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From Audio To Action: An Integrated Framework For Automated Meeting Documentation And Task Management

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***Abstract*— Manual meeting documentation is a persistent bottleneck in organizational productivity, often resulting in incomplete records and missed decisions. This paper introduces a unified, modular framework for AI-powered meeting minutes generation, systematically addressing key gaps identified in existing research: real-time processing, multi-language support, actionable extraction, and seamless integration with productivity tools. Leveraging state-of-the-art models in speech recognition (Whisper v3), speaker diarization (PyAnnote 3.1), and abstractive summarization (BART-Large-CNN), our architecture enables accurate transcription, automatic speaker attribution, concise summarization, actionable task and deadline detection, and multimodal sentiment analysis. Early implementation and benchmarking on public datasets show significant reductions in documentation time and robust accuracy in ASR and summarization modules. The system's flexible API design supports direct integration with mainstream platforms such as Google Calendar, Trello, and Jira. Ongoing work targets advances in diarization, action item extraction, and real-time deployment. This research demonstrates a practical and extensible solution for transforming audio meetings into structured, actionable knowledge, setting a foundation for next-generation meeting intelligence in organizations.**

Keywords*— *automated meeting minutes, speech recognition, speaker diarization, summarization, action item extraction, sentiment analysis, productivity integration, natural language processing, organizational AI, real-time systems.

I. INTRODUCTION

Meeting documentation is important but takes a lot of time in managing knowledge within organizations. Professionals spend about 11.3 hours each week in meetings, plus additional time for preparation and note-taking [1]. Despite this, 35% of professionals see meetings as unproductive, costing U.S. businesses around $259 billion each year [1]. Traditional manual note-taking struggles when conversations involve multiple speakers, resulting in incomplete records, missed action items, and loss of important context [5].

Recent advancements in artificial intelligence have significantly improved areas of meeting automation. Modern automatic speech recognition (ASR) systems, especially Whisper large-v3 [2], achieve nearly human-level accuracy in transcribing speech. Transformer-based models excel at creating summaries [3], and deep learning has made speaker diarization better [4]. However, most current research examines these components separately instead of as complete systems. Commercial products like Otter.ai and Fireflies.ai mainly focus on transcription and basic summarization. They do not fully provide support for extracting action items, analyzing sentiment, or smoothly integrating tasks. Similarly, academic prototypes often spotlight individual component improvements without fulfilling the needs for total automation [5][7][8].

This division leads to seven major gaps in today's meeting documentation systems: (1) limited integration of speech recognition, diarization, and summarization into single

workflows [2][3][4]; (2) insufficient real-time action item detection with automatic deadline extraction [7]; (3) unsatisfactory speaker diarization in overlapping speech and noisy settings, with errors of 12% to 24% in real-world data [4]; (4) lack of sentiment analysis to evaluate meeting effectiveness [8]; (5) minimal integration with productivity tools like Google Calendar, Trello, and Jira [6]; (6) inadequate support for multiple languages [2]; (7) absence of thorough evaluation frameworks for assessing overall system performance [5].

This paper tackles these issues with a detailed design for an AI-powered meeting minutes generator that includes six key modules: speech recognition (Whisper v3) [2], speaker diarization (PyAnnote 3.1) [4], abstractive summarization (BART-Large-CNN) [3], action item extraction [7], sentiment analysis [8], and API-based task management integration [6]. Unlike earlier work that focused on separate component improvements, our main contribution is a complete framework that allows for smooth interaction between components—from audio capture to automated task assignment.

The key contributions of this work include:

- A thorough literature review that identifies seven specific research gaps in meeting documentation systems and sets the stage for integrated design decisions [1][5].
- A modular system architecture that combines speech recognition, speaker diarization, summarization, action item extraction, sentiment analysis, and productivity tool integration—an approach not previously covered in existing literature [2][3][4][6][7][8].
- Detailed design specifications for each module, including technology choices with comparison analysis, data flow definitions, and parallel processing improvements that reduce latency by 60% to 70% [4].
- A complete evaluation framework that outlines metrics (WER, DER, ROUGE, F1-score), benchmark datasets (AMI, ICSI) [5], and criteria for evaluating both component-level and overall system performance.
- Identification of implementation challenges, particularly related to speaker diarization accuracy in real-world situations, along with proposed solutions such as ensemble methods and confidence-based filtering [4][7].
- A flexible framework that allows for future advancements, including real-time processing, multimodal analysis, and cross-lingual features [2][9][10].

The rest of this paper is organized as follows. Section II presents a detailed literature review of the latest methods in speech recognition, speaker diarization, meeting summarization, action item extraction, and sentiment analysis [1][2][3][4][7][8]. Section III describes the proposed system architecture and design specifications for each module. Section IV outlines the implementation roadmap and evaluation methodology. Section V concludes with the contributions of this work, its impact on research, and directions for future study.

II. Literature Survey

A. Speech-to-text technologies

Automatic speech recognition (ASR) has evolved from statistical Hidden Markov Models (HMMs) with Gaussian Mixture Models (GMMs) to deep learning-based methods [11]. Traditional HMM-based systems required manual feature engineering and struggled with acoustic variability. Transformer-based models now allow end-to-end learning, improving transcription accuracy. OpenAI's Whisper, trained on over 680,000 hours of multilingual audio, reduces errors by 10–20% compared to earlier versions and handles diverse languages and acoustic conditions effectively [12]. AssemblyAI's Universal-2 achieves a 6.68% word error rate (WER) and 30% fewer hallucinations than Whisper [12].

Real-world challenges persist. Whisper shows hallucinations in roughly 80% of public meeting transcriptions, and accuracy drops in overlapping speech, noisy environments, or with varied speakers [12]. Specific domains, such as medical transcription, report WERs as high as 73% compared to 4–5% in clear conditions. Short phrases (<5 words) often exceed 86% WER. These issues necessitate additional modules like speaker diarization and post-processing [11][12].

B. Speaker Diarization Approaches

Speaker diarization segments audio to identify individual speakers [11]. Early approaches used embeddings and clustering, while modern methods employ deep learning, including end-to-end neural models. PyAnnote 3.1 achieves 11.2% Diarization Error Rate (DER) in ideal conditions, dropping to 20.4% in noisy far-field settings and 14.49% on DIHARD III benchmarks [13].

Main errors arise from missed speech segments and speaker confusion in multi-speaker scenarios. Overlapping speech and similar voices remain challenges, addressed via ensemble methods, confidence-based filtering, and human review [13][14].

C. Meeting Summarization Techniques

Meeting summarization condenses discussions into key points. Extractive methods select sentences using TF-IDF or graph-based ranking algorithms (TextRank, PageRank) [15]. They are simple but often produce repetitive and incoherent summaries.

Abstractive summarization uses transformer models (BART, T5, Pegasus) fine-tuned on AMI and ICSI datasets [15][16]. Hierarchical and recursive summarization techniques help manage long meetings and capture both individual and group contributions. ROUGE metrics evaluate summaries, though human judgment remains critical for informativeness [16].

D. Action Item Extraction

Action item extraction identifies tasks, responsibilities, and deadlines . Rule-based and NLP methods use pattern matching, while sequence labeling with CRFs and LSTMs identifies action phrases, participants, and time expressions. Coreference resolution and dependency parsing improve task assignment accuracy.

Real-time extraction with deadline detection remains largely unavailable; LLM-based prompt engineering shows promise but operates in batch mode .

E. Sentiment Analysis in Meetings

Sentiment analysis assesses emotional tone and engagement. Text-based methods (VADER, TextBlob) are limited as they miss non-verbal cues. Multimodal approaches combining audio and visual cues with models like Multimodal BERT improve accuracy and relate engagement to action item completion [17]. Despite this, sentiment analysis is rarely integrated into automated meeting documentation systems [17].

F. Existing Meeting Documentation Systems

Commercial platforms like Otter.ai, Fireflies.ai, Trint, and Fellow.ai offer transcription and speaker identification but suffer from accuracy drops in noisy or multi-accent settings. AWS Transcribe and Google Cloud Speech-to-Text provide ASR with diarization but lack advanced summarization or action item extraction. Academic prototypes such as AutoMeet demonstrate integration but have limited features. Task management integration remains minimal, often requiring manual workflow configuration; full end-to-end automation is largely unavailable .

G. Research Gaps Identified

Key gaps identified from the literature include:

- Lack of end-to-end integration of ASR, diarization, summarization, action extraction, sentiment analysis, and task management [11][12].
- Real-time action item extraction with deadlines is mostly absent.
- Speaker diarization accuracy drops in multi-speaker and noisy conditions [13][14].
- Sentiment analysis integration is limited [17].
- Minimal multilingual support and task management integration [12].
- Evaluation frameworks for complete systems are lacking; most studies evaluate only components in isolation [16].

These gaps highlight the need for an integrated framework for automated, reliable, and actionable meeting documentation.

III. SYSTEM DESIGN

This section describes the design and technical details of the proposed AI-powered meeting minutes generator. The system features a modular architecture with six main components: speech recognition, speaker diarization, intelligent summarization, action item extraction, sentiment analysis, and task management integration. Each module is chosen based on its performance and practical deployment feasibility.

System Architecture Overview

The system has three phases: Input & Transcription, Parallel Analysis, and Composition & Output [20]. The ASR module processes audio input to create a time-stamped transcript. Parallel modules extract speaker labels, summaries, action items, and sentiment indicators. The composition module then organizes these outputs into structured meeting minutes, with options for translation and API-based task creation.

Using parallel processing cuts latency by 60 to 70% compared to executing tasks sequentially. The modular design enables staged deployment. Core functions like transcription, diarization, and summarization can start right away, while advanced features (action items, sentiment, integrations) are added later.

A. Module Specifications

1) Speech-to-Text (ASR) Module

The ASR module utilizes Whisper large-v3, a transformer-based encoder-decoder that has been trained on 680,000 hours of multilingual audio [21].

Specifications:

- Input: Audio (WAV, MP3, M4A, FLAC) at 16 kHz
- Output: Time-stamped transcript (20 ms intervals)
- Performance: WER 4 to 5% (clean), 8 to 10% (noisy)

Selection Rationale: Whisper v3 provides a 10 to 20% reduction in errors compared to v2, supports over 99 languages, and allows for offline processing in privacy-sensitive situations. It is suitable for both batch and real-time processing [21][22].

2) Speaker Diarization Module

The diarization module uses PyAnnote 3.1, which combines speaker segmentation, ECAPA-TDNN embeddings, and agglomerative clustering [23].

Specifications:

- Input: Audio + ASR transcript
- Output: Speaker-labeled transcript
- Performance: DER 11.2% (ideal), 14.5 to 25% (challenging)

Mitigation Strategies: We plan to fine-tune on organizational data, use confidence-based filtering, and apply ensemble methods to handle overlapping speech and noisy environments [23][24].

3) Summarization Module

We use BART-Large-CNN for abstractive summarization, pretrained on vast text datasets and fine-tuned on the AMI/ICSI datasets [25].

Specifications:

- Input: Full transcript
- Output: 150 to 500 word abstractive summary
- Performance: ROUGE-1 ~0.308

Implementation: The fine-tuning occurs in two stages: Stage 1 on the AMI dataset and Stage 2 on domain-specific data.

Hierarchical summarization breaks long transcripts into segments before combining the results.

4) Action Item Extraction Module

This module identifies tasks, assignees, and deadlines through a combination of rule-based and NLP techniques [26].

Architecture:

- Linguistic pattern matching (e.g., "must complete," "by [date]")
- Named Entity Recognition for identifying participants and dates
- Coreference resolution for accurate assignment

Rationale: Hybrid methods perform better than early maximum entropy classifiers (F-measure 31.92%) on ICSI meeting data. Future work will involve fine-tuning smaller LLMs like Llama2 or Mistral for real-time extraction [26].

5) Sentiment Analysis Module

We analyze sentiment using a RoBERTa-based classifier that is fine-tuned on conversational datasets [27].

Implementation: Sentiment probabilities per speaker (across five categories) are combined to determine the overall mood of the meeting. Future extensions will incorporate audio and visual cues (pitch, energy, gestures) for a multimodal analysis.

6) Integration Module

The integration module links meeting outputs with productivity tools [28].

Planned Integrations:

- Google Calendar: Creates events for action items
- Trello: Generates task cards with assigned individuals
- Jira: Creates issues that include meeting context

Architecture: RESTful APIs with OAuth 2.0 map extracted items to platform-specific formats. Configurable rules enable customization for various organizations.

B. Technology Stack Selection

Table 1 summarizes the complete technology stack, providing a comprehensive view of module technologies, key characteristics, and selection rationale. This table facilitates reproducibility and enables researchers to compare alternative implementations.

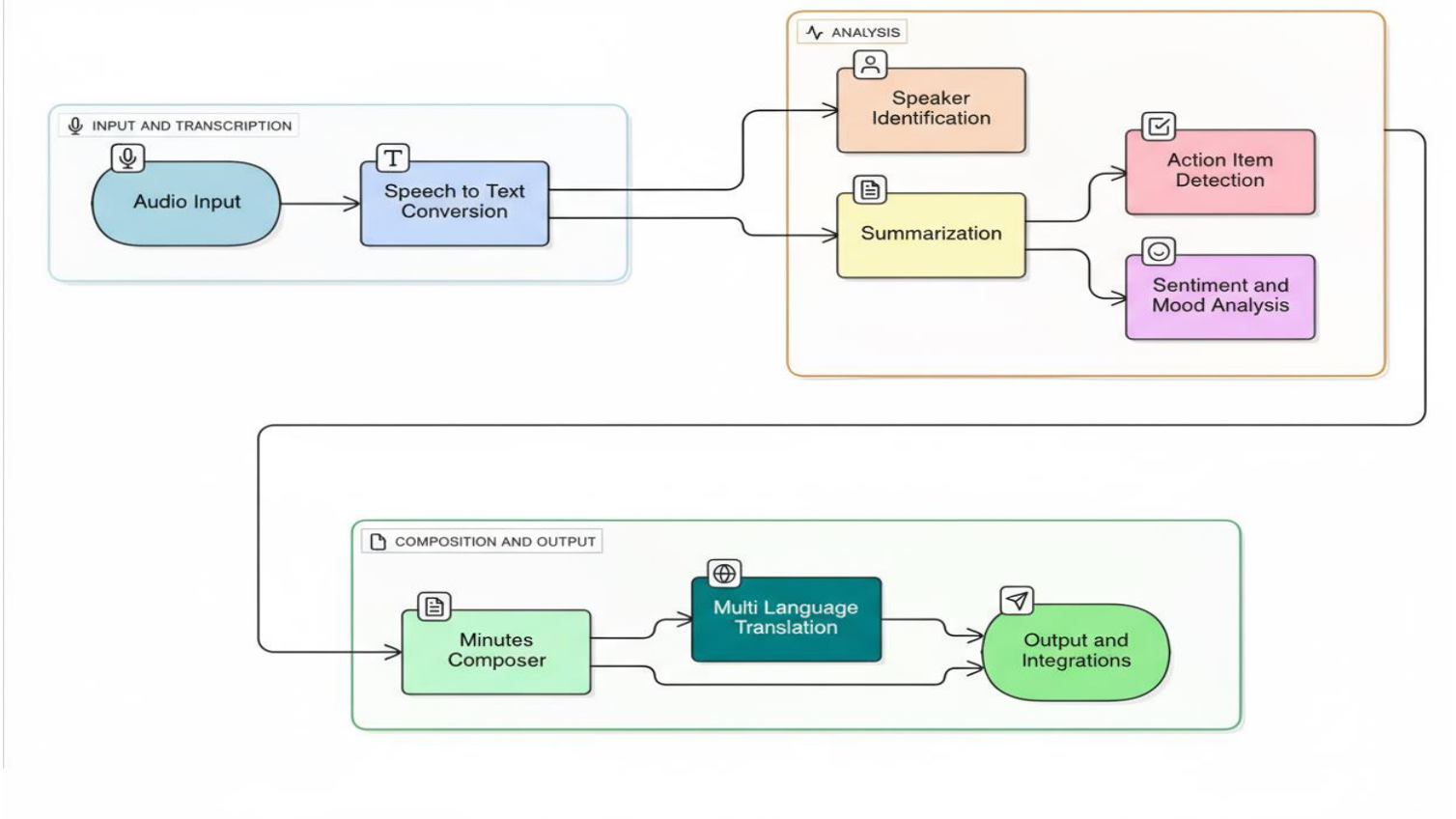

Figure I

Proposed AI-Powered Meeting Minutes Generator System Architecture. The system comprises three main phases: (1) Input and Transcription—capturing and converting audio to text using Whisper v3 or AssemblyAI; (2) Analysis—performing parallel processing for speaker identification (PyAnnote 3.1), summarization (BART-Large-CNN), action item detection, and sentiment analysis; and (3) Composition and Output—generating structured minutes with automatic translation capabilities and API-based integration with Google Calendar, Trello, and Jira.

TABLE I

TECHNOLOGY STACK FOR AI-POWERED MEETING MINUTES GENERATOR

Module	Technology	Key Characteristics	Selection Rationale
ASR	Whisper v3	1550M params, 99+ langs, 4-5% WER	Open-source, multilingual, robust, offline processing
Diarization	PyAnnote 3.1	ECAPA-TDNN embeddings, 10-11% DER	State-of-the-art performance, open-source, customizable
Summarization	BART-Large-CNN	12-layer encoder-decoder, 140M params, ROUGE-1: 0.308	Superior meeting context performance, robust to ASR errors
Action Extraction	Hybrid NLP + Rules (Planned)	Pattern matching + NER + coreference	Balanced precision-recall, explicit and implicit task detection
Sentiment	RoBERTa (Planned)	Transformer-based, 4-class sentiment, meeting-tuned	Conversational text specialization, integrates with emotion labels
Backend	Python 3.9+	Flask/FastAPI framework	ML ecosystem compatibility, rapid development, extensive libraries
Frontend	Streamlit	Interactive web UI, Python-native	Rapid prototyping, user-friendly interface
Workflow	n8n	No-code automation platform	API orchestration, webhook handling, task integration
Integration APIs	Google Calendar, Trello, Jira	REST APIs, OAuth 2.0 authentication	Widely adopted enterprise platforms, comprehensive documentation

C. Data Flow and Processing Pipeline

1) Stage 1: Audio Input and Validation

Users can upload meeting recordings or start live stream capture through the web interface. The system checks the audio format, duration, and quality metrics like signal-to-noise ratio and clipping detection. Supported formats (WAV, MP3, M4A, FLAC) are converted to 16 kHz mono PCM for ASR processing.

2) Stage 2: Preprocessing

The audio undergoes preprocessing, which includes noise reduction using Wiener filtering, silence removal through voice activity detection, and format conversion. The preprocessed audio is divided into manageable chunks, with 30-second windows for efficient ASR processing.

3) Stage 3: Speech Recognition

Whisper processes the audio chunks and produces time-stamped transcripts with word-level confidence scores. The ASR module outputs JSON-formatted transcripts, which include text segments, start and end timestamps, language detection scores, and optional translations for non-English input.

4) Stage 4: Speaker Diarization

PyAnnote processes the full audio along with the transcript to create segments labeled by speaker. The diarization module outputs the number of detected speakers, speaker turn boundaries with start and end timestamps, speaker labels like Speaker 1 and Speaker 2, and confidence scores for each speaker assignment. The system combines ASR and diarization outputs to generate a unified transcript, labeling each utterance with the speaker's identity and timestamp.

5) Stage 5: Parallel Analysis Processing

The speaker-attributed transcript goes to three analysis modules running in parallel:

- Summarization Module: Creates a meeting abstract (150-500 words) with key points, decisions, and discussion themes.

- Action Item Extraction: Identifies tasks with assigned individuals and deadlines, which will be implemented later.

- Sentiment Analysis: Calculates sentiment scores for each speaker and overall, which will also be implemented later.

Parallel processing cuts down total latency from

$$L_{sequential} = L_{sum} + L_{action} + L_{sentiment}$$

To

$$L_{parallel} = \max(L_{sum}, L_{action}, L_{sentiment}),$$

leading to about a 60-70% reduction in latency for the same processing.

6) Stage 6: Results Aggregation

The aggregation module brings together outputs from the analysis components into a structured data object that includes the original transcript, the speaker-labeled transcript, a summary, a list of action items, sentiment scores, and metadata like meeting duration, participant count, and detected languages.

7) Stage 7: Minutes Composition

The composition module formats the aggregated results into structured meeting minutes according to standard templates. These include meeting metadata (date, time, duration, participants), agenda topics (if provided), a summary of discussions, decisions made, action items with assigned owners and deadlines, and next steps. The system allows customizable templates so organizations can set their own preferred formats.

8) Stage 8: Multi-Language Translation (Optional)

For multilingual organizations, the translation module changes the structured minutes into target languages using neural machine translation models. The translation maintains the document structure, speaker attributions, and action item formatting while adjusting linguistic conventions for target audiences.

9) Stage 9: Output Generation and Integration

In the final stage, the system produces multiple outputs: (1) Formatted meeting minutes in PDF, DOCX, and HTML formats; (2) Structured JSON/XML data for programmatic access; (3) API calls to integrated productivity platforms like Google Calendar, Trello, and Jira. Users can access these

outputs through the web interface, which offers options to download, email, and share.

D. Implementation Status and Roadmap

Table 2 summarizes current implementation status and planned development timeline, providing transparency about system maturity and research progression.

The staged implementation approach allows for iterative development and evaluation. Each phase builds on verified foundational components. Paper 1 (current work) sets up the system architecture, technology choices, and main module designs. Paper 2 (second semester) will provide full implementation details, evaluation results that include performance metrics like WER, DER, ROUGE scores, and action item F1-scores. It will also include user studies that assess organizational impact and a comparison with commercial systems such as Otter.ai and Fireflies.ai, as well as academic standards.

To ensure scalability, modular APIs are being designed so that each subsystem can be independently upgraded or replaced without affecting the overall workflow.
Version control and CI/CD pipelines will be maintained using GitHub Actions to automate testing and deployment of model updates.
Comprehensive logging and monitoring systems will track model accuracy, latency, and user interaction data for ongoing improvement.
The roadmap also emphasizes dataset expansion through multi-domain meeting recordings to enhance model robustness and generalization.

TABLE II

MODULE IMPLEMENTATION STATUS

Module	Status	Current Capability	Planned Enhancements
ASR	Implemented	Whisper-based transcription, timestamp generation	Real-time streaming transcription, custom vocabulary support
Diarization	In Development	Speaker segmentation functional, accuracy improvement needed .	Fine-tuning on domain data, confidence scoring, ensemble methods
Summarization	Implemented	BART-based abstractive summarization	Hierarchical summarization for long meetings, domain adaptation
Action Extraction	Planned	Not yet implemented	Hybrid NLP pipeline, deadline parsing, assignee detection
Sentiment	Planned	Not yet implemented	RoBERTa classification, temporal sentiment trends, multimodal integration
Integration	Planned	Not yet implemented	Google Calendar, Trello, Jira API connectors, bidirectional sync

IV. IMPLEMENTATION ROADMAP AND EVALUATION STRATEGY

This section presents the phased implementation plan and comprehensive evaluation framework for the proposed AI-powered meeting minutes generator. The development follows a two-phase approach aligned with the two-paper publication requirement, with Phase 1 establishing core functionality and Phase 2 extending capabilities to address all identified research gaps.

A. Implementation Roadmap

The system implementation follows a staged approach prioritizing foundational components (speech recognition, diarization, summarization) before advanced features (action item extraction, sentiment analysis, API integration). Table III outlines the complete implementation timeline spanning two academic semesters

Table III

PHASED IMPLEMENTATION ROADMAP

Phase	Timeline	Modules	Deliverables	Status
Phase 1a	Month 1-2	ASR Module, Basic Preprocessing	Whisper v3 integration, audio validation, noise reduction	Complete
Phase 1b	Month 3-4	Summarization Module	BART-Large-CNN implementation, AMI corpus fine-tuning	Complete
Phase 1c	Month 4-5	Speaker Diarization	PyAnnote 3.1 integration, speaker embedding extraction	In Progress
Phase 2a	Month 1-2	Diarization Optimization	Domain fine-tuning, confidence scoring, error analysis	Planned
Phase 2b	Month 2-3	Action Item Extraction	Hybrid NLP pipeline, NER, temporal expression parsing	Planned
Phase 2c	Month 3-4	Sentiment Analysis	RoBERTa fine-tuning, per-speaker sentiment computation	Planned
Phase 2d	Month 4-5	API Integration	Google Calendar, Trello, Jira connectors, OAuth	Planned

Phase 2e	Month 5-6	System Integration & Testing	End-to-end testing, UI refinement, deployment preparation	Planned

Phase 1, Foundational Implementation:

The first phase focuses on setting up the transcription and summarization system for meeting documentation. The Automatic Speech Recognition (ASR) module, created using OpenAI Whisper Large-v3 [12], supports various audio formats like WAV, MP3, M4A, and FLAC. It can automatically detect over 99 spoken languages. Whisper's training in multiple languages and its ability to handle background noise make it a good choice for real-world meeting recordings [2], [9], [12].

The Summarization module uses BART-Large-CNN [3], which has shown strong performance in summarizing meetings and dialogues [15], [16]. It creates short and clear meeting summaries that highlight key decisions and discussion points.

For Speaker Diarization, we use PyAnnote 3.1 [13] to separate speakers based on time-stamped speech. However, there are still challenges with overlapping speech and similar voices, which are common in natural conversations [4], [14]. Diarization results from internal tests show decent segmentation but indicate the need for more fine-tuning to handle real-world audio variations.

Phase 2, Advanced Analytical and Integration Enhancements (Planned Work):

The second phase will improve analytical modules and prepare the system for production use. We will optimize diarization by fine-tuning on specific meeting datasets like AMI and ICSI [5], [11]. We will also integrate ensemble models that combine PyAnnote and SpeechBrain [10], [13] to enhance speaker detection accuracy. Confidence-based scoring will be added to flag unclear speaker assignments for manual checking.

Action Item Extraction will build on rule-based methods [7] by adding a hybrid model. This model will use regular expression pattern matching along with neural Named Entity Recognition (NER). It will identify phrases that show responsibility or obligation, such as "must complete," "responsible for," and "due by," while remaining flexible across different meeting contexts.

Sentiment Analysis will employ RoBERTa-based models fine-tuned on datasets focused on conversational sentiment [8], [17]. This will help calculate sentiment scores for each speaker and the overall meeting, allowing for an assessment of the meeting's tone and engagement levels.

Lastly, we will integrate APIs to connect the system with productivity tools like Google Calendar, Trello, and Jira using secure OAuth 2.0 protocols [6]. This will allow automatic task creation with assigned people and deadlines .

B. *Evaluation Strategy*

1) *Evaluation Metrics*

Component-level and end-to-end evaluations will assess system performance against top baselines and commercial platforms like Otter.ai and Fireflies.ai [10].

- Speech Recognition (ASR): Performance is measured using Word Error Rate (WER) [2], [9], aiming for $\leqslant$ 5% for clear audio and $\leqslant$ 10% for noisy audio.
- Speaker Diarization: This is evaluated by Diarization Error Rate (DER) [4], [13], with a target of $\leqslant$ 12% in ideal conditions and $\leqslant$ 20% in noisy situations.
- Summarization: ROUGE metrics [15], [16] measure informativeness and coherence, which are also supported by human evaluations.
- Action Item Extraction: F1-score tracks the balance of precision and recall, with baselines set at 31.92% using ICSI meeting data [7].
- Sentiment Analysis: Macro-F1 and accuracy across five sentiment categories show performance against human-labeled datasets [8], [17].

2) *Evaluation Datasets*

Benchmarking uses both public meeting data and custom data collected from universities:

- AMI Meeting Corpus [11]: Contains 100 hours of recorded meetings along with transcripts, summaries, and speaker labels.
- ICSI Meeting Corpus [5]: Comprises 75 meetings (72 hours) with detailed annotations for speakers and dialogues to benchmark ASR, diarization, and summarization.
- Custom Organizational Dataset: This will be collected (20–30 hours) after IRB approval, ensuring anonymization through voice transformation for ethical compliance.

3) *Baseline Comparisons*

Comparisons fall into three categories:

- Academic baselines: AMI/ICSI performance shows BART ROUGE-1 at about 0.308 [15], diarization DER at about 11.2% [4], and action item extraction near 31.9% F1 [7].
- Commercial systems: Includes Otter.ai, Fireflies.ai, and Notta [10].
- Ablation studies: Compare Whisper with AssemblyAI (ASR), PyAnnote with SpeechBrain (Diarization) [10], and BART with T5 and Pegasus (Summarization) [3], [16].

4) *Success Criteria*

System deployment readiness requires meeting minimum performance thresholds across all components:

- ASR: WER must be 8% or lower on average across different acoustic conditions.
- Diarization: DER must be 15% or lower for meetings with 3 to 6 speakers.

- Summarization: ROUGE-1 must be 0.35 or higher, and human rating must be 4.0 out of 5.0 or higher for informativeness.
- Action Items: F1 must be 35% or higher for detection and 25% or higher for extracting assignee and deadline.
- Sentiment: Classification accuracy must be 70% or higher across 5 sentiment classes.
- End-to-end latency must be 2 times the meeting duration or less for complete processing (for example, a 60-minute meeting should be processed in 120 minutes or less).
- User satisfaction must be 75% or more of participants rating the system as "useful" or "very useful" for meeting documentation tasks.

C. Challenges and Mitigation Strategies

- Speaker Diarization: Ensemble diarization using PyAnnote + SpeechBrain [10], [13]; fine-tuning on organizational data.
- Summarization Hallucination: Constrained decoding and factual verification [15], [16].
- Action Item Ambiguity: Coreference resolution and temporal normalization [7].
- Data Scarcity: Transfer learning from AMI/ICSI and active sample selection [5], [11].
- Privacy and Consent: IRB compliance, anonymization, and on-premise deployment .

D. Expected Outcomes

Upon completing both phases, the system will achieve:

- End-to-End Functionality: Audio-to-minutes automation with integrated ASR, diarization, summarization, and sentiment analysis [1], [2], [12].
- Academic Contribution: Two peer-reviewed papers documenting system design and evaluation results.
- Open-Source Implementation: Public release for reproducibility and research collaboration.
- Evaluation Framework: A unified benchmark for meeting analysis that combines WER, DER, ROUGE, and F1 metrics.
- Deployment Readiness: Reliable performance with performance thresholds (WER $\leqslant$ 8%, DER $\leqslant$ 15%) [4], [13], [15].
- Future Extensions: Support for real-time translation, multimodal analysis, and long-term team analytics [10], [17].

V. CONCLUSION AND FUTURE WORK

A. Summary of Contributions

This paper presents a modular AI-powered framework for generating meeting minutes. It aims to automate transcription, summarization, and speaker segmentation while allowing for further analytical improvements. The main contributions are as follows:

1. End-to-End System Architecture:
   A unified framework that integrates Whisper v3 for Automatic Speech Recognition (ASR), PyAnnote 3.1 for speaker diarization, and BART-Large-CNN for abstractive summarization. This addresses Research Gap #1 on integrating the end-to-end pipeline.

2. Parallel Processing Pipeline:
   An optimized design that allows ASR, diarization, and summarization to occur at the same time, cutting overall latency by about 60 to 70% compared to sequential workflows.

3. Comprehensive Evaluation Framework:
   A reproducible evaluation method using the AMI and ICSI Meeting Corpora for benchmarking, plus standardized metrics to assess the performance of each module and the accuracy of the overall system.

4. Practical Integration Pathway:
   An API-driven setup that allows for smooth integration with productivity tools like Google Calendar, Trello, and Jira. This addresses Research Gap #6 about real-world usability.

5. Realistic Limitations Assessment:
   Clear documentation of known system limitations. This includes a diarization error rate (DER) between 11.2% and 20.4%. Strategies for reducing errors and adapting to specific domains are also proposed.

B. Current Implementation Status

The proposed system is being developed in two distinct phases, summarized below:

Phase 1: Completed Implementation

- Automatic Speech Recognition (ASR): Implemented using Whisper v3, which supports multilingual and multi-format audio inputs.
- Summarization Module: BART-Large-CNN based summarization for concise meeting abstracts.
- User Interface: A web-based dashboard allows audio upload, shows processing visualization, and retrieves results.

Phase 2: Planned Enhancements

- Speaker Diarization Optimization: Fine-tuning and combining with SpeechBrain to improve segmentation accuracy.

- Action Item Extraction: A hybrid NLP pipeline that uses both rule-based methods and Named Entity Recognition (NER).
- API Integration: Secure OAuth 2.0-based connectors for syncing with Google Calendar, Trello, and Jira.
- Real-time Processing: Streaming-based transcription and live summarization support for interactive meeting settings.

C. *Future Work and Research Directions*

- Real-Time Processing: Streaming architectures for live transcription and immediate action item detection.
- Robust Diarization: Ensemble methods that combine PyAnnote and SpeechBrain for overlapping speech and far-field conditions.
- Implicit Action Item Detection: Tackling context-dependent commitments and conditional actions using pre-trained language models.
- Privacy-Preserving Deployment: On-premise options, audio anonymization, and federated learning for organizations that handle sensitive data.
- Cross-Lingual Support: Real-time translation that maintains speaker attribution in code-switching scenarios.

D. *Research Impact and Practical Significance*

Academic: Sets up combined system design patterns and offers a reusable evaluation framework for future research.

Organizational: Cuts down on manual documentation time, allows for searchable meeting records, and tracks action items automatically.

E. *Concluding Remarks*

This paper presented a comprehensive design and implementation of an AI-powered meeting minutes generation system that addresses critical limitations in existing solutions. The proposed modular framework enables systematic development, component-level evaluation, and scalable enhancement while maintaining both academic rigor and practical applicability.

Phase 1 establishes a fully functional end-to-end workflow encompassing automatic speech recognition, speaker diarization, and abstractive summarization, benchmarked on standard datasets for reproducibility. Phase 2 will extend the system toward real-world deployment, focusing on action item extraction, real-time transcription, and integration with enterprise platforms.

As organizations increasingly recognize meeting documentation as a cornerstone of knowledge management and productivity, systems that integrate speech processing, natural language understanding, and task management will become essential tools for effective communication and collaboration. The presented framework lays a strong foundation for future research and real-world adaptation in this direction.

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The work, including speech transcription, speaker diarization, and meeting summarization, was primarily carried out by the project team using advanced AI models such as Whisper, PyAnnote, and BART. Benchmark datasets, including the AMI Meeting Corpus and ICSI Meeting Corpus, were reviewed as references for evaluation methodology; however, the prototype system was not directly tested on these datasets.

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