SUMMARY EVALUATION.

At this last stage of the system, the summaries are evaluated to address their quality. Techniques like ROUGE scores are used in these evaluations.

Abstract view of the process undergoing

1. Data collection and Speech to text Conversion [Rev API or Azure Speech Recognition]
2. Pre-processing [cleaning the transcript]
3. Extractive Summarization [TF-IDF for feature Extraction and Text Rank algorithm for top-ranking sequences]
4. Abstractive Summarization [to generate new sentences using RNN-LSTM and attention mechanism]
5. Experiments and Evaluation [to find the correct fit where it generalizes and evaluates with metrics to find accuracy score]

This system meets the objectives with the help of NLP approaches like semantic and syntactic understanding for deep understanding [P3]. Make use of extractive summary for general meetings and abstractive summary for more specific technical meetings [P4].

In this way, the system analyzes the meeting transcripts thereby providing critical key insights of information and summaries which are effective and concise.

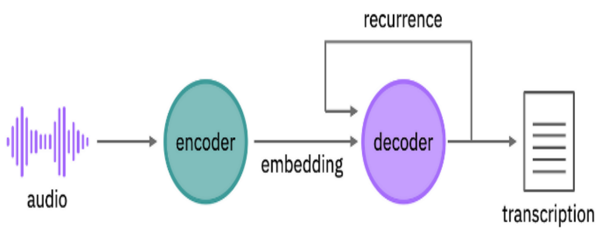

Fig 1: Speech-to-Text Conversion

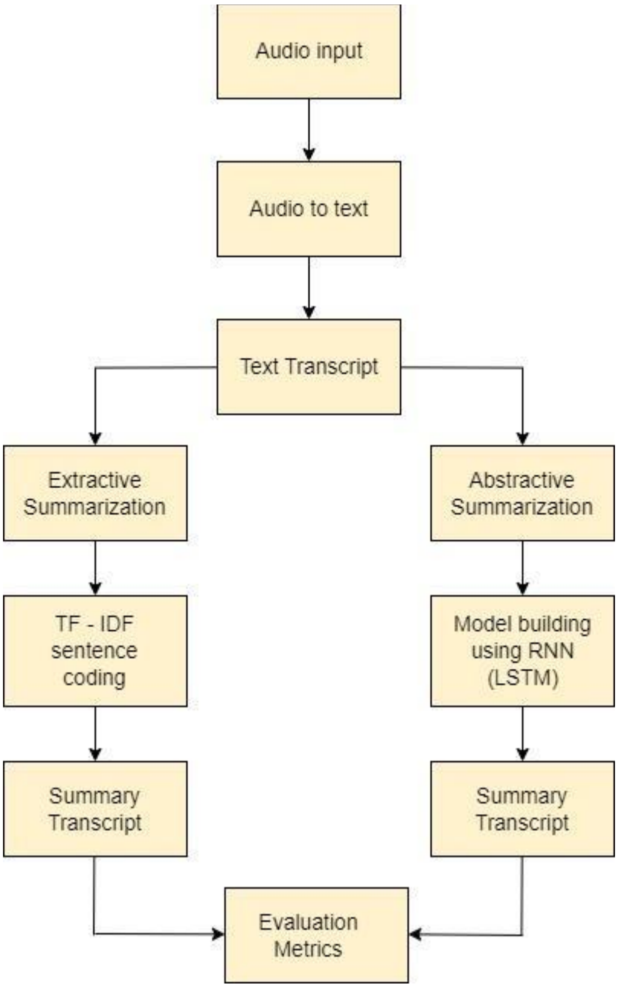

Fig 2: Detail Architecture of the proposed system

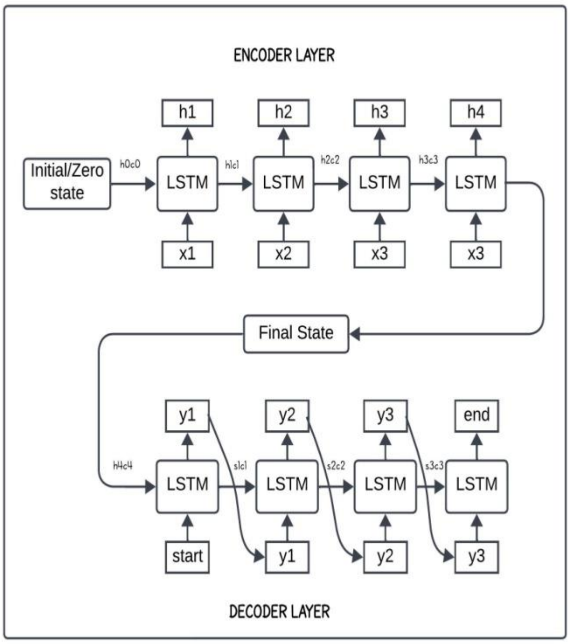

Fig 3: LSTM Encoder – Decoder Model

V. STIMULATED OUTPUT

Firstly, the spoken content from the audio file undergoes transcription, capturing all aspects of the conversation or speech. Then, extractive summarization comes into play, where sentences directly extracted from the transcript are carefully chosen based on their relevance and significance. Despite being condensed, this summary retains the original wording and structure, preserving the context of the dialogue.

Moving on to the abstractive summarization phase, a more polished summary emerges. Here, new sentences are crafted to effectively convey the essence of the transcript. Unlike extractive summarization, which relies solely on existing sentences, abstractive summarization involves rephrasing and restructuring the content using advanced natural language processing techniques and RNN-LSTM model. The model is trained under different corpus of meeting transcripts through which the training and testing accuracy score are retrieved by consistent trial and error modifications of dense layer sizes. The outcome is a succinct yet diverse summary, enhancing coherence and readability.

In essence, the summarization process yields a clear and concise overview of the original audio transcript. It enables readers to easily grasp the main ideas and significant points discussed during the conversation, facilitating better understanding and retention.

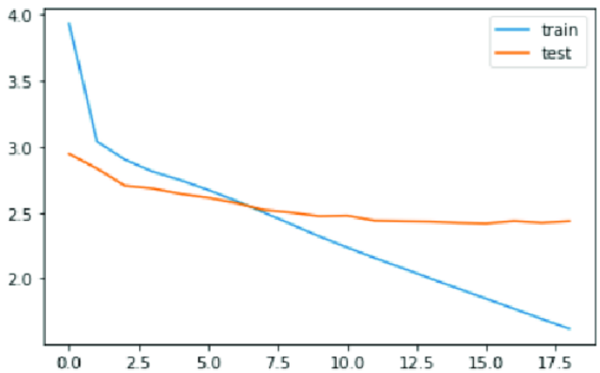

Fig 4: Graph plot of Training and Testing accuracy score

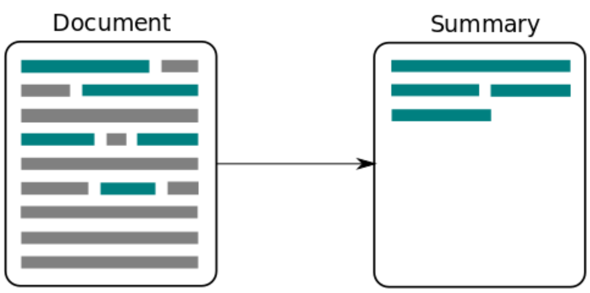

Fig 5: [AI Generated] Original transcript Vs Summary Transcript

VI. 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.

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