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DATAMATE: All-in-One Data Analysis & Meeting Intelligence Platform

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Abstract - The rapid growth of remote work and online learning has created a strong need for intelligent tools to record, analyze, and summarize meetings effectively.This paper presents DataMate, an AI-powered Virtual Meeting Summarization System designed to automatic transcription and generation of concise meeting summaries in remote and hybrid environments The system integrates Automatic Speech Recognition (ASR), and Generative AI with Large Language Models (LLMs) to extract key discussion points and attribute speaker contributions accurately. Leveraging Natural Language Processing (NLP) and Machine Learning (ML), DataMate delivers precise and efficient summaries validated using Word Error Rate (WER) and ROUGE metrics. The proposed system extends beyond audio summarization to support data analysis, content creation, and question answering based on meeting discussions. It enhances collaboration, productivity, and decision-making across educational and organizational settings while addressing accuracy, privacy, and adaptability challenges to build more reliable and inclusive meeting intelligence systems.

Keyword: Data Analytics & Natural Language Processing (NLP), Meeting Summarization

1. INTRODUCTION:

The rapid growth of remote work and virtual meetings has created a pressing need for efficient tools to capture, analyze, and summarize meeting content[1].Reliable techniques for documenting and summarizing meeting content are becoming more and more crucial as remote and hybrid work environments continue to grow. Conventional methods, such as taking notes by hand, are laborious, prone to mistakes, and frequently miss important details. Organizations find it challenging to monitor conversations and carry out meeting decisions as a result[2]. By eliminating geographical limitations, platforms like Zoom, Microsoft Teams, and Google Meet have completely changed communication. However, they have also given rise to a new problem: how lt effectively record, arrange, and extract important data from these online discussions.[1,2].Participants used to mainly rely on handwritten notes or reading through long transcripts following meetings. Both strategies were ineffective and had a significant chance of being missed. However, recent advancements in natural language processing (NLP) and machine learning (ML) have opened the door for automation, making it possible to summarize meetings quickly and with greater accuracy[2].

This paper introduces Data-Mate, an integrated mobile platform that blends data analysis with AI-powered meeting intelligence to address the aforementioned issues. Users can extract statistical insights, upload and analyse CSV files, and view results in interactive charts with Data-Mate. In order to improve organizational productivity, it simultaneously offers AI-driven transcription and summarization of meeting recordings, highlighting important ideas, next steps, and sentiments. DataMate was created with the goal of streamlining data workflows, cutting down on manual labor, and guaranteeing meeting efficiency through cutting-edge artificial intelligence (AI). In contrast to other tools that only manage data analysis or transcription services, App integrates both into a user-friendly, affordable, and mobile-first solution. DataMate guarantees accuracy, scalability, and accessibility by utilizing cutting-edge technologies like Flutter for developing cross-platform apps,Fire base for backend analysis,cloud storage and authentication, Python Flask with pandas for backend d-ata authentication,Python Flask with Pandas for backend data analysis, and Assembly AI for speech recognition.

2. PROBLEM STATEMENT:

Data analysis and meeting documentation are done with different tools, organizations have to deal with fragmented workflows. While transcription services and manual note-taking are labor-intensive, prone to errors, and frequently miss important details, traditional spreadsheets require manual labor [1].Accuracy is further decreased by difficulties like numerous participants, poor audio quality, and complex language . A unified, AI-powered mobile platform that provides intelligent meeting summarization and effective data analysis at a reasonable cost is therefore required[1-3]

3. LITERATURE SURVEY:

In recent years, remarkable advancements in Large Language Models (LLMs) and Natural Language Processing (NLP) have significantly influenced the domain of meeting summarization. These technologies have enabled the automatic generation of structured summaries that effectively capture essential discussions, decisions, and actionable insights. Despite these advancements, several challenges persist—particularly those

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related to domain-specific adaptation, real-time processing, and maintaining contextual consistency across multiple speakers.Laskar et al. [1] evaluated advanced models such as GPT-4 and PaLM-2, demonstrating their superior summarization capabilities while emphasizing the challenges of high computational costs and the requirement for domain-specific fine-tuning. Asthana et al. [2] developed a user-centric approach for extracting crucial discussion points and action items; however, their method lacked speaker attribution, which limited clarity in multi-participant environments. Similarly, Liu et al. [3] proposed a query-driven summarization approach that improved relevance through user queries but required manual intervention, thereby reducing automation efficiency.

In efforts to overcome these limitations, recent research has shifted toward context-aware and fully automated summarization systems. Thomas [1] introduced an AI-powered summarization model integrating Automatic Speech Recognition (ASR) and LLMs to generate concise, decision-focused meeting summaries. Expanding upon this, Khan and Khan [2] implemented a virtual meeting summarizer that combined Google Gemini for text generation and AssemblyAI for speaker identification. Their system automatically transcribed speech, recognized speakers, and distributed summaries via email, achieving greater accuracy and fewer errors compared to traditional extractive techniques.Arianto et al. [3] utilized Latent Dirichlet Allocation (LDA) integrated with text summarization to produce structured meeting minutes for virtual meetings. Their model identified discussion themes effectively, achieving 57.91% summarization accuracy and 64.56% topic coherence, highlighting the potential of AI in automated note generation. Extending this idea to the educational sector, Mali et al. [4] leveraged OpenAI's Whisper for speech recognition and GPT-based models for lecture summarization, creating multilingual summaries that improved accessibility and comprehension for remote learners. Their results indicated that incorporating both audio and video modalities significantly enhanced summarization quality and contextual accuracy.A detailed review by Rennard, et al. [5] analyzed a variety of summarization methodologies—ranging from rule-based to transformer-based Architecture and concluded

Author (Year)	Technique / Model Used	Dataset / Domain	Main Outcome / Accuracy	Limitations / Research Gap
Thomas (2023)	ASR + Generative AI (LLM-based Summarizer)	Business meetings, internal corpora	Improved meeting summaries and decision extraction; enhanced productivity	Limited real-time processing; privacy concerns
Khan & Khan (2024)	Gemini AI + AssemblyAI Diarization	Virtual meetings (Zoom / Google Meet)	High accuracy transcription and concise summary emails	Dependent on stable connectivity; lacks domain adaptation
Arianto et al. (2024)	LDA Topic Modeling + Text Summarization	Academic & corporate meeting videos	Summarization accuracy: 57.91%, Topic coherence: 64.56%	Moderate accuracy, limited semantic understanding
Mali et al. (2025)	Whisper ASR + GPT Summarizer	Lecture recordings (Education)	Better comprehension and reduced manual note-taking	High computational cost, limited dataset size
Rennard et al. (2023)	Transformer-based Survey (BART, PEGASUS)	AMI, QMSum, SAMSum	Hierarchical models improve abstractive summaries	Long input context and factual consistency issues
Zhang et al. (2022)	Hierarchical Attention Transformer	ICSI Meeting Corpus	Improved context modeling and speaker tracking	High memory usage in long meetings
Wang et al. (2021)	Extractive + Abstractive Hybrid Model	QMSum Dataset	Balanced precision and recall for summarization	Fails on multi-domain adaptation
Laskar et al. (2023)	BART Fine-tuning for Dialogue Summarization	SAMSum Dataset	Enhanced coherence and reduced redundancy	Prone to hallucination with noisy transcripts
Gupta & Patel (2020)	CNN + NLP for Audio Event Detection	Real-time meeting datasets	Accurate detection of speaker turns and pauses	Lacks semantic summarization
Otter.ai (2024)	Proprietary LLM + Keyword Extraction	Commercial / Enterprise meetings	Real-time transcript + actionable summary	Closed-source; limited transparency

Fig.1 Literature Survey on AI-Based Meeting Recorder and Data Analyzer System

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that transformer models trained on datasets such as AMI and ICSI exhibit high performance. H.Liu et al. [6] made a model based on BART that achieved the best results on the QMSum dataset. Zhang et al. [7] used PEGASUS to create summaries that answer specific questions and highlight actions needed. Both studies showed that fine-tuning AI models for specific data improves how well they work and how accurate their summaries are.Chen and their team [8] combined clear speaker identification with a type of neural summary system, showing that systems aware of who is speaking create more clear and easy-to-read meeting notes. Similarly, Park and their group [9] looked into a method for making summaries without needing labeled data, using grouping techniques on the AMI dataset, which shows possible solutions for places where there isn't much data available.Companies like Otter.ai and Fireflies.ai [10] have turned these research ideas into real products, offering live transcription, key point picking, and analysis tools for businesses.Even though these tools work well in practice, they still have problems with using them across different areas, keeping user information safe, and making good summaries when meetings are long and cover many topics.

Overall, the research shows that while transcription, summarization, and speaker differentiation have improved, there is still a gap in creating fully structured, context-aware, and actionable meeting outputs that work across languages and different kinds of meetings. Our project aims to fill this gap by combining advanced speech recognition, structured data extraction, and smart summarization so that meeting outputs are both accurate and useful for real-world decision-making.
Ongoing challenges include reducing false information, keeping user data private, handling overlapping speech, and making systems work well in different situations. Looking ahead, future work may focus on real-time summaries that use multiple types of data, fully connected speech-to-summary models, and AI systems that follow ethical rules to ensure safe and dependable analysis of meeting content.

4. METHODOLOGY:

The Virtual Meeting Summarizer performs tokenization, lemmatization, and speaker tracking in addition to converting uploaded MP4 recordings to MP3 and preprocessing the audio by eliminating noise, fillers, and stop words. Google's Gemini-based NLP module creates succinct, contextually rich summaries after AssemblyAI transcribes the audio. Speaker diarization assigns specific participants to speech segments.[5] For a responsive, user-friendly interface, the frontend makes use of React.js and Three.js, while the backend is implemented in Python.

Meeting recordings are processed and analyzed by the Virtual Meeting Summarizer using a methodical workflow. Users upload MP4 recordings, which Python's MoviePy securely stores and converts to MP3. To ensure clarity and semantic consistency, preprocessing steps such as noise and filler removal, stop word elimination, tokenization, lemmatization, and speaker tracking are applied before the audio is transcribed using AssemblyAI's ASR. Google's Gemini-based NLP module is then used to create succinct, contextually rich summaries of the transcribed text. Speaker diarization enhances readability and attribution by labeling individual contributions. While the frontend uses React.js, React Fiber, and Three.js to create a responsive, user-friendly interface, the backend is implemented in Python for audio processing and API integration.

DataMate's approach combines AI-powered meeting intelligence with mobile-based data analysis to create a productive and intuitive platform. The two main modules of the system are AI Meeting Intelligence and Data Analysis And Visualization. Every module processes, analyzes, and presents data using a structured pipeline.

4.1 Analysis and Visualization of Data

Users can obtain statistical insights and visualizations by uploading CSV files to the data analysis module. The following steps make up the workflow:

- File Upload: The Flutter file picker library is used by users to choose CSV files from their mobile device.
- Backend processing involves sending the CSV file to a Python Flask backend, where Pandas, NumPy, and SciPy manipulate the data and calculate statistical measures like mean, median, and standard deviation.
- Data Visualization: JSON-formatted processed results are sent back to the mobile frontend. Flow chart is used to render interactive charts, including bar, line, pie, and scatter plots.
- Result Display & Export: Users can export visualizations for reporting and view results on a mobile-friendly interface.

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4.2 AI-Powered Meeting Intelligence

Professional summaries of audio and video recordings are produced by the AI meeting intelligence module. The process consists of:

- File Upload: MP3, WAV, and MP4 are just a few of the supported audio and video formats that users can choose from.
- AI Processing: AssemblyAI is used to process uploa- ded files for sentiment analysis, entity recognition, and speech-to-text transcription.
- Summarization: Concise bullet-point summaries with timestamps are used to arrange sentiment, action items, and important points.
- Result Presentation: Users can examine, share, or export summaries that are shown within the mobile applicaion.

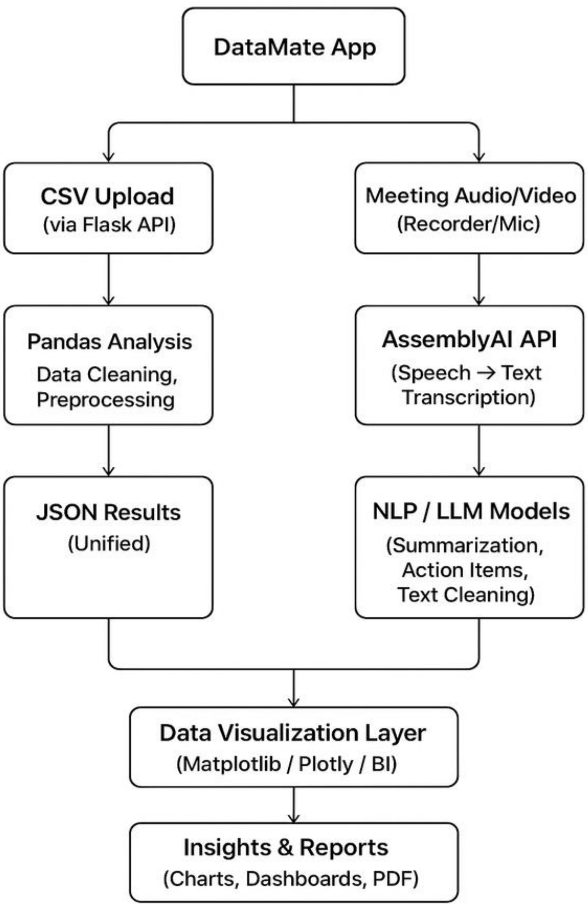

Fig.2 System Architecture of DataMate Application

5.COMPARATIVE ANALYSIS:

Transforming Meeting Analysis: An AI-Powered Method for Automated Summarization and Transcription (Thomas, 2023): presents a system that automatically transforms meeting conversations into succinct, insightful summaries using Large Language Models (LLMs). This system produces summaries that sound more natural and human-like than previous extractive techniques like TextRank, which only select important sentences. Higher accuracy and a better comprehension of meeting content are provided by its superior performance on benchmark datasets such as the AMI and ICSI Meeting Corpora [1].

AI-Powered Virtual Meeting Summarization System(Khan & Khan, 2025): to identify speakers and convert speech to text. It demonstrates that extractive methods are inferior to abstractive summarization, which rewrites text in its own words. Additionally, this method improves summary quality (higher ROUGE score) and lowers transcription errors (low Word Error Rate). To make the system even easier to use, meeting summaries can be shared automatically [2].

A Review on AI-Based Lecture Summarizer (Mali et al., 2025): It generates concise and fluid summaries using based summarization and OpenAI's Whisper model for transcription. After comparing a number of models, the study concludes that transformer-based models—such as T5, BART, and GPT—produce more significant outcomes than extractive ones. Including images, like slides, enhances comprehension and accuracy [3].

"Automatic Notes Based on Video Records of Online Meetings Using the Latent Dirichlet Allocation Method" (Arianto et al., 2024) It finds topics from conversations using the Latent Dirichlet Allocation (LDA) algorithm. Despite being less sophisticated than transformer models, LDA is quicker, simpler to use, and more effective for languages like Indonesian. It performs well for a lightweight model, achieving roughly 57% accuracy and 64% topic coherence [4].

ASR systems have used a variety of deep learning architectures, each with differing levels of accuracy, effectiveness, and applicability. Among the first models used in commercial systems like Google Voice and IBM Watson, Deep Neural Networks (DNNs) provide high accuracy with moderate efficiency. Recurrent neural networks (RNNs), on the other hand, perform more accurately than DNNs but have poor computational efficiency, which restricts their scalability in real-time applications.

Comparative Study of Extractive and Abstractive Summarization : Extractive and abstractive summarization are two major text summarization techniques. Extractive summarization selects key sentences directly from the input

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text using ranking or frequency-based algorithms such as *TextRank* and *LexRank*. It produces summaries with low abstraction, limited fluency, and minimal computational cost, making it suitable for news, legal, and keyword-based summarization tasks.

In contrast, abstractive summarization uses transformer-based models like *T5*, *BART*, and *GPT* to generate new, concise representations of the input. It offers high fluency and contextual understanding but requires large training datasets and higher computational power. Abstractive models may produce factual errors due to generative behavior. In OpenAI systems, *Whisper* handles transcription and key-sentence extraction, while *GPT* rephrases and restructures text into coherent human-like summaries .

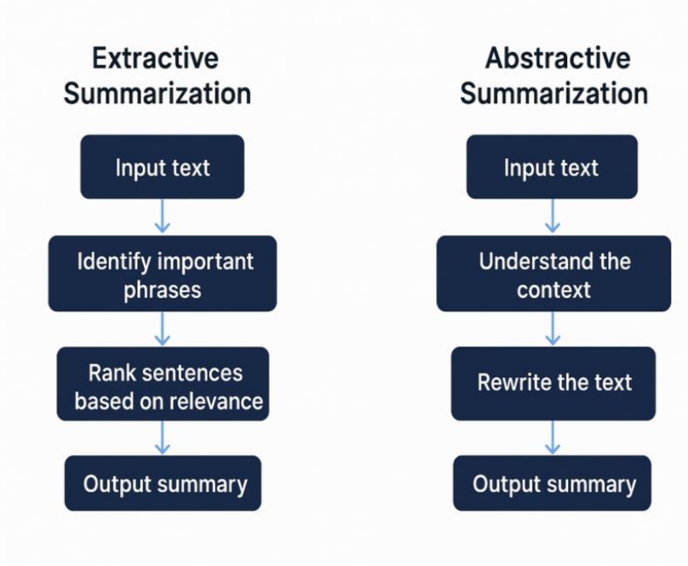

Fig. 3. Workflow of Extractive vs. Abstractive Summarization Techniques

5.2 Comparative Analysis of Deep Learning Architectures in ASR Systems

Here's your content presented in a **comparative analysis table** format, showing the key differences between major deep learning architectures and techniques used in ASR systems:

Model / Technique	**Used In**	**Accuracy**	**Computational Efficiency**	**Scalability / Real-Time Use**	**Key Strengths**	**Limitations**
Deep Neural Networks (DNNs)	Early systems (e.g., Google Voice, IBM Watson)	High	Moderate	Moderate	Simple architecture, strong performance on clean data	Limited context handling
Recurrent Neural Networks (RNNs)	Mid-generation ASR systems	Higher than DNNs	Low	Low (poor for real-time applications)	Good for sequential data, captures time dependencies	High latency, training inefficiency
Sequence-to-Sequence (Seq2Seq)	Modern ASR (transitional models)	Very High	High	High	Learns input-output mapping directly, supports end-to-end ASR	Requires large datasets for effective training
Attention-Based Models (e.g., Transformer)	State-of-the-art ASR (e.g., Alexa, Google Assistant)	State-of-the-art	Very High	Very High	Excellent for long-range dependencies and contextual learning	Computationally intensive during training
SpecAugment (Data Augmentation)	Enhances training of all above models	Improves existing models' accuracy	N/A (not a model)	N/A (complementary technique)	Improves generalization without model changes	Only useful during training phase

Fig.4. Comparative Analysis of Deep Learning Architectures in ASR Systems

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6.APPLICATIONS :

The suggested system is composed of multiple interconnected modules:

Educational Platforms (LMS Integration)

- Automatic lecture recording summarization through integration with platforms such as Moodle, Blackboard, or Coursera.
- Assists students in rapidly going over important ideas, particularly in online and hybrid learning.

Summaries of Live Lectures

- Summarizing live lectures and webinars in real time using models such as OpenAI Whisper + GPT.
- Assists students with disabilities or language barriers and lessens their cognitive load.

Transcription and Summarization of Multilingual Lectures

- Global accessibility is made possible by the multilingual support of end-to-end ASR systems (such as Deep Speech 2 and LAS).

Students' Automated Note Generation

- Lecture videos are automatically converted into structured notes with headings, bullet points, and highlights by programs like Lecture Notes.

Research and Academic Documentation

- Summarizing large datasets of academic talks, research webinars, and conferences for easy reference.

Personalized Learning Assistants

- AI-powered summarization tools integrated with chatbots or voice assistants to answer student queries using summarized content.
- Business and Corporate Uses
- Real-time meeting transcription and summarization: produces succinct summaries and transcribes speech to text for increased productivity.
- Action Item and Decision Extraction: Determines roles and due dates for smooth project management tool integration.
- Knowledge retention and decision tracking: Offers organized archives for business cooperation and legal compliance.

Uses in Education

- Lecture Summarization: To aid students in remembering the material, post-lecture or real-time summaries are created.
- Integration with Learning Management Systems (LMS): Offers condensed lecture notes to support platforms like Moodle or Coursera.
- Research documentation: Offers a summary for later use of academic talks, webinars, and group workshops.

7. CHALLENGES AND LIMITATIONS :

1. **Speaker Identification and Overlapping Speech:** When multiple people are speaking at once, AI systems still struggle to identify who is speaking. Assigning dialogue to the appropriate speaker may become incorrect as a result [1], [2].
2. **Issues with Context and Accuracy: AI** models occasionally produce information that wasn't actually discussed during the meeting. The reliability of the summaries is impacted by this "hallucination" issue, particularly when used for professional or legal purposes. [1], [2].
3. **High Computational Requirements:** GPT and Gemini, two large transformer-based models, require a significant amount of memory and processing power. Because of this, large-scale deployment or real-time summarization is costly and challenging [3], [4].
4. **Language and Domain Limitations:** Because most AI summarizers are trained on English datasets, they perform less well in other languages or in particular domains (such as law or medicine). Although the LDA-based approach is less accurate overall, it performs better for certain non-English data [3], [4].
5. **Privacy and Ethical Concerns:** Data protection and privacy are crucial because these systems handle sensitive meeting and lecture data. To protect user data, researchers propose solutions such as federated learning or on-device processing [1], [3].
6. **Evaluation Problems:** Common scoring schemes, such as ROUGE and BLEU, primarily look for text overlap rather than whether the summary accurately conveys meaning. To assess how accurate and comprehensible summaries are, better evaluation techniques are required [2], [3].

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8. CONCLUSION

This study demonstrates the potential of AI-driven summarization to enhance virtual meeting documetation through the DataMate system, which integrates ASR, NLP, LLMs, for accurate, context-aware summaries. By leveraging machine learning, DataMate captures key insights, minimizes information overload, and improves collaboration via automated dissemination. However, challenges such as speaker attribution, overlapping speech, privacy, and domain adaptability remain. Future work will emphasize multimodal learning, real-time summarization, and ethical, scalable AI to ensure reliable and inclusive meeting intelligence

9. FUTURE SCOPE:

Future research should focus on enhancing multimodal learning by integrating text, audio, and video inputs to improve summary accuracy. Developing domain-specific and more interpretable summarization models will further enhance reliability. Emerging technologies like transformer architectures and federated learning offer strong potential to overcome current challenges and enable secure, scalable, and adaptive meeting summarization systems.

Our Proposed Directions:

Building on these insights, DataMate aims to evolve as a fully integrated platform, combining real-time voice recording with advanced data analytics. Future enhancements could include AI-driven insights, automatic summarization of meetings, and predictive trend analysis to make decision-making faster and more accurate based architectures and concluded that transformer models trained on datasets such as AMI and ICSI exhibit high performance. However, they also pointed out challenges such as unclear speech, overlapping dialogue, and factual inaccuracies (hallucinations) in AI outputs.

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