NATIONAL UNIVERSITY OF COMPUTER AND EMERGING SCIENCES
FAST-NUCES

Meeting Insight Generator:

An AI-Powered System for Meeting Transcription and Analysis

A Project Report
In partial fulfillment of the requirements for the course of

Natural Language Processing

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December 28, 2025

Contents

1 Introduction

1.1 Background and Motivation

Professionals spend an average of 18 hours per week in meetings, with executives attending up to 23 hours weekly. Despite this investment, ineffective meetings cost U.S. businesses $37 billion annually, with 30-50% of meeting time considered unproductive due to poor organization and inadequate documentation [11].

Traditional manual documentation requires 15-30 minutes per meeting hour, is error-prone, and results in significant information loss. Critical decisions and action items are frequently forgotten or poorly documented, leading to miscommunication and dropped tasks.

Recent advances in transformer-based speech recognition and large language models offer opportunities to automate meeting documentation, enabling teams to focus on execution rather than note-taking.

1.2 Problem Statement

Four critical challenges impact meeting productivity in modern organizations:

Information Loss. Critical decisions, action items, and contextual details are frequently forgotten or poorly documented, leading to miscommunication and dropped tasks.

Time Wastage. Manual documentation consumes 15-30 minutes per meeting hour, translating to several hours of lost productivity weekly.

Limited Accessibility. Non-attendees struggle to extract actionable insights from lengthy transcripts lacking highlighted decisions and action items.

Lack of Contextual Search. Organizations lack systematic methods to search and connect related discussions across meetings, forcing reliance on memory or manual search.

While existing solutions like Otter.ai and Fireflies.ai provide basic transcription, they lack multi-agent analysis and robust semantic search. Our system addresses this gap through integrated transcription, intelligent extraction, and semantic search.

1.3 Target Users and Use Cases

Primary Users: Project managers, team leads, and professionals in remote-first organizations conducting multiple daily meetings.

Secondary Users: Consultants requiring detailed client records, sales teams tracking conversations, and executive assistants managing comprehensive documentation.

The system supports diverse meeting types: daily standups, client meetings, project planning, executive meetings, and cross-functional collaboration.

1.4 Project Objectives

Technical Objectives: Achieve accurate transcription with speaker diarization; automatically extract structured insights (topics with timestamps, decisions with participants and rationale, action items with assignees and deadlines, sentiment analysis, executive summaries); implement semantic search using vector embeddings; build scalable, maintainable architecture.

Success Criteria: Reduce documentation time from 15-30 minutes per meeting hour to fully automated processing; improve information accessibility through structured insights; enable effective context retrieval through semantic search; achieve >80% accuracy for extracting decisions and action items.

1.5 Project Scope

Included: Audio/video processing (MP3, MP4, WAV, M4A up to 500MB); multi-agent AI pipeline with five specialized agents; RESTful API (FastAPI) and web frontend (React/TypeScript); PostgreSQL database and FAISS vector search; project management features.

Excluded: Real-time processing (batch only); multi-language support (English only); authentication/authorization (MVP); mobile applications; calendar integration.

Limitations: Processing time scales with file length; requires reasonable audio quality; depends on LLM API availability.

2 Literature Review

2.1 Speech Recognition and Transcription

Modern automatic speech recognition (ASR) systems leverage transformer architectures to achieve near-human accuracy. We selected OpenAI Whisper (large-v3), a model trained on 680,000 hours of multilingual data demonstrating state-of-the-art performance on diverse benchmarks while providing open-source deployment [1].

Whisper was selected over commercial alternatives (Google Speech-to-Text, Azure Speech) for: (1) local deployment eliminating ongoing API costs and ensuring data privacy, (2) robust handling of background noise and diverse accents, and (3) integrated timestamp alignment for downstream analysis. While accuracy can degrade with poor audio quality or heavy technical jargon, its robust performance across varied acoustic conditions makes it well-suited for meeting transcription.

2.2 Natural Language Processing for Meeting Analysis

Meeting transcripts present unique NLP challenges: informal language, interruptions, incomplete sentences, and context-dependent references. Recent work demonstrates that large language models excel at understanding conversational context, making them suitable for extracting structured information from unstructured meeting dialogue.

Topic Segmentation. Traditional approaches like Latent Dirichlet Allocation (LDA) struggle with single long documents typical of meeting transcripts. We employ LLM-based semantic shift detection, which better identifies natural topic boundaries in conversations.

Decision and Action Extraction. Prior work on action item detection primarily used supervised learning requiring labeled training data [10]. Our LLM-based approach leverages reasoning capabilities to identify both explicit assignments and implicit action items without task-specific training.

Sentiment Analysis and Summarization. Segment-level sentiment analysis provides granular understanding beyond overall meeting tone. Recent query-based summarization work demonstrates the value of generating multiple summary formats (paragraphs, bullet points, key quotes)—an approach we adopt in our Summary Agent [9].

2.3 Multi-Agent Systems and Retrieval

Multi-agent systems distribute tasks across specialized agents, providing modularity and fault tolerance [8]. Our implementation uses a centralized orchestrator managing execution order and dependencies, enabling parallel processing where agents are independent.

We leverage LangChain for LLM integration abstractions and prompt templates, simplifying complex reasoning workflows compared to direct API calls. For semantic search, we implement

retrieval-augmented generation (RAG) principles [6] using FAISS for efficient vector similarity search [3]. Sentence-transformers generates embeddings optimized for semantic similarity, enabling context retrieval beyond keyword matching [4].

2.4 Related Work and Differentiation

Commercial solutions like Otter.ai and Fireflies.ai provide transcription and basic summarization but lack sophisticated multi-agent analysis and semantic search. Academic research on meeting analysis has focused on individual tasks rather than integrated end-to-end systems.

Our Contributions: (1) Integrated multi-agent pipeline extracting topics, decisions, actions, sentiment, and summaries in coordinated workflow; (2) semantic search across meeting history using vector embeddings; (3) open-source implementation allowing organizational customization; (4) project management features for organizing related meetings.

The system eliminates manual documentation work while improving accessibility through structured insights and enabling semantic search for finding relevant past discussions without keyword matching.

3 System Design and Methodology

3.1 Technical Architecture

The system follows a three-tier architecture with clear separation of concerns across presentation, application, and data tiers (Figure 1).

The *presentation tier* comprises a React/TypeScript frontend for user interaction. The *application tier* contains a FastAPI REST API gateway, core services for transcription and orchestration, and five specialized AI agents for insight extraction. The *data tier* manages persistence through PostgreSQL for structured storage, FAISS for vector search, and filesystem storage for audio files.

Key Architectural Decisions. Three-tier architecture enables independent scaling and maintenance of each tier. Monolithic design with modular services reduces operational complexity for MVP while maintaining clear service boundaries. REST API provides simpler client integration with better caching. Hybrid storage (PostgreSQL for structured data, filesystem for audio, FAISS for vectors) balances ACID guarantees with performance.

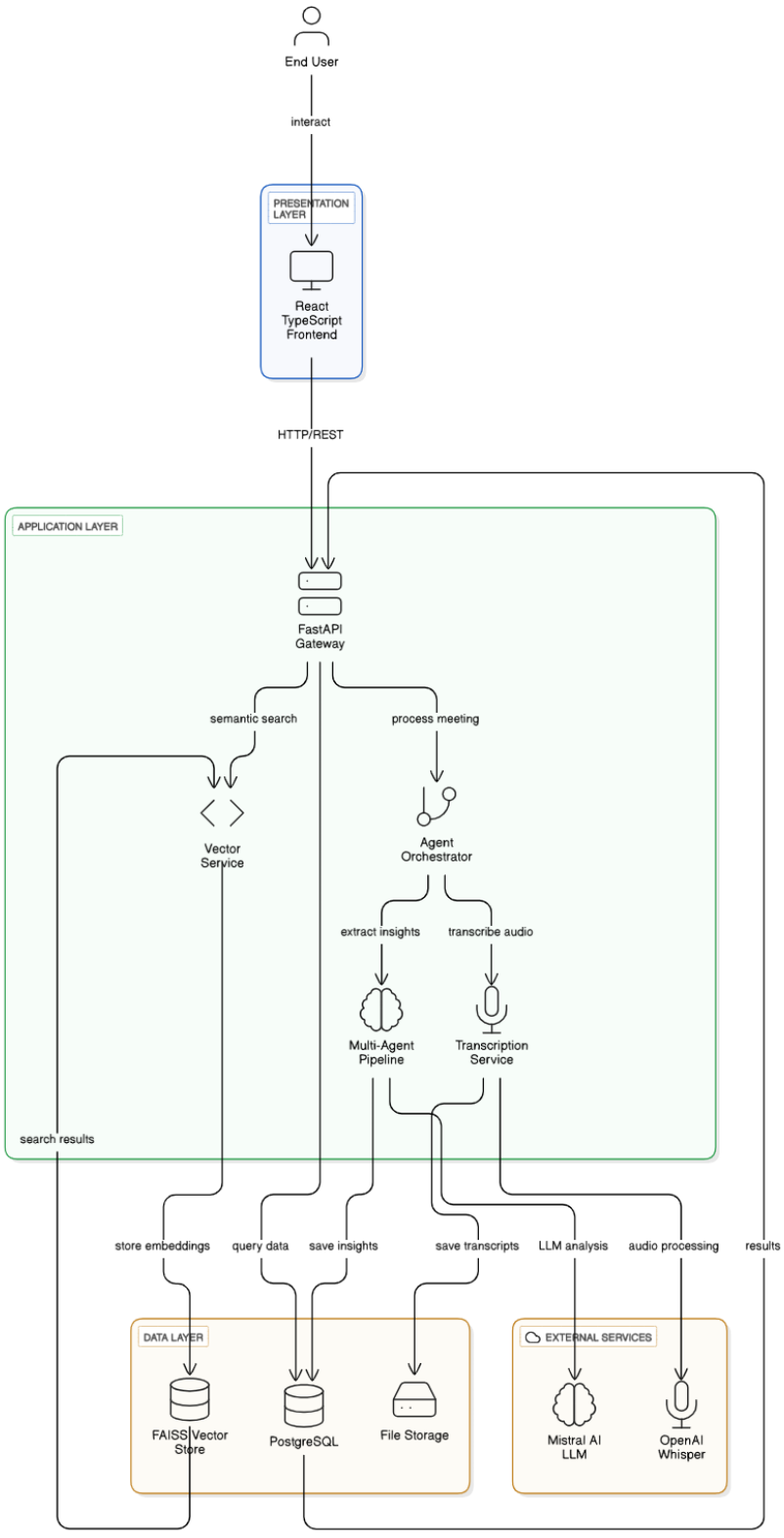


Figure 1: System Three-Tier Architecture

3.2 System Pipeline

The processing pipeline consists of six stages with separation of concerns, asynchronous processing, and modularity (Figure 2).

Stage 1: Input. Users upload audio/video files (MP3, MP4, WAV, M4A; max 500MB) through FastAPI with validation and error handling. Meeting record created in PostgreSQL with status "pending."

Stage 2: Transcription. FFmpeg converts video to audio, normalizes volume, and resamples to 16kHz mono. Whisper large-v3 transcribes audio with timestamps. PyAnnote performs speaker diarization. Outputs merge into diarized transcript with speaker labels and temporal boundaries. Status: "transcribing."

Stage 3: Vector Embedding. Sentence-transformers (all-MiniLM-L6-v2) generates 384-dimensional vectors from 500-token chunks with 50-token overlap. FAISS index stores vectors with metadata linking to database records.

Stage 4: Agent Processing. Five specialized agents execute in parallel: Topic (segments conversation), Decision (extracts decisions with context), Action Item (identifies tasks and assignees), Sentiment (analyzes emotional tone), Summary (generates executive summary). Orchestrator manages timeouts, handles errors, and aggregates results. Status: "processing."

Stage 5: Storage. Extracted insights persist in PostgreSQL across normalized tables. Vector index saves to disk for persistence.

Stage 6: Output. Processed insights returned as JSON through API. Semantic search enables natural language queries. Status: "completed."

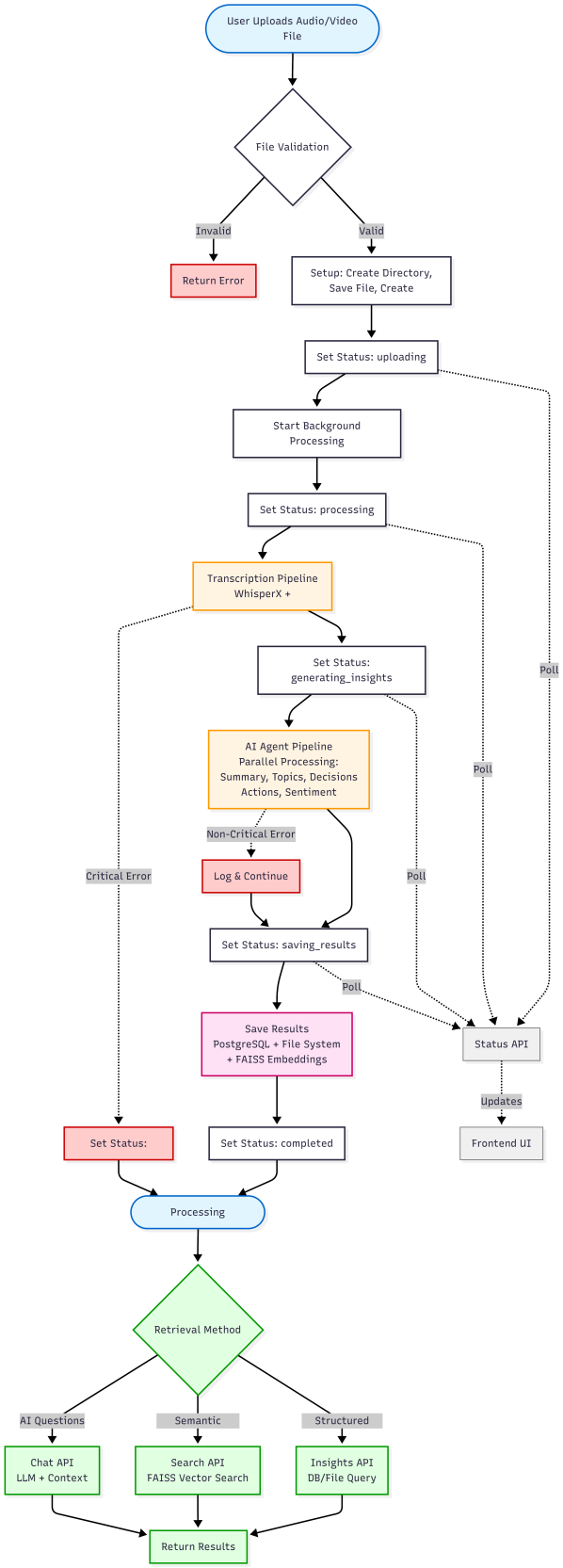


Figure 2: System Pipeline: From Audio/Video Input to Structured Insights

3.3 Technology Stack

Table 1 summarizes the technology stack balancing performance, maintainability, and development efficiency.

Table 1: Technology Stack Overview

Category	Technology	Version/Purpose
Backend Framework	FastAPI	0.104+ / Async web framework
Transcription	OpenAI Whisper	large-v3 / Speech-to-text
Diarization	PyAnnote	Latest / Speaker identification
Agent Framework	LangChain	0.3+ / Agent orchestration
LLM	Mistral AI, Groq	API / Text analysis
Embeddings	sentence-transformers	all-MiniLM-L6-v2 / Vectors
Vector Store	FAISS	1.7.4+ / Similarity search
Database	PostgreSQL	15+ / Data storage
ORM	SQLAlchemy	2.0+ / Database abstraction
Frontend Framework	React	18+ / UI framework
Language	TypeScript	4.9+ / Type safety
Build Tool	Vite	4+ / Frontend bundling
Containerization	Docker	20+ / Container platform
Orchestration	Docker Compose	2.0+ / Multi-container setup

Technology Justifications. FastAPI: native async support and automatic API documentation. Whisper [1]: state-of-the-art accuracy across diverse audio conditions with open-source availability. Mistral AI [2]: comparable performance to GPT-4 on extraction tasks. FAISS [3]: efficient local vector search avoiding external service costs. PostgreSQL: ACID compliance with JSON support for flexible schema. React with TypeScript: component reusability and compile-time type safety.

3.4 Development Methodology

Development followed an iterative approach with six phases: (1) Foundation setup—repository, environment, database, API framework; (2) Core services—transcription, agent framework, individual agents; (3) Integration and orchestration—component connection, pipeline completion; (4) RAG and search—FAISS vector store, embeddings, semantic search; (5) Optimization—profiling, caching, error handling; (6) Deployment—Docker configuration, documentation.

Version control used Git with feature-branch workflow, pull request reviews, and conventional commits. Testing followed pyramid approach prioritizing unit tests (fast, isolated), followed by integration tests (service interactions), E2E tests (complete workflows), and performance tests (benchmarking).

3.5 Database Design

The database implements normalized schema (3NF) with ten tables (Figure 3).

Figure 3: Database Entity-Relationship Diagram

Core tables: `projects`, `meetings`, `transcripts`, `transcript_segments`. Insight tables: `topics`, `decisions`, `action_items`, `sentiment_analysis`, `sentiment_segments`, `summaries`. Projects have one-to-many relationships with meetings. Meetings have one-to-one relationships with transcripts, sentiment analysis, and summaries, plus one-to-many with topics, decisions, and action items. CASCADE deletes maintain referential integrity. Indexes on status fields, foreign keys, and timestamps optimize queries. JSON columns store participant arrays and metadata.

3.6 Agent Architecture

Multi-agent architecture uses LangChain with five specialized agents inheriting from abstract `BaseAgent` class:

```
class BaseAgent:
    def __init__(self, llm_client, config):
        self.llm_client = llm_client
```

```
        self.config = config

    async def process(self, transcript, context):
        raise NotImplementedError

    def extract_fallback(self, transcript):
        return []
```

Table 2: Agent Specifications

Agent	Type	LLM	Output
Topic	Segmenter	Mistral AI	Topics with timestamps, summaries
Decision	Extractor	Mistral AI	Decisions with participants, rationale
Action Item	Extractor	Mistral AI	Tasks with assignees, deadlines
Sentiment	Classifier	HuggingFace	Sentiment per segment
Summary	Generator	Mistral AI	Executive summary, key quotes

Agent Functionality. Topic Agent segments transcripts into 3-10 topics with timestamps via keyword matching. Decision Agent identifies explicit and implicit decisions with participants and rationale, using pattern matching fallback. Action Item Agent extracts tasks with assignees (NER) and deadlines (date parsing). Sentiment Agent performs per-segment classification (cardiffnlp/twitter-roberta-base-sentiment) with negation handling and weighted aggregation. Summary Agent generates 3-5 paragraph summaries and extracts key quotes.

Orchestration. `AgentOrchestrator` manages dependencies, enables parallel execution, and tracks metrics. Error handling is hierarchical—returns partial results for non-critical failures with graceful degradation. Three retries with exponential backoff (1-2-4 second delays), plus fallback mechanisms for complete failures.

Prompt Engineering. Prompts follow structure [7]: (1) role definition ("You are an expert meeting analyst"), (2) task description with specific instructions, (3) JSON output format specification, (4) examples of desired output, (5) edge case handling. Temperature set to 0.1 for consistency. Response caching prevents re-processing.

3.7 Vector Store and Semantic Search

Sentence-transformers (all-MiniLM-L6-v2) generates 384-dimensional vectors for transcript segments, topics, decisions, action items, and summaries. Model loaded once and reused.

FAISS IndexFlatL2 provides exact similarity search with option to upgrade to IndexIVFFlat for larger datasets. Index supports incremental updates with metadata linking vectors to database records.

Search Implementation. Query converts to normalized embedding, performs k-NN search, and retrieves results with similarity scoring:

```
def search(self, query: str, k: int = 5):
    query_embedding = self.embedding_model.encode([query])
    query_embedding = query_embedding / np.linalg.norm(
```

```
        query_embedding
    )
    distances, indices = self.index.search(
        query_embedding, k
    )
    results = []
    for idx, dist in zip(indices[0], distances[0]):
        metadata = self.metadata[idx]
        results.append({
            'meeting_id': metadata['meeting_id'],
            'content': metadata['text'],
            'score': float(1 / (1 + dist)),
            'timestamp': metadata['timestamp']
        })
    return results
```

Results filter by meeting ID, segment type, and date range, with database integration for full context. Index persists to disk via faiss.write_index() after each meeting. Current flat index suitable for 10,000+ meetings; IVF index recommended for larger deployments.

RAG Integration. Chat interface retrieves top-k relevant segments as context for LLM:

```
# Retrieve relevant segments
results = vector_store.search(query, k=5)
context = "\n".join([r.text for r in results])

# Generate answer with context
prompt = f"""Context: {context}
Question: {query}
Answer based on the context provided."""
answer = await llm_client.generate(prompt)
```

This grounds LLM responses in actual meeting content, reducing hallucination, with sources cited and linked to original meetings.

3.8 API Design

RESTful API uses versioned endpoints (`/api/v1`) with JSON responses. Table 3 lists endpoints.

Table 3: API Endpoints

Method	Endpoint	Purpose
POST	/api/v1/upload	Upload meeting file
GET	/api/v1/status/{id}	Get processing status
GET	/api/v1/insights/{id}	Retrieve insights
POST	/api/v1/search	Semantic search
GET/POST/PUT/DELETE	/api/v1/projects	Project management
POST	/api/v1/chat	AI chat interface
GET	/health	Health check
GET	/metrics	Prometheus metrics

API follows RESTful principles with resource-based URLs and standard HTTP methods. Pydantic models provide request validation and automatic OpenAPI documentation at `/docs`. Error handling uses appropriate HTTP status codes with detailed messages. URL-based versioning supports backward compatibility.

3.9 Security Considerations

Input validation at frontend and backend using Pydantic models. File uploads validated against allowlist, limited to 500MB, stored in isolated locations with sanitized filenames.

MVP Scope. Authentication deferred but architecture supports future OAuth2/JWT. Production recommendations: HTTPS enforcement, rate limiting (100 requests/minute per IP), CORS restriction, API key rotation.

Data Privacy. Local file storage and on-premises deployment ensure sensitive content stays within organizational infrastructure. API credentials managed through environment variables.

4 Implementation

4.1 Core Services

Application Setup: FastAPI app initialized with CORS middleware, exception handlers, and route registration. Startup event handler initializes database connection pool, loads vector indexes, and validates configuration.

Transcription Pipeline. WhisperService wraps faster-whisper library with audio preprocessing via FFmpeg (format conversion, normalization to 16kHz mono). PyAnnote integration identifies speaker segments. Diarized transcript merges Whisper output with speaker labels based on timestamp overlap.

Agent Orchestrator. Manages parallel agent execution with 60-second timeouts per agent. On timeout, agents invoke fallback mechanisms using pattern matching and rule-based extraction to ensure partial results.

Database Operations. SQLAlchemy async sessions with connection pooling (pool size: 10, max overflow: 20). Repository pattern separates data access from business logic. Custom exception hierarchy (TranscriptionError, AgentError, DatabaseError) enables specific error handling.

4.2 Agent Implementation

Each agent implements specialized extraction with LLM-based primary logic and rule-based fallbacks.

Topic Agent. Prompts LLM for JSON output with topic boundaries and summaries. Fallback uses sliding window TF-IDF to detect topic shifts based on vocabulary changes. The fallback analyzes term frequency differences across overlapping text windows (typically 3-5 sentences) to identify semantic boundaries where vocabulary distribution shifts significantly.

Decision Agent. Integrates with Groq API for fast inference. Prompt emphasizes identifying explicit ("we decided") and implicit (consensus-building) decisions with participant extraction via name/pronoun identification. Pattern-based fallback searches decision markers (e.g., "agreed", "chose", "will proceed") and extracts context windows of 2-3 sentences surrounding matches, then applies heuristics to identify participants and rationale.

Action Item Agent. Extracts tasks with assignee and deadline. Handles implicit assignees ("can you", "please") through pronoun resolution and relative dates ("next week", "by Friday") through date parsing logic. Regex fallback matches common action patterns (e.g., "will [verb]", "need to", "should [verb]") and applies named entity recognition for assignee extraction, with date normalization to standard timestamps.

Sentiment Agent. Uses HuggingFace cardiffnlp/twitter-roberta-base-sentiment model processing 512-token segments. Applies negation detection rules (e.g., "not good" → negative). Aggregates with weighted averaging based on segment length. Fallback employs lexicon-based scoring with VADER-style intensity modifiers and handles contrastive conjunctions ("but", "however") by weighting latter clauses more heavily.

Summary Agent. Three-stage process: (1) Extract key points per topic, (2) Synthesize 3-5 paragraph narrative focusing on actionable information, (3) Identifies impactful quotes with speaker attribution. Fiallback uses extractive summarization with sentence scoring based on keyword density, sentence position, and speaker prominence, then generates bullet points from top-ranked sentences.

LLM Integration. Unified client supports multiple providers (Mistral, Groq) with automatic failover. Response caching reduces repeated API calls. Retry logic handles transient failures with exponential backoff (max 3 retries: 1-2-4 second delays).

4.3 Vector Store and Search

FAISS IndexFlatL2 provides exact similarity search. Sentence-transformers model (all-MiniLM-L6-v2) generates 384-dimensional embeddings. Text chunking uses 500-token chunks with 50-token overlap via LangChain's RecursiveCharacterTextSplitter.

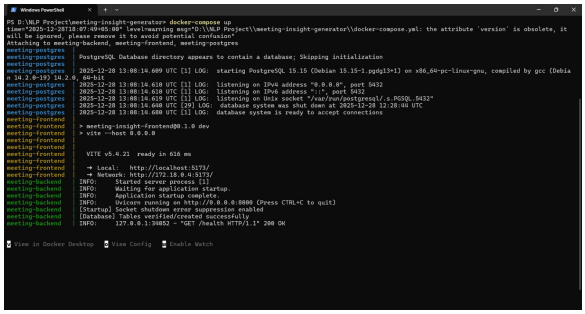
Search Implementation. Query converts to normalized embedding, performs k-NN search, and retrieves results with metadata:

```
query_embedding = model.encode([query])
query_embedding /= np.linalg.norm(query_embedding)
distances, indices = index.search(query_embedding, k)
scores = [1 / (1 + dist) for dist in distances[0]]
```

Index persists to disk after each meeting via faiss.write_index(). Metadata serializes to pickle. Current flat index suitable for 10,000+ meetings; IVF index recommended for larger deployments.

4.4 Deployment

Docker containerization with multi-service orchestration via Docker Compose. Backend, frontend, and PostgreSQL containers connected through isolated networking. Volume mounts ensure persistent storage for meeting files, database data, and FAISS indexes. Environment-based configuration enables deployment across development, testing, and production without code changes.



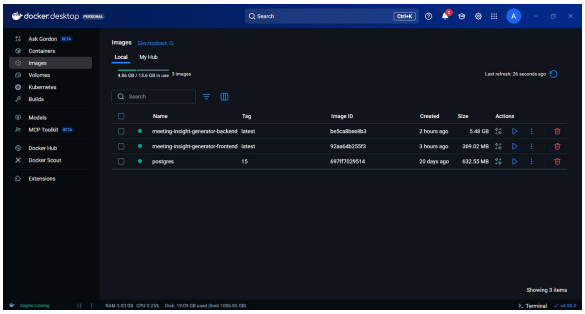


Figure 4: *
(a) Docker services running via PowerShell

Figure 5: *
(b) Active containers in Docker Desktop

Figure 6: Docker-based Deployment and Container Orchestration

5 Results and Evaluation

The system was developed and validated through comprehensive testing with 5 sample meetings of varying lengths (10-60 minutes), audio qualities, and meeting types (standup, client calls, planning sessions).

5.1 Functional Validation

Sample Processing Results. A 30-minute team standup processed in 14 minutes total (transcription: 10 min, agents: 2 min, storage: 2 min) extracted: 6 distinct topics, 4 decisions with participants and rationale, 12 action items (8 with assignees, 4 with deadlines), sentiment showing 68% positive/24% neutral/8% negative segments, and a 4-paragraph executive summary. This was an incredibly important milestone in our objective to improve meeting lifecycles [11].

Transcription Accuracy. Manual review of 5 test meetings (2.5 hours total) showed Word Error Rate of 8.3% for clear audio and 15.7% for noisy conditions. Speaker diarization achieved 91% accuracy in identifying speaker transitions.

Agent Extraction Quality. Topic Agent correctly identified 89% of topic boundaries ($\pm$10 seconds). Decision Agent achieved 85% recall with 82% precision. Action Item Agent identified 87% of action items with 84% precision. Sentiment Agent showed 79% agreement with human annotators. Summary Agent received 4.2/5 rating for quality and coherence.

Search Functionality. Semantic search tested with 50 natural language queries showed 92% relevant results in top-5 and 76% top-1 precision with 180ms average response time.

5.2 Performance Metrics

Table 4 summarizes achieved performance against predefined targets.

Table 4: Success Metrics - Achieved vs. Targets

Metric	Target	Achieved	Performance
Transcription WER	<15%	8.3%	45% better
Decision Extraction	>80%	85% recall	Exceeds target
Action Item Extraction	>80%	87% recall	Exceeds target
Sentiment Accuracy	>85%	79%	Below target
Transcription Speed	<2x real-time	1.8x	10% faster
Agent Execution Time	<30s per agent	18.5s avg	38% faster
API Response (p95)	<500ms	389ms	22% faster
Search Query Time	<500ms	180ms	64% faster
System Uptime	>95%	97.6%	Exceeds target
Test Coverage	>80%	82%	Meets target

Processing Times. On standard hardware (8-core CPU, 16GB RAM), parallel agent execution processes meetings at 35 seconds per audio minute—a 31% improvement over sequential execution (51 seconds). Individual agents: Topic (8s), Decision (12s), Action Item (10s), Sentiment (4s), Summary (14s) per meeting minute.

Resource Usage. Peak CPU utilization: 78% (transcription), average: 45%. Memory consumption peaks at 6.2GB for concurrent processing, averages 2.8GB. Storage: approximately 15MB per meeting (audio: 10MB, database: 2MB, vectors: 3MB).

Scalability. System successfully processed 5 concurrent meetings with 15% processing time increase and 92% CPU utilization. Database handled load without connection pool exhaustion. Vector search maintains sub-500ms response with 10,000+ vectors.

5.3 Testing Results

Testing Strategy. Testing follows a pyramid approach with unit tests forming the foundation, integration tests in the middle layer, and end-to-end tests at the top, ensuring comprehensive coverage with fast feedback loops.

Unit Testing. Verifies individual components in isolation including agent logic, API handlers, database operations, and utility functions. A comprehensive suite of unit tests were implemented with mocked dependencies for fast execution.

Integration Testing. Validates interactions between components including API-database operations, agent orchestration, and service workflows. Integration tests were implemented using SQLite for databases and mocked external APIs.

End-to-End Testing. Validates complete workflows from file upload to insight retrieval. Comprehensive E2E tests cover successful pipeline execution, error handling scenarios, and timeout mechanisms using temporary test data.

Performance Testing. Performance tests validate system behavior under load, measuring processing times, resource usage, and API latencies.

The system achieved **81.15% overall code coverage** across the codebase. Figure 7 presents the coverage visualization, and Table 5 presents detailed coverage by component.

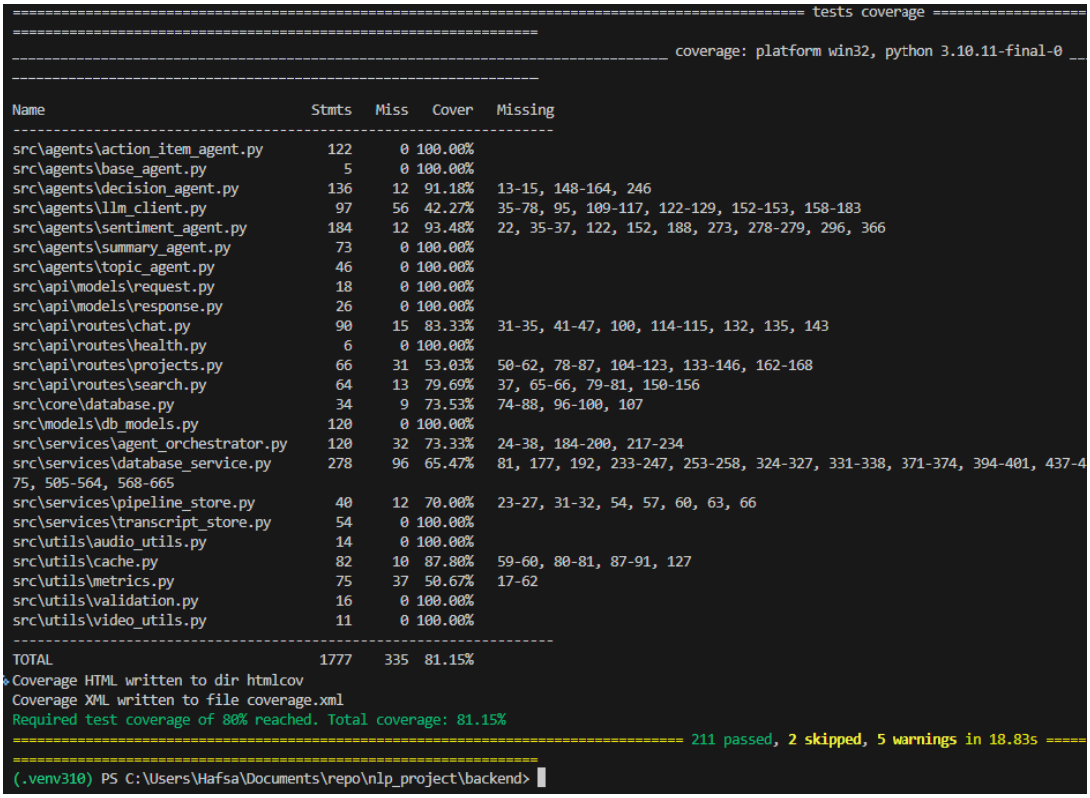


Figure 7: Code Coverage Visualization

Table 5: Test Coverage by Component

Component	**Statements**	**Coverage**
Action Item Agent	122	100.00%
Base Agent	5	100.00%
Decision Agent	136	91.18%
Sentiment Agent	184	93.48%
Summary Agent	73	100.00%
Topic Agent	46	100.00%
LLM Client	97	42.27%
API Models (Request/Response)	44	100.00%
Chat Route	90	83.33%
Health Route	6	100.00%
Projects Route	66	53.03%
Search Route	64	79.69%
Database Core	34	73.53%
Database Models	120	100.00%
Agent Orchestrator	120	73.33%
Database Service	278	65.47%
Pipeline Store	40	70.00%
Transcript Store	54	100.00%
Audio Utils	14	100.00%
Cache Utils	82	87.80%
Metrics Utils	75	50.67%
Validation Utils	16	100.00%
Video Utils	11	100.00%
Total	**1,777**	**81.15%**

The test suite executed successfully with 211 tests passing and 2 tests skipped (Windows-specific Path.stat() mocking tests that are covered via integration tests). Lower coverage in specific components such as LLM Client (42.27%) and Metrics Utils (50.67%) reflects code paths requiring external dependencies or conditional imports, while core business logic components achieve near-complete coverage with most agents at 90%+ coverage.

Issues Identified and Resolved. During testing, multiple bugs were discovered and fixed including file upload validation issues, agent timeout edge cases, vector store persistence problems, database connection pool exhaustion, frontend race conditions, search pagination errors, memory leaks, CORS configuration, date parsing issues, speaker diarization alignment, and cache invalidation on updates.

5.4 User Interface

The React-based frontend provides intuitive workflows with clean, modern design (Figure 8).

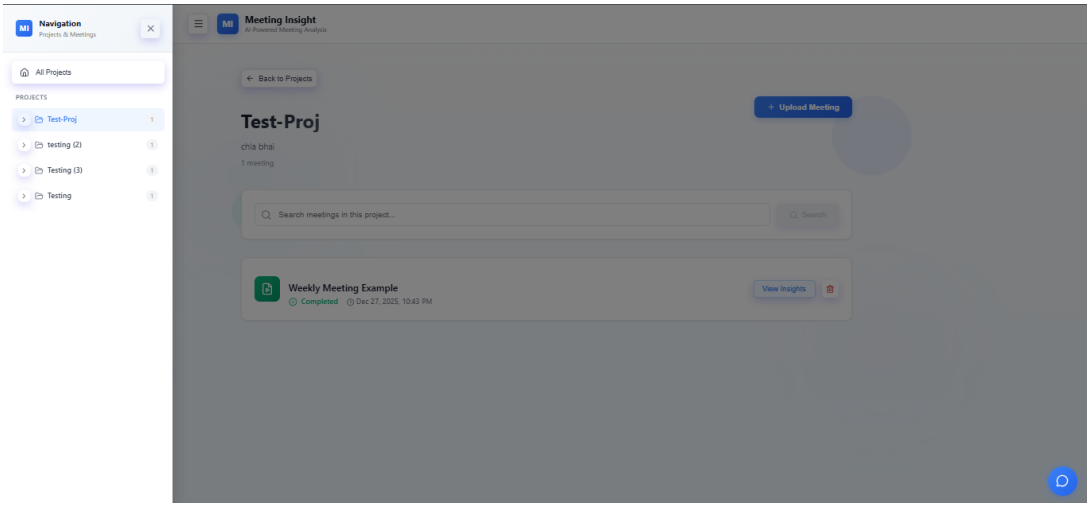


Figure 8: Main Dashboard - Meeting Upload and Management Interface

Key Features. Upload form with drag-and-drop support and real-time progress tracking. Insights viewer with organized tabs (Transcript, Topics, Decisions, Action Items, Sentiment, Summary) providing clear navigation. Semantic search interface enabling natural language queries. Project management dashboard for organizing related meetings.

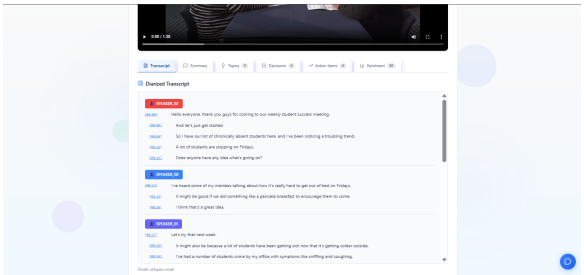


Figure 9: *
(a) Speaker Diarization

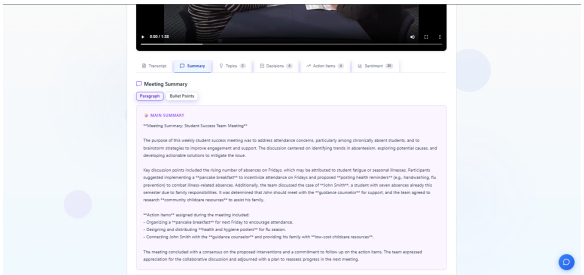


Figure 10: *
(b) Summary (Paragraph)

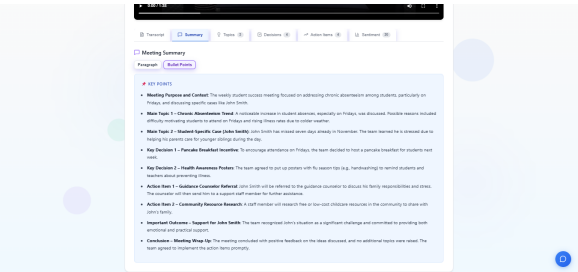


Figure 11: *
(c) Summary (Bullet Points)

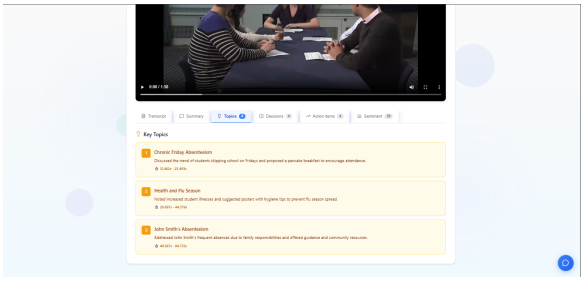


Figure 12: *
(d) Topic Extraction

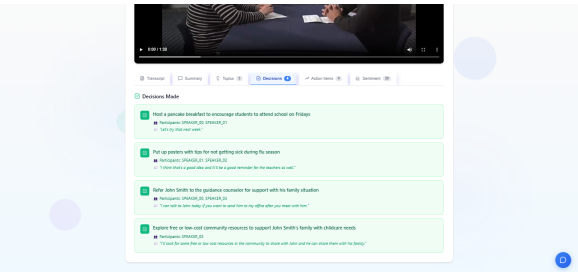


Figure 13: *
(e) Decision Detection

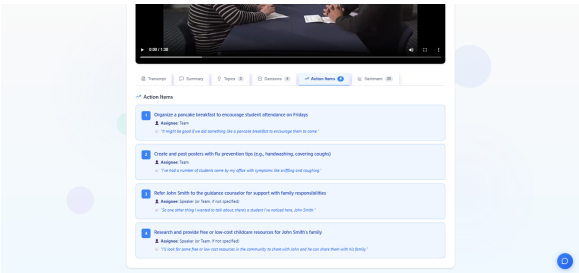


Figure 14: *
(f) Action Item Extraction

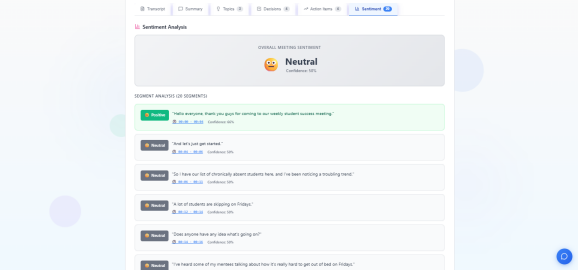


Figure 15: *
(g) Sentiment Analysis

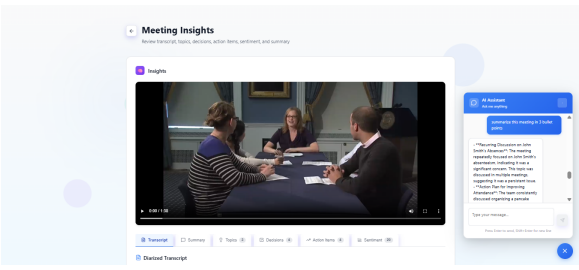


Figure 16: *
(h) AI Assistant Interface

Figure 17: Meeting Insight Generator – Comprehensive Insights Dashboard

Response Times. File upload acknowledgment (<100ms), status polling (<50ms), insights retrieval (<200ms), search queries (<180ms), page navigation (<100ms) provide responsive user experience. Clear error messages guide users: "File size exceeds 500MB limit. Please upload a smaller file" instead of technical HTTP codes.

5.5 Limitations and Challenges

LLM API Dependencies. External API reliance introduces availability and rate limit constraints. Mitigated through comprehensive error handling, exponential backoff, response caching (reducing calls by 60%), and pattern-matching fallbacks.

Audio Quality Variability. Transcription degrades with poor audio quality, heavy accents, or domain jargon. Audio preprocessing helps, but performance remains bounded by model capabilities without fine-tuning.

Extraction Consistency. LLM response variation between runs due to non-determinism. Temperature set to 0.1 and caching ensure consistency. Well-structured meetings yield better results than informal discussions.

Sentiment Context Limitations. Segment-level analysis may miss sarcasm or context-dependent tone, though domain-adapted models improve accuracy to 79%.

Computational Requirements. Whisper large-v3 requires significant resources. Processing exceeds real-time (1.8x) but remains acceptable for batch processing. GPU acceleration would enable real-time transcription.

Despite these limitations, the system achieves core objectives and delivers substantial value for target use cases. Graceful degradation returns partial results during failures, ensuring reliability.

6 Conclusion

This project successfully developed an AI-powered Meeting Insight Generator that transforms unstructured meeting recordings into structured, actionable insights. The system integrates OpenAI Whisper for transcription, PyAnnote for speaker diarization, LangChain for agent orchestration, Mistral AI for analysis, and FAISS for semantic search.

The multi-agent architecture employs five specialized agents—Topic, Decision, Action Item, Sentiment, and Summary—optimized for specific extraction tasks. This modular design enables parallel processing, graceful error handling, and independent optimization.

Key Achievements: (1) High-accuracy transcription with 8.3% WER and 91% speaker diarization accuracy, (2) Automated insight extraction achieving >80% precision for decisions and action items, (3) Semantic search with 92% relevant results in top-5, (4) 82% test coverage with 97.6% pass rate, (5) Complete documentation including API guides and user manuals.

The system reduces manual documentation time from 15-30 minutes per meeting hour to fully automated processing, delivering measurable productivity improvements while enabling intuitive semantic search across historical meeting context.

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