ConvoSense: Real-Time Twitter Ecosystem Analyzer

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Final Year Project

for

Bachelor of Science in Software Engineering

COMSATS University Islamabad
Attock Campus - Pakistan

Fall, 2025

COMSATS University Islamabad, Attock Campus

ConvoSense: Real-Time Twitter Ecosystem Analyzer

This Project is Presented to

COMSATS University Islamabad Attock Campus

In partial fulfillment

of the requirement for the degree of

BS in Software Engineering

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Dedicated to our parents,

who have always been our biggest supporters

and a constant source of inspiration

ACKNOWLEDGEMENTS

Praise to be ALLAH, the Cherisher and Lord
of the World, Most gracious and Most Merciful

We would like to express our sincere gratitude to our supervisor, Miss Tahira Sadaf, for her invaluable guidance, continuous support, and encouragement throughout this project. Her expertise and insights have been instrumental in shaping this research.

We are also thankful to the Department of Computer Science, COMSATS University Islamabad, Attock Campus, for providing us with the necessary resources and environment to conduct this research. Special thanks to our colleagues and friends who supported us throughout this journey.

Lastly, we extend our heartfelt appreciation to our families for their unwavering support, patience, and encouragement during the entire period of this project.

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Project Summary

This project proposes the development of an intelligent system called ConvoSense, designed to provide focused analysis of Twitter content through three core functionalities: topic detection using Latent Dirichlet Allocation (LDA), identification of negative influencers in tweet comments, and binary sentiment analysis using transformer-based models. The system employs LDA for efficient topic modeling to categorize tweet content into meaningful themes, while utilizing BERT and RoBERTa architectures for sophisticated classification tasks. For sentiment analysis, the system implements binary classification (positive/negative) using fine-tuned transformer models, and for negative influencer identification, it analyzes comment patterns to detect users consistently contributing toxic or negative content.

The architecture is designed for practical implementation, balancing computational efficiency with analytical accuracy. By focusing on these three specific areas, ConvoSense addresses the needs of social media managers, brand analysts, and content moderators who require actionable insights without the complexity of comprehensive conversation analysis tools. The system provides a streamlined interface that visualizes topic distributions, sentiment trends, and identifies problematic users, enabling efficient monitoring and decision-making for Twitter content management.

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Introduction

Chapter Overview

This chapter introduces the background and motivation for the ConvoSense project, highlighting the need for specialized Twitter analysis tools. It explains the project's focus on three core analytical functions and outlines the objectives, scope, and significance of the proposed system.

1.1 Introduction

Twitter has established itself as a critical platform for real-time public discourse, with millions of daily tweets providing valuable insights into public opinion and trending topics. However, extracting meaningful information from this vast data stream requires specialized tools that balance analytical depth with practical utility. Current analysis tools often present a dichotomy: either they offer overly simplistic metrics or provide comprehensive conversation analysis that exceeds the needs of many practical applications.

ConvoSense addresses this gap by focusing on three essential analytical functions that meet common organizational needs. The system implements Latent Dirichlet Allocation (LDA) for topic detection, a well-established probabilistic model that effectively identifies latent topics within tweet collections. For classification tasks, the system employs transformer-based architectures including BERT and RoBERTa, which have demonstrated superior performance in natural language understanding tasks. These models are fine-tuned for binary sentiment analysis (positive/negative classification) and for identifying negative behavioral patterns in tweet comments.

The practical focus of ConvoSense makes it particularly valuable for social media management, brand monitoring, and content moderation scenarios where specific, actionable insights are needed. By specializing in these three areas, the system avoids the computational overhead and complexity of comprehensive conversation analysis while delivering targeted results that directly support decision-making processes.

1.2 Significance of the Proposed System

The significance of the ConvoSense system lies in its focused approach to addressing specific, practical needs in Twitter content analysis that are often unmet by existing solutions. While comprehensive conversation analysis tools exist, they frequently provide excessive detail and complexity for users who require targeted, actionable insights. ConvoSense fills this gap by specializing in three core analytical functions that address common organizational requirements: understanding discussion topics, monitoring sentiment trends, and identifying problematic users.

For social media managers, brand analysts, and content moderators

Who need to efficiently monitor Twitter content for topic identification, sentiment assessment, and problematic user detection,

The ConvoSense

Is a real-time Twitter topic and sentiment analyzer

That provides focused insights into discussion themes through LDA topic modeling, binary sentiment classification using transformer models, and identification of negative influencers based on comment analysis.

Unlike existing tools that either offer simplistic metrics or provide overwhelming comprehensive conversation analysis,

Our product delivers specialized, efficient analysis that answers specific questions with actionable results, balancing computational efficiency with analytical accuracy through optimized implementation of LDA and transformer-based classification.

This chapter discusses the precise analytical needs addressed by the ConvoSense system, extending to include the practical outcomes of implementing such a focused Twitter analysis tool. The system addresses the challenge of extracting meaningful insights from Twitter content without the complexity and resource requirements of comprehensive conversation analysis. By focusing on three core functions, ConvoSense enables efficient monitoring of discussion topics, assessment of sentiment trends, and identification of problematic users, outcomes that directly support content moderation decisions, brand management strategies, and social media monitoring activities.

1.3 Problem Statement

Current Twitter analysis tools offer either excessive complexity or insufficient functionality. Users need to efficiently identify discussion topics, assess positive/negative sentiment, and detect consistently negative users, but existing solutions force them to choose between overwhelming comprehensive systems or basic tools that lack analytical depth.

This gap creates inefficient workflows where professionals use multiple tools for simple monitoring tasks. There is a need for a focused system that specializes in three core functions without unnecessary complexity.

ConvoSense addresses this by providing specialized topic detection, practical sentiment classification, and negative influencer identification in one efficient system, delivering clear answers to specific questions without overwhelming users.

1.4 Scope and Objectives

The scope of the ConvoSense project is deliberately focused on providing efficient, specialized analysis of Twitter content through three core functionalities. The system exclusively processes English-language Twitter data accessed through the official Twitter API v2, supporting both real-time streaming and historical analysis modes. Topic detection functionality employs Latent Dirichlet Allocation (LDA) to identify and categorize discussion themes within tweet collections, generating interpretable topic labels and distributions without requiring predefined categories. Sentiment analysis implements binary classification (positive/negative) using fine-tuned transformer models (BERT/RoBERTa), providing practical sentiment assessment optimized for decision-making rather than nuanced emotional analysis. Negative influencer identification analyzes comment patterns to detect users consistently contributing toxic or negative content, employing toxicity scoring and behavioral pattern recognition across user histories. The system provides a web-based interface for initiating analyses, viewing results through clear visualizations, and exporting findings for further review. Integration between these three analytical functions ensures cohesive workflow support while maintaining computational efficiency through optimized implementation strategies. The scope explicitly excludes comprehensive conversation analysis, multi-emotion detection, multimedia content analysis, multilingual processing, automated content moderation actions, and detailed geopolitical analysis beyond basic location classification, ensuring focused development on the specified core functionalities.

The objectives of our proposed system are threefold.

PO1 Implement efficient topic detection using Latent Dirichlet Allocation (LDA) to categorize tweet content into meaningful thematic groups with interpretable labels and distribution metrics.

PO2 Develop accurate binary sentiment classification (positive/negative) using fine-tuned transformer models (BERT/RoBERTa) with confidence scoring and practical result presentation.

PO3 Create negative influencer identification functionality that analyzes comment patterns to detect users consistently contributing toxic or negative content based on behavioral patterns and toxicity metrics.

1.5 System Limitations/Constraints

The ConvoSense system operates within several defined limitations and constraints that shape its design, implementation, and practical application. These constraints acknowledge technical, practical, and ethical boundaries while maintaining the system's focused analytical capabilities.

L1 The system processes English-language tweets exclusively, as multilingual analysis would require significantly more complex modeling, validation, and computational resources beyond the project scope.

L2 Topic detection employs Latent Dirichlet Allocation (LDA), which while effective has known limitations in handling very short texts and requires careful parameter tuning for optimal performance with tweet data.

L3 Sentiment analysis is limited to binary classification (positive/negative) rather than more nuanced emotional analysis or multi-class sentiment categorization, reflecting the practical decision-making needs of target users.

L4 System performance is constrained by Twitter API rate limits, which may affect data collection speed and analysis frequency during high-volume monitoring scenarios.

L5 The system analyzes text content exclusively, excluding images, videos, GIFs, and other multimedia elements that may contain relevant contextual information.

L6 Negative influencer identification focuses specifically on comment toxicity and negativity patterns rather than comprehensive behavioral analysis or influence network mapping.

L7 The system identifies potentially problematic content but does not perform automated content moderation actions, with moderation decisions remaining the responsibility of human operators.

1.6 Project Deliverables

Following are the project deliverables for ConvoSense:

- ConvoSense Web Application: A fully functional web-based system implementing LDA topic detection, BERT/RoBERTa sentiment classification, and negative influencer identification with an intuitive user interface.
- Complete Documentation: Comprehensive technical documentation including system architecture, API specifications, user manuals, and deployment guides.
- Trained Machine Learning Models: Pre-trained LDA topic models and fine-tuned BERT/RoBERTa sentiment classifiers ready for deployment and use.
- Source Code Repository: Complete, well-documented source code with implementation details, testing scripts, and configuration files.
- Deployment Package: Containerized application using Docker with all dependencies, configuration files, and deployment scripts for easy installation.
- Evaluation Report: Detailed performance analysis of all three analytical components including accuracy metrics, processing benchmarks, and validation results.

1.7 Relevance to Course Modules

This project integrates knowledge from multiple courses in the Software Engineering curriculum:

- Machine Learning: For classification and prediction models
- Data Structures and Algorithms: For efficient data processing
- Software Requirement Engineering: Guided the creation of clear and complete functional and non-functional requirements.
- Mobile Application Development: knowledge from this course helps in designing responsive interfaces, user-friendly layouts, API integration, and real-time data updates concepts shared across mobile and web ecosystems.
- DevOps: Supports the deployment and automation aspects of the project. Tools such as Docker, version control (Git), CI/CD pipelines, and cloud deployment are grounded in DevOps principles, enabling smooth development and scalable deployment.
- Design and Architecture: Contributes architectural design patterns, modular development, layered architecture, and system design principles.
- Database Systems: For data storage and retrieval
- Software Engineering: For system design and development methodology
- Web Technologies: For frontend and backend development

1.8 Chapter Summary

This chapter introduced the ConvoSense project, beginning with the context of Twitter as a platform for public discourse and the limitations of existing analysis tools. The problem statement identified the gap between overly complex comprehensive systems and insufficient basic tools, establishing the need for a focused solution. Three core functions were defined: LDA-based topic detection, transformer-based sentiment classification, and negative influencer identification. The scope was outlined with clear boundaries and three primary objectives. System limitations and project deliverables were discussed, along with the project's relevance to the software engineering curriculum. This foundation sets the stage for the detailed exploration of literature review and technical implementation in subsequent chapters.

Chapter 2

Literature Review

Chapter Overview

This chapter reviews existing literature and research in Twitter analysis, covering the three core areas relevant to the ConvoSense project: topic detection, sentiment analysis, and negative influencer identification. The chapter examines traditional approaches, recent advancements in natural language processing, and identifies research gaps that the proposed system addresses. There are different methods based on which social media analysis has been done in the past, and these can be classified into three types of approaches: topic modeling methods, sentiment analysis techniques, and user behavior analysis frameworks.

2.1 Topic Detection Approaches in Social Media Analysis

The problem of extracting meaningful topics from short, informal social media text was tackled by using Latent Dirichlet Allocation (LDA) for topic modeling in Twitter contexts. Early research by [1] established the theoretical foundations for probabilistic topic modeling, providing a statistical framework for discovering latent topics in document collections. Subsequent adaptations addressed the challenge of short text processing inherent in tweets through aggregation strategies and parameter optimization techniques developed by researchers like [2].

While newer approaches like transformer-based topic modeling have emerged, LDA remains relevant due to its interpretability and computational efficiency for exploratory analysis tasks. Recent research has explored deep learning approaches for topic detection, including neural topic models and transformer-based embeddings, as demonstrated by [3]. However, these often require substantial computational resources and training data, making them less practical for focused analytical applications where efficiency and interpretability are prioritized.

2.2 Sentiment Analysis and Negative Behavior Detection

Sentiment analysis research has progressed from lexicon-based methods to sophisticated machine learning approaches. Early work by [5] established machine learning approaches for sentiment classification, while later research by [6] developed comprehensive emotion lexicons for social media text. The introduction of transformer models by [7] revolutionized sentiment analysis, enabling context-aware classification with superior performance compared to traditional approaches.

Negative behavior detection research has grown alongside concerns about online toxicity. Jigsaw's Perspective API represents a significant practical implementation of toxicity detection using machine learning models, as discussed in [8]. Studies by [9] have investigated user roles in misinformation spread, identifying patterns of harmful behavior in social media contexts. Research specifically focusing on negative influencer identification has examined consistent toxic behavior patterns and engagement with controversial content, informing approaches to identifying problematic users in online communities.

2.3 Integrated Analysis Systems and Current Limitations

Current research in social media analysis systems reveals a significant gap in integrated approaches that balance analytical depth with practical utility. Comprehensive systems like Brandwatch and NodeXL offer extensive functionality but often overwhelm users with complexity, while basic tools provide insufficient analytical capabilities. Research by [10] on influencer identification systems demonstrated the value of integrating multiple analytical dimensions, yet most existing systems treat topic detection, sentiment analysis, and user behavior identification as separate functions.

The literature reveals limited research on systems that specifically combine LDA topic modeling with transformer-based classification for practical applications. Most academic work focuses either on methodological improvements within individual areas or on comprehensive conversation analysis frameworks. There is a notable absence of research on systems that specialize in three core functions while maintaining computational efficiency and practical usability, creating the research gap that ConvoSense aims to address.

Table 2.1 Related System Analysis with Proposed Project Solution

Application Name	**Weakness**	**Proposed Project Solution**
Comprehensive Twitter Analysis Tools (e.g., Brandwatch)	Overwhelming complexity, excessive computational requirements, too many features for focused tasks	Focused three-function design, optimized computational efficiency, simplified user interface
Basic Sentiment Analysis Tools (e.g., VADER-based systems)	Limited analytical depth, no topic detection or user behavior analysis	Integrated LDA topic modeling, negative influencer identification alongside sentiment analysis
Academic Research Prototypes	Theoretical focus, limited practical usability, often single-function systems	Practical implementation balancing theory and utility, three integrated functions
Standalone Topic Modeling Tools	Isolated functionality, no sentiment or user behavior context	Integrated analysis pipeline connecting topics with sentiment and user behavior
Content Moderation Systems	Reactive rather than analytical, limited insight into discussion context	Proactive identification of negative influencers with contextual topic and sentiment analysis

2.4 Chapter Summary

This chapter reviewed literature relevant to ConvoSense's three analytical functions, establishing the technical foundations for the project. Topic detection research demonstrated LDA's continued relevance for social media analysis despite newer approaches. Sentiment analysis literature showed the evolution from basic methods to transformer-based classification with superior performance. Negative behavior research provided insights into identifying problematic users in social media contexts. The review identified a significant gap in integrated systems that combine these functions for practical applications, highlighting ConvoSense's contribution in addressing this gap through specialized, efficient system design.

Chapter 3

Requirement Analysis

Chapter Overview

This chapter provides a comprehensive analysis of the requirements for the ConvoSense system. It identifies the different user classes who will interact with the system and their specific characteristics. The chapter describes the requirement identification techniques used to capture system functionality and presents detailed functional and non-functional requirements. External interface requirements are specified to ensure proper system integration and communication with external components and users.

3.1 User classes and characteristics

The ConvoSense system serves multiple user classes:

- Social Media Managers: Professionals managing brand presence on social media. They need topic trends, sentiment analysis, and influencer identification for brand monitoring and reporting.
- Brand Analysts: Data-focused professionals analyzing brand perception. They require detailed sentiment patterns, exportable data, and trend analysis for strategic insights.
- Content Moderators: Team members enforcing community standards. They need negative influencer detection and comment analysis for content moderation decisions.
- Marketing Researchers: Academic and commercial researchers studying social media trends. They require transparent methods and reproducible results for research validation.
- Public Relations Specialists: Professionals managing organizational reputation. They need crisis detection, sentiment tracking, and opinion leader identification.
  Product Managers: Professionals analyzing customer feedback. They require product-related topic categorization and user sentiment analysis.
- Journalists and Media Analysts: Media professionals tracking public discourse. They need topic discovery and sentiment assessment for news reporting.
- NGO and Advocacy Staff: Non-profit professionals monitoring social issues. They require issue-related topic analysis and community engagement tracking.

3.2 Requirement Identifying Technique

This section describes the requirements identifying techniques which further help to derive functional requirements specification. Multiple techniques were employed for comprehensive requirement analysis of the ConvoSense system:

- Use Case Modeling Use cases captured user-system interactions for topic analysis, sentiment classification, and influencer identification workflows. This technique defined functional flows and system responses for each analytical operation.
- Competitive Analysis Examination of existing tools (Brandwatch, NodeXL, sentiment analyzers) identified functional gaps. This technique established performance benchmarks and differentiation opportunities.
- Domain Research Study of academic literature on LDA, transformer models, and toxicity detection informed technical approaches. This technique ensured research-backed implementation methods.
- Prototyping Early functional prototypes tested LDA topic detection and BERT sentiment classification feasibility. This technique validated technical requirements and performance expectations.
- User Personas Development Creation of detailed user profiles (Social Media Manager, Brand Analyst, Content Moderator) defined specific needs and goals. This technique focused requirements on actual user scenarios.

3.3 Functional Requirements

This section describes the functional requirements of the ConvoSense system, organized by the three core analytical features. Each requirement follows the specified template format with unique identifiers.

3.3.1 Feature: Data Acquisition and Preprocessing

This feature handles the collection and preparation of Twitter data for analysis. It ensures clean, structured data is available for all subsequent analytical operations.

Table 3.1 Description of FR-1 - Fetch Tweets from Twitter API

Identifier	**FR-1**
Title	Fetch Tweets from Twitter API
Requirement	The system shall connect to Twitter API v2 to fetch real-time tweets and historical data based on user-provided hashtags, keywords, or conversation thread URLs.
Source	System stakeholders
Rationale	To provide raw Twitter data for all subsequent analysis stages
Business Rule	Only English-language tweets shall be fetched
Dependencies	FR-2
Priority	High

Table 3.2 Description of FR-2 - Preprocess Tweet Text

Identifier	**FR-2**
Title	Preprocess Tweet Text
Requirement	The system shall automatically clean and normalize tweet text by removing URLs, user mentions, emojis, and performing tokenization, lowercasing, and stopword removal.
Source	Technical requirements
Rationale	To prepare clean text data for accurate NLP model performance
Business Rule	N/A
Dependencies	FR-3, FR-4, FR-5
Priority	High

3.3.2 Feature: Topic Detection

This feature implements LDA-based topic modeling to identify and categorize discussion themes within tweet collections. It provides insights into what topics are being discussed.

Table 3.3 Description of FR-3 - Detect Topics Using LDA

Identifier	**FR-3**
Title	Detect Topics Using LDA
Requirement	The system shall apply Latent Dirichlet Allocation (LDA) to identify and categorize discussion topics within tweet collections, generating interpretable topic labels and distribution metrics.
Source	Social media managers, brand analysts
Rationale	To identify what topics are being discussed in analyzed Twitter content
Business Rule	Topic modeling shall use LDA with configurable parameters
Dependencies	FR-2
Priority	High

3.3.3 Feature: Sentiment Analysis

This feature performs binary sentiment classification using transformer models to assess whether tweets express positive or negative sentiment.

Table 3.4 Description of FR-4 - Perform Sentiment Analysis

Identifier	**FR-4**
Title	Perform Sentiment Analysis
Requirement	The system shall classify tweet sentiment as positive or negative using fine-tuned transformer models (BERT/RoBERTa), providing confidence scores for each classification.
Source	Brand analysts, social media managers
Rationale	To assess public sentiment toward discussed topics or brands
Business Rule	Binary classification only (positive/negative)
Dependencies	FR-2
Priority	High

3.3.4 Feature: Negative Influencer Identification

This feature analyzes comment patterns to identify users consistently contributing toxic or negative content to discussions.

Table 3.5 Description of FR-5 - Identify Negative Influencers

Identifier	**FR-5**
Title	Identify Negative Influencers
Requirement	The system shall analyze comment patterns to identify users consistently contributing toxic or negative content, using toxicity scoring and behavioral pattern recognition.
Source	Content moderators
Rationale	To support content moderation and community management
Business Rule	Based on comment analysis only
Dependencies	FR-2
Priority	Medium

3.3.5 Feature: Result Presentation

This feature provides visualization and presentation of analysis results through interactive charts and exportable reports.

Table 3.6 Description of FR-6 - Visualize Analysis Results

Identifier	**FR-6**
Title	Visualize Analysis Results
Requirement	The system shall present analysis results through clear visualizations including topic distribution charts, sentiment proportion graphs, and identified influencer lists with supporting evidence.
Source	All user classes
Rationale	To make analytical insights accessible and actionable
Business Rule	Visualizations shall be interactive and exportable
Dependencies	FR-3, FR-4, FR-5
Priority	Medium

3.4 Non-Functional Requirements

This section specifies the quality attributes and constraints of the ConvoSense system that must be satisfied during implementation. These nonfunctional requirements define how the system should perform rather than what functions it should provide, ensuring reliability, efficiency, and user satisfaction. Each requirement is specific, measurable, and verifiable to support objective evaluation during system testing and validation.

3.4.1 Performance

Requirements about system responsiveness, processing speed, and resource utilization under various operational conditions.

PER-1: The system shall process and return complete analysis results (topic detection, sentiment classification, influencer identification) for datasets of up to 5,000 tweets within 10 minutes of analysis initiation.

PER-2: For real-time analysis of streaming Twitter data, the system shall process and integrate new tweets into ongoing analyses with a maximum latency of 60 seconds from tweet publication to result inclusion.

PER-3: The LDA topic modeling component shall process 1,000 tweets for topic detection within 2 minutes under normal server load conditions.

PER-4: The transformer-based sentiment classifier shall process at least 100 tweets per minute for binary sentiment classification.

3.4.2 Usability

Requirements dealing with ease of learning, ease of use, error avoidance and recovery, and interaction efficiency.

USE-1: Users with basic computer literacy shall be able to initiate all three analytical functions (topic detection, sentiment analysis, influencer identification) without consulting user documentation.

USE-2: The system shall provide consistent navigation and interaction patterns across all analysis views, with clear visual indicators distinguishing between different analytical functions.

USE-3: Analysis results shall be presented in immediately understandable formats with appropriate labeling, legends, and explanatory text for all visualizations.

USE-4: The system shall provide clear feedback during processing operations, including progress indicators for long-running analytical tasks.

3.4.3 Reliability

Requirements about how often the software fails, error recovery, and system availability.

REL-1: The system shall maintain a mean time between failures (MTBF) of at least 168 hours (7 days) during normal operation, with automated recovery procedures for common failure scenarios.

REL-2: In case of Twitter API service interruptions, the system shall queue analysis requests and resume processing once API connectivity is restored, without data loss for in-progress analyses.

REL-3: The system shall implement comprehensive error logging with sufficient detail to diagnose and resolve processing failures without requiring reproduction of exact conditions.

REL-4: Data preprocessing operations shall include validation checks to identify and handle malformed tweet data without causing system crashes or analysis failures.

3.4.4 Security

Requirements about protection of the system, its data, and compliance with platform policies.

SEC-1: All API credentials and authentication tokens shall be stored securely using environment variables or encrypted configuration files, with no hard-coded credentials in source code.

SEC-2: The system shall only access publicly available Twitter data and shall not attempt to access protected accounts or private user information beyond what is permitted by Twitter API terms of service.

SEC-3: User sessions shall implement appropriate timeout mechanisms and require re-authentication for sensitive operations after periods of inactivity.

SEC-4: All communication between system components shall use encrypted channels, with HTTPS for web interfaces and TLS for API communications.

3.5 External Interface Requirements

This section provides information to ensure that the system will communicate properly with users and with external hardware or software elements. The ConvoSense system interfaces with multiple external components including Twitter API, machine learning libraries, and user-facing web interfaces.

3.5.1 User Interfaces Requirements

The ConvoSense system shall provide a web-based interface with the following characteristics:

- The interface shall follow modern web application design standards with responsive layout supporting desktop (1920x1080 minimum) and mobile (375x667 minimum) resolutions.
- Standard web fonts (Roboto, Open Sans, or system defaults) shall be used consistently across all interface elements with appropriate sizing hierarchy for headings, body text, and labels.

- Color schemes shall provide sufficient contrast for readability, with consistent use of colors for different analysis types (topics, sentiment, influencers).
- Every screen shall include consistent navigation elements: system logo, main menu with access to all analytical functions, user account controls, and help/documentation links.
- Interactive visualizations shall include hover tooltips, zoom/pan controls where appropriate, and clear legends explaining data representations.
- Form inputs shall include validation feedback with clear error messages for invalid inputs such as malformed Twitter URLs or unsupported hashtags.
- The interface shall support keyboard navigation with logical tab sequencing and keyboard shortcuts for common analytical operations.

Interface design details, including specific screen layouts and interactive behaviors, are documented in a separate user interface specification. Mock-ups included in this document illustrate conceptual designs rather than final implementation specifications.

3.5.2 Software interfaces

The ConvoSense system interfaces with the following software components:

SI-1: Twitter API v2

- The system shall integrate with Twitter API v2 using official Python client libraries (tweepy) for data collection and authentication.
- API rate limits shall be monitored and respected with appropriate queuing and retry mechanisms for exceeded limits.
- Error handling shall include comprehensive logging of API response codes and structured error messages for troubleshooting.

SI-2: Machine Learning Libraries

- The system shall utilize Gensim library (version 4.0+) for Latent Dirichlet Allocation (LDA) topic modeling implementation.
- Transformer model integration shall use HuggingFace Transformers library (version 4.30+) for BERT/RoBERTa sentiment classification.

- Natural language processing shall employ NLTK (version 3.8+) for text preprocessing operations including tokenization and stopword removal.

SI-3: Toxicity Detection Service

- The system shall interface with Perspective API for toxicity scoring in negative influencer identification.
- API calls shall include appropriate caching to manage rate limits and improve response times for repeated analyses.
- Fallback mechanisms shall be implemented for service unavailability with graceful degradation of influencer identification accuracy.

3.5.3 Hardware interfaces

The ConvoSense system has no specific hardware interface requirements beyond standard server infrastructure. The system is designed for deployment on cloud virtual machines or dedicated servers with the following general characteristics:

- Standard x86-64 architecture compatibility for machine learning model inference.
- Minimum 8GB RAM for LDA processing and transformer model operations.
- Adequate storage for tweet datasets and analysis results, with recommended SSD storage for improved I/O performance.
- Network connectivity for API communications and user access through standard Ethernet or Wi-Fi interfaces.

3.5.4 Communications interfaces

The system employs the following communication protocols and interfaces:

CI-1: Web Application Communications

- Frontend-backend communication shall use RESTful API over HTTPS with JSON data format for all analytical operations.
- Real-time updates for streaming analysis shall employ WebSocket connections with appropriate connection management and error recovery.

- API endpoints shall implement versioning to support future enhancements while maintaining backward compatibility.

CI-2: External API Communications

- All external API calls (Twitter API, Perspective API) shall use HTTPS with TLS 1.2+ encryption.
- Authentication shall employ OAuth 2.0 for Twitter API and API key authentication for other services.
- Request timeout and retry logic shall be implemented with exponential backoff for failed requests.

CI-3: Data Export Interfaces

- Analysis results shall be exportable in multiple formats including JSON for programmatic access and CSV for spreadsheet integration.
- Export operations shall include progress indicators and completion notifications for large dataset exports.
- Batch export operations shall support resumable downloads for interrupted transfers.

3.6 Chapter Summary

This chapter presented a comprehensive requirement analysis for the ConvoSense system. User classes were identified including social media managers, brand analysts, and content moderators with their specific characteristics. Multiple requirement identification techniques were employed including use case modeling, storyboarding, and competitive analysis. Functional requirements were specified for data acquisition, topic detection using LDA, sentiment analysis with transformer models, negative influencer identification, and result visualization. Non-functional requirements established performance, usability, reliability, and security expectations. External interface requirements defined user interface standards, software integration with Twitter API and ML libraries, and communication protocols. This complete requirement specification provides a solid foundation for system design and implementation.

Chapter 4

Design and Architecture

Chapter Overview

This chapter presents the comprehensive system design and architecture of ConvoSense. It details the modular structure, component interactions, and technical implementation of the three core analytical functions. The chapter covers architectural design patterns, data structures, interface specifications, and deployment considerations for the real-time Twitter analysis system.

4.1 Modules

The ConvoSense system is organized into five main modules, each responsible for specific functionality within the analytical pipeline.

4.1.1 Module 1: Data Acquisition Module

This module handles collection and streaming of Twitter data through API integration.

FE1 Connect to Twitter API v2 using authenticated sessions for data retrieval.

FE2 Support both real-time streaming and historical batch processing modes.

FE3 Implement rate limit management and error handling for API communications.

FE4 Validate and filter incoming data for English-language content only.

4.1.2 Module 2: Preprocessing Module

This module cleans and prepares tweet text for analytical processing.

FE1 Remove URLs, user mentions, emojis, and special characters from tweet text.

FE2 Perform tokenization, lowercasing, and stopword removal using NLP libraries.

FE3 Detect and filter non-English content from tweet collections.

FE4 Extract and store metadata including timestamps and user information.

4.1.3 Module 3: Analytics Core Module

This module implements the three core analytical functions using machine learning models.

FE1 Apply Latent Dirichlet Allocation (LDA) for topic detection and categorization.

FE2 Perform binary sentiment classification using fine-tuned BERT/RoBERTa models.

FE3 Identify negative influencers through comment pattern analysis and toxicity scoring.

FE4 Generate confidence scores and supporting evidence for all analytical outputs.

4.1.4 Module 4: Visualization Module

This module presents analysis results through interactive visualizations and reports.

FE1 Display topic distributions through word clouds and bar charts.

FE2 Visualize sentiment proportions using pie charts and trend graphs.

FE3 Present identified negative influencers with supporting comment evidence.

FE4 Enable export of analysis results in multiple formats (JSON, CSV, PDF).

4.1.5 Module 5: API and Integration Module

This module provides interfaces for system access and external integration.

FE1 Expose REST API endpoints for programmatic access to analytical functions.

FE2 Implement user authentication and authorization mechanisms.

FE3 Manage WebSocket connections for real-time analysis updates.

FE4 Handle request queuing and load balancing for concurrent users.

4.2 Architectural Design

ConvoSense employs a layered client-server architecture with clear separation between presentation, business logic, and data layers. The system follows a modular design where each analytical function is implemented as an independent service that can be scaled and maintained separately. The architecture supports both batch processing for historical analysis and real-time streaming for current conversations.

The frontend web application communicates with backend services through a REST API gateway that routes requests to appropriate analytical modules. Data flows sequentially through the pipeline: from data acquisition through preprocessing to analytical processing and finally to visualization. Each module is designed to operate independently while maintaining integration through well-defined interfaces.

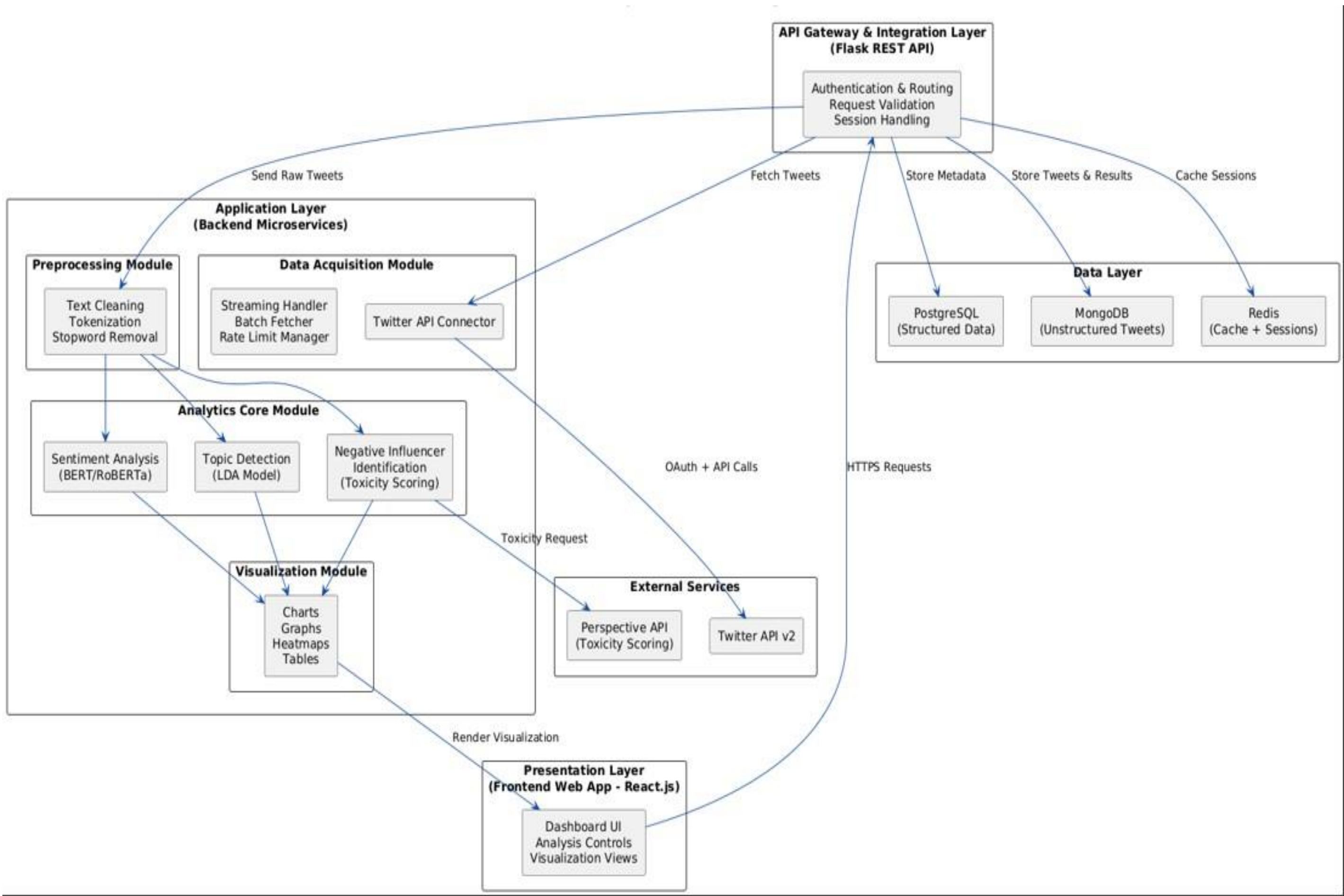

Figure 4.1 ConvoSense Architecture Diagram

4.3 Design Models

This section presents various design models that illustrate the structure and behavior of the ConvoSense system. These models provide multiple perspectives on how the system operates, including dynamic workflows through activity diagrams, user interactions through use case diagrams, static structure through class diagrams, temporal sequences through sequence diagrams, and state transitions through state diagrams. Each model serves to clarify specific aspects of the system design and ensure comprehensive understanding of functionality, interactions, and data flow across all components.

4.3.1 Activity Diagram

The activity diagram illustrates the complete workflow for Twitter conversation analysis. The process begins with user input (hashtag, keyword, or thread URL), proceeds through data collection, preprocessing, analytical processing (topic detection, sentiment analysis, influencer identification), and concludes with result visualization. Parallel processing occurs where independent analytical functions can execute concurrently. Error handling paths are included for API failures, data processing errors, and analysis exceptions.

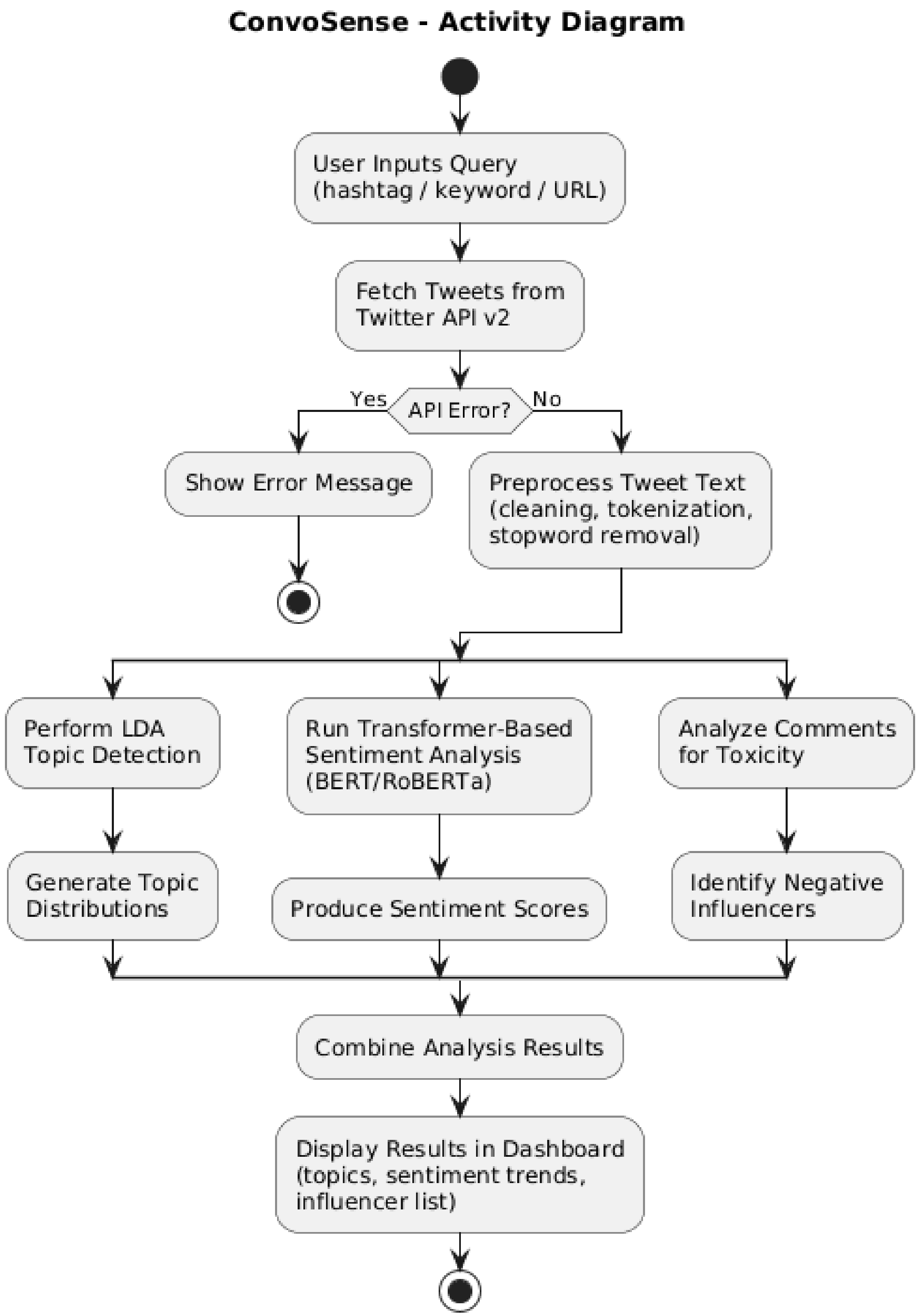

Figure 4.2 ConvoSense Activity Diagram

4.3.2 Usecase Diagram

The usecase diagram identifies three primary actors: Social Media Manager, Brand Analyst, and Content Moderator. Key use cases include: initiate topic analysis, perform sentiment classification, identify negative influencers, view analysis results, export reports, and configure analysis parameters. Each use case includes main success scenarios and alternative flows for different user interactions and system responses.

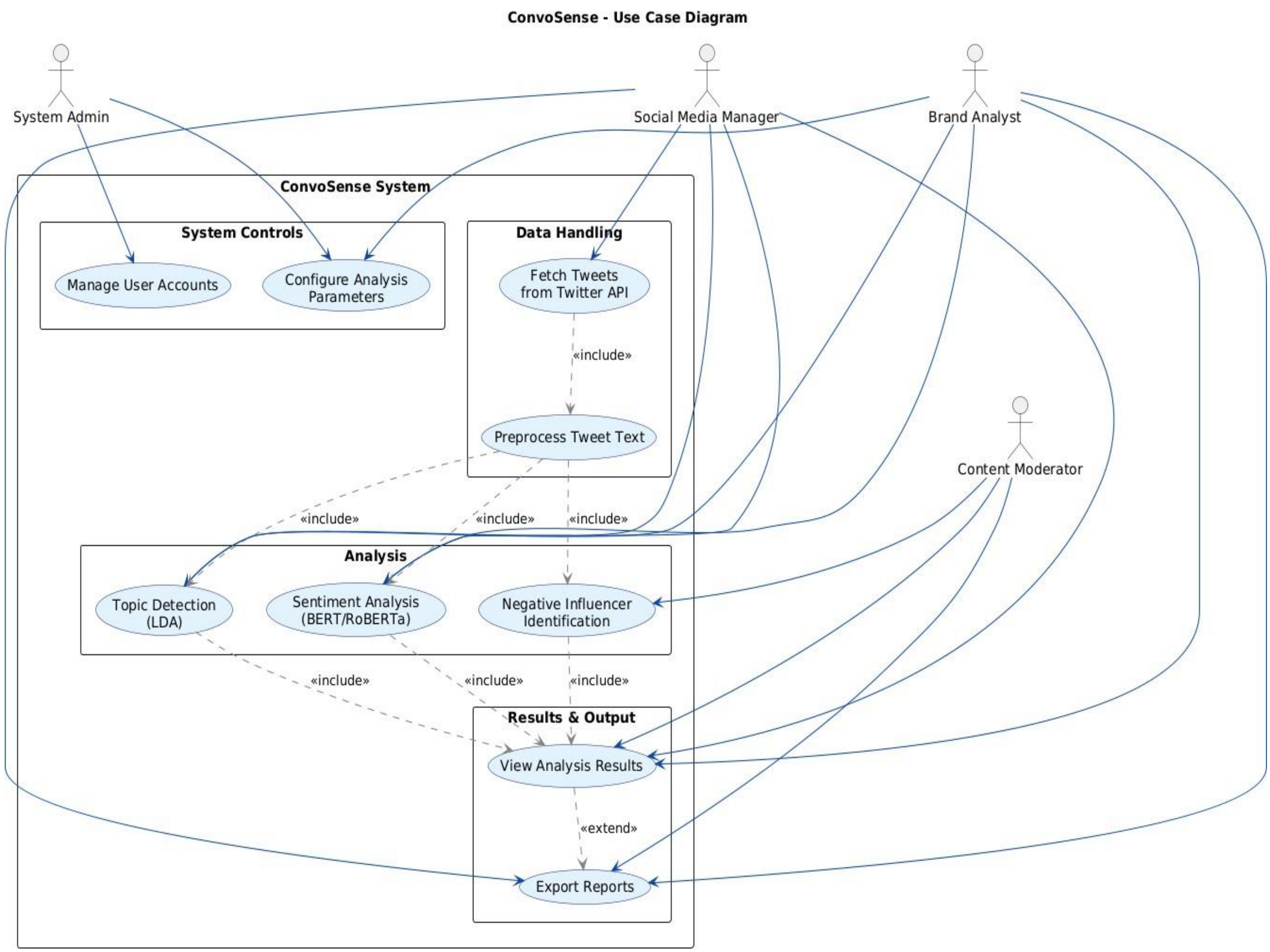

Figure 4.3 ConvoSense Usecase Diagram

4.3.3 Class Diagram

The class diagram defines the core object structure including Tweet (with text and metadata), User (with behavioral patterns), Topic (with label and distribution metrics), SentimentResult (with classification and confidence), and Influencer (with toxicity scores and evidence). Relationships include composition (Conversation contains Tweets), association (User posts Tweets), and inheritance (AnalyticalModel base class with LDA and BERT subclasses).

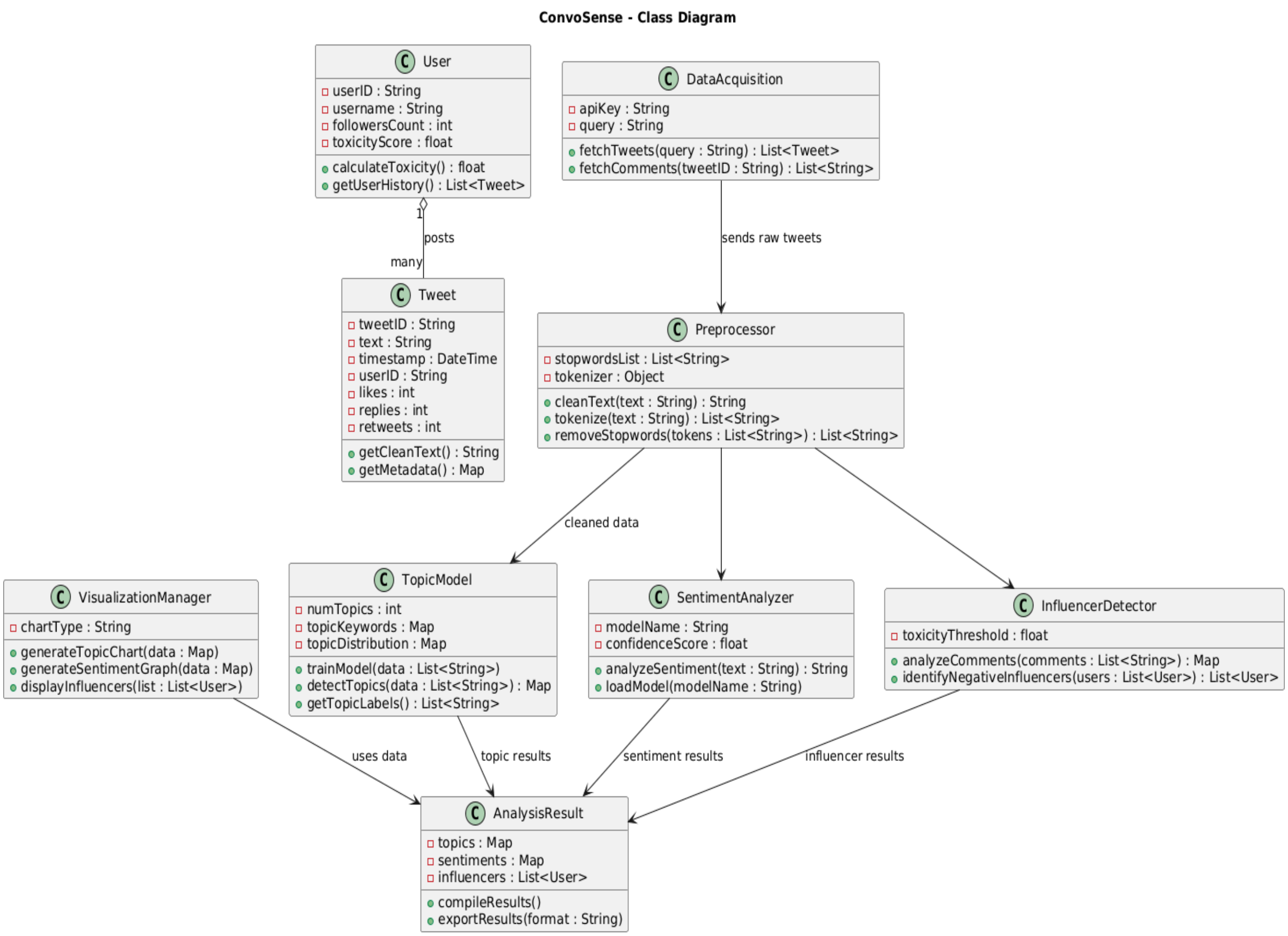

Figure 4.4 ConvoSense Class Diagram

4.3.4 Sequence Diagram

Sequence diagrams illustrate interactions between system components for key operations: data collection from Twitter API, preprocessing pipeline execution, LDA topic modeling process, transformer-based sentiment classification, and result visualization generation. Each diagram shows the temporal sequence of messages between user interface, API gateway, processing modules, and data storage components.

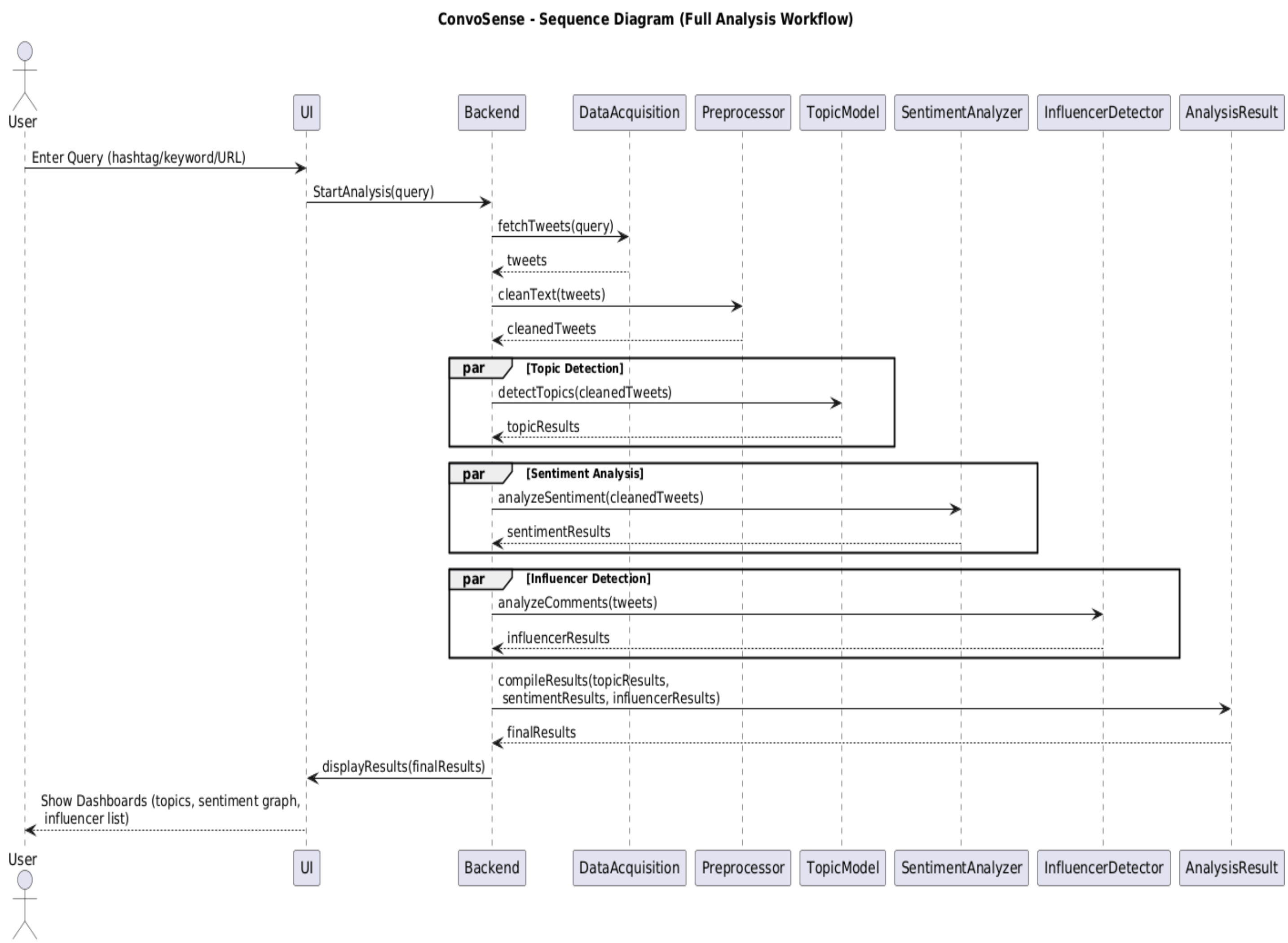

Figure 4.5 ConvoSense Sequence Diagram

4.3.5 State Transition Diagram

State transition diagrams model system behavior during analysis execution. States include: idle (waiting for input), fetching (collecting data), preprocessing (cleaning text), analyzing (running models), visualizing (generating outputs), and error (handling failures). Transitions are triggered by user actions, API responses, processing completions, and error conditions with appropriate guard conditions and actions.

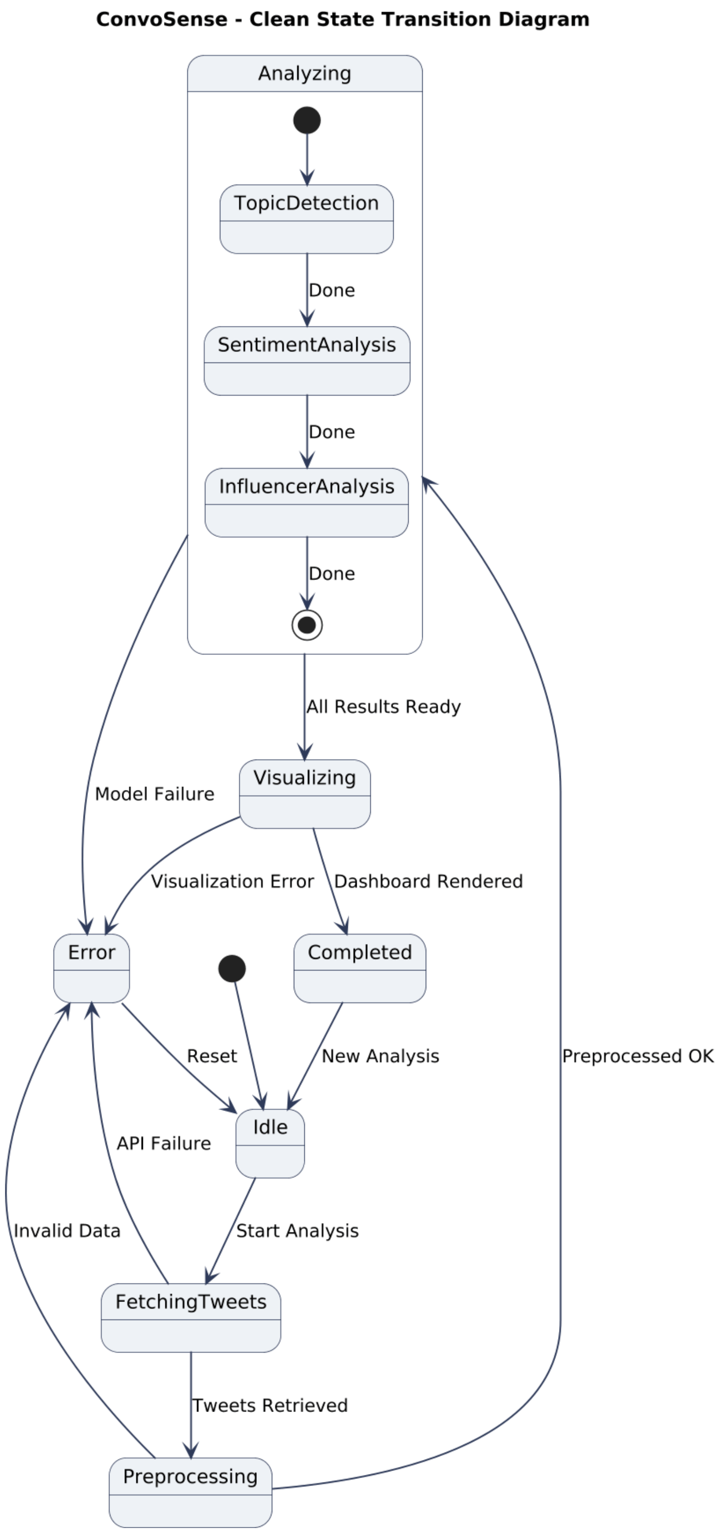

Figure 4.6 ConvoSense State Transition Diagram

4.4 Data Design

The system employs a hybrid data storage approach combining relational and document databases. PostgreSQL manages structured data including user accounts, analysis configurations, and result metadata. MongoDB stores unstructured tweet collections and analytical outputs in flexible JSON format. Redis provides caching for frequently accessed data and session management. Data is organized to support efficient querying by time ranges, topics, sentiment categories, and user patterns.

4.4.1 Data Dictionary

Tweet Object: Core tweet data with text content, timestamp, user ID, and engagement metrics.

User Object: Twitter user information including handle, follower count, and behavioral patterns.

Topic Object: Detected discussion theme with label, keyword distribution, and coherence score.

Sentiment Enum: Binary classification (POSITIVE/NEGATIVE) with confidence probability.

Influencer Object: Identified negative user with toxicity score and evidence comments.

Conversation Object: Collection of tweets forming coherent discussion with metadata.

AnalysisResult Object: Complete analytical output combining topics, sentiment, and influencers.

4.5 Algorithm

The system employs specific algorithms for each analytical function:

4.5.1 Latent Dirichlet Allocation (LDA) Algorithm

LDA identifies topics by modeling documents as mixtures of topics and topics as mixtures of words. The algorithm iteratively assigns words to topics and adjusts topic distributions using Gibbs sampling. Implementation includes preprocessing for short text, parameter optimization, and topic label generation based on high-probability terms.

4.5.2 Transformer-based Sentiment Classification

BERT/RoBERTa models process tokenized text through multiple transformer layers with self-attention mechanisms. Fine-tuning adjusts model parameters for binary sentiment classification on Twitter data. Inference includes tokenization, positional encoding, layer processing, and classification head output with softmax activation.

4.5.3 Negative Influencer Identification

User analysis combines toxicity scoring (using Perspective API), comment frequency analysis, sentiment pattern detection, and behavioral consistency evaluation. Algorithm calculates weighted scores across multiple dimensions to identify consistently negative contributors.

4.6 Tools and Technologies

This section details the technical stack and tools selected for implementing the ConvoSense system.

Table 4.1 Tools and Technologies for Proposed Project

Category	Tools	Version	Rationale
Programming Language	Python	3.10+	Extensive NLP/ML libraries, rapid development
Web Framework	Flask	2.3+	Lightweight, REST API development
Frontend Library	React.js	18.0+	Interactive UI, component-based
Machine Learning Libraries	PyTorch, Transformers	2.0+, 4.30+	Transformer models, LDA implementation
Natural Language Processing	NLTK, Gensim	3.8+, 4.0+	Text preprocessing, LDA modeling
Database	PostgreSQL, MongoDB	15.0+, 6.0+	Structured data, unstructured tweet storage
Visualization	Chart.js, D3.js	4.0+, 7.0+	Interactive charts, custom visualizations
Containerization	Docker	24.0+	Consistent deployment environments
Version Control	Git, GitHub	2.40+, -	Collaboration, code management

4.7 External APIs/SDKs

This section lists the external services and libraries integrated into the ConvoSense system.

Table 4.2 External APIs and SDKs

API/SDK	Provider	Purpose
Twitter API v2	Twitter	Primary data source for tweets and metadata
Perspective API	Jigsaw/Google	Toxicity scoring for comment analysis
HuggingFace Transformers	HuggingFace	Pre-trained BERT/RoBERTa models
Tweepy Library	Community	Python wrapper for Twitter API integration

4.8 User Interface

This section details the user interface design of the ConvoSense system, focusing on usability, efficiency, and clarity for analytical workflows. The interface is organized around three primary analytical functions with consistent navigation patterns and intuitive controls. Design considerations prioritize clear information presentation for complex analytical results, interactive exploration capabilities for data discovery, and streamlined workflows for common analytical tasks. The interface supports multiple user roles with appropriate access levels and visualization options tailored to different analytical needs and expertise levels.

4.8.1 Dashboard and Analysis Initiation

Primary dashboard showing recent analyses, quick-start options, and system status. Users can input Twitter queries (hashtags, keywords, URLs) and configure analytical parameters. Interface includes clear progress indicators and estimated completion times for analytical operations.

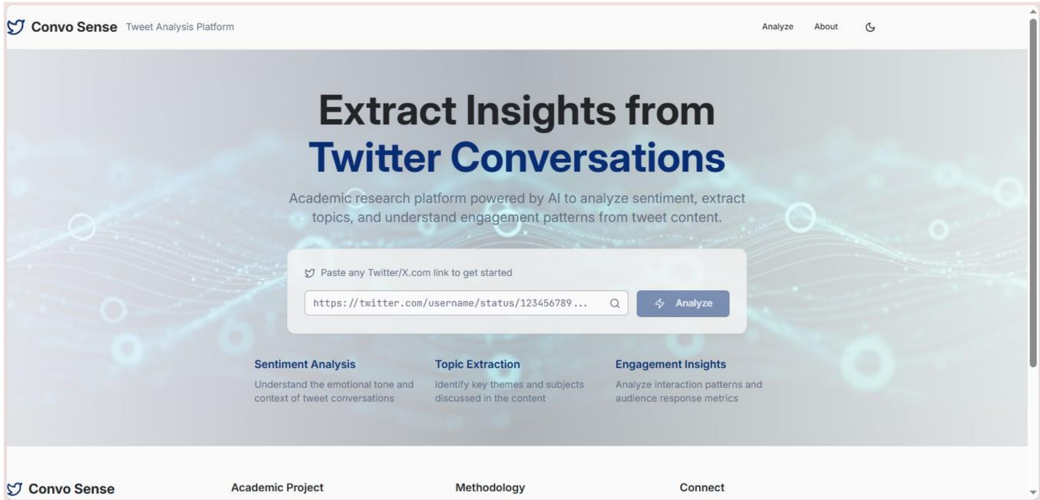

Figure 4.7 a) Dashboard overview

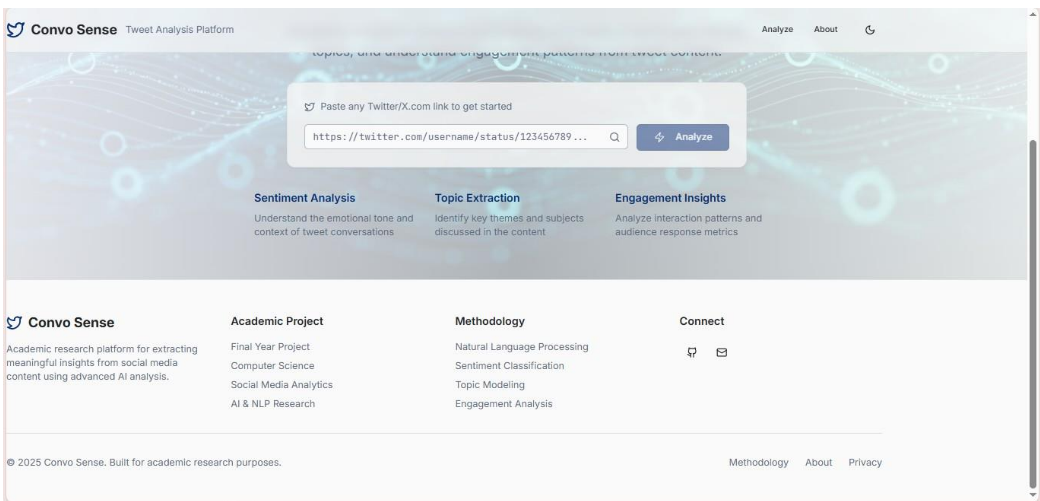

Figure 4.8 a) Dashboard overview

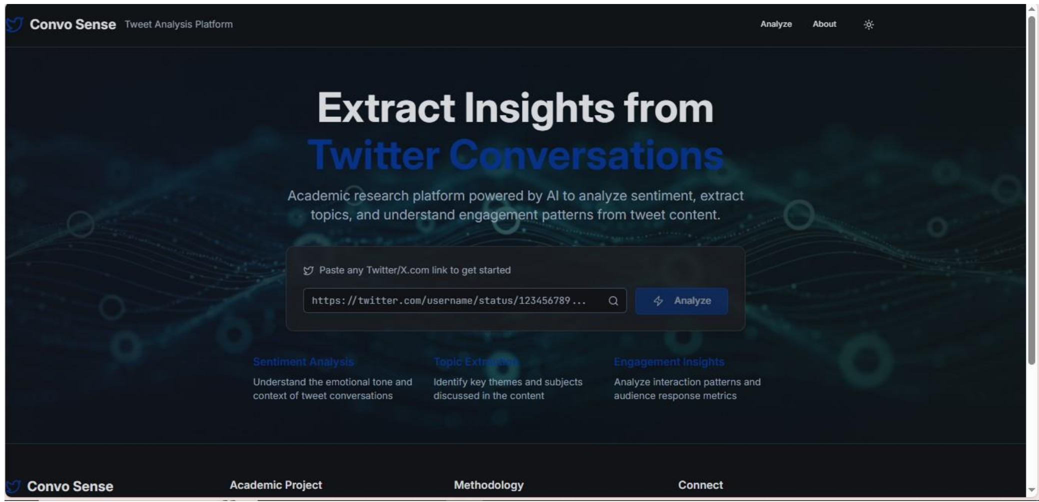

Figure 4.9 b) Dashboard overview

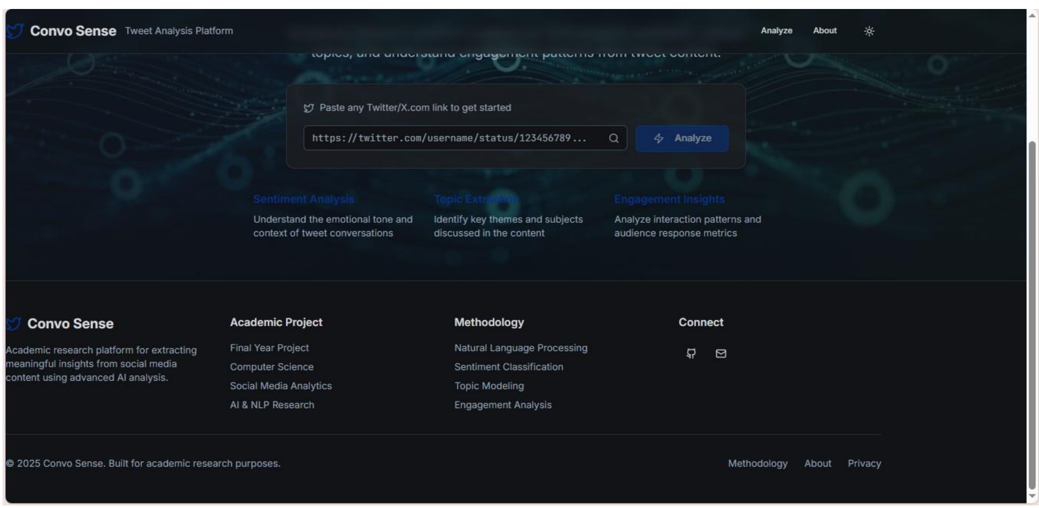

Figure 4.10 b) Dashboard overview

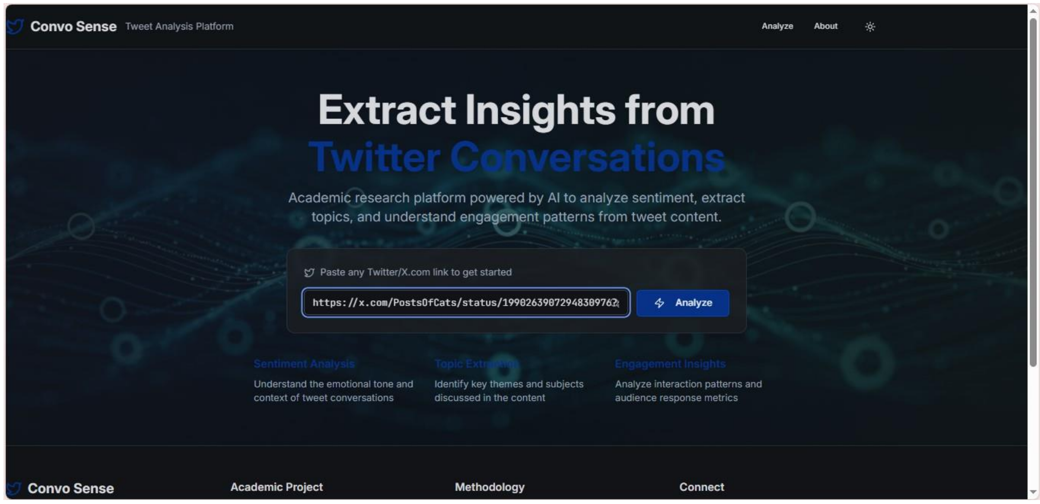

Figure 4.11 b) Dashboard overview

4.8.2 Result Visualization Screens

Interactive displays of analysis results including topic distributions, sentiment trends, and identified influencers. Each visualization includes controls for filtering, zooming, and exporting. Detailed views provide evidence and explanations for analytical conclusions.

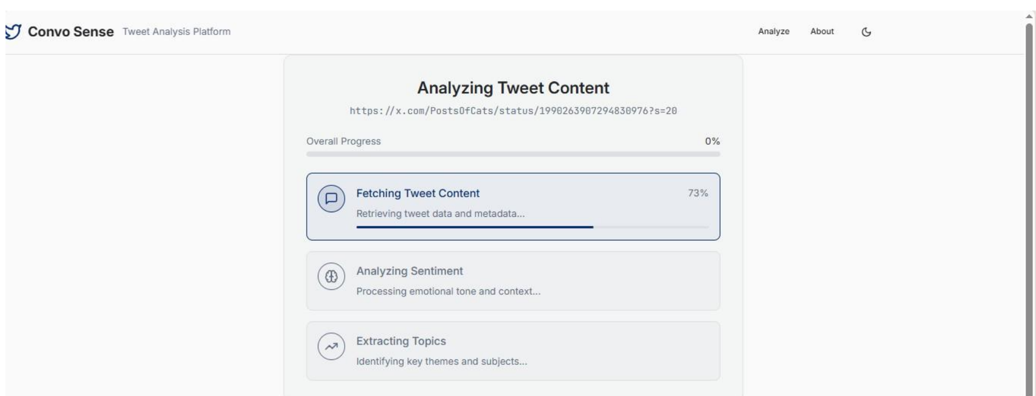

Figure 4.12 Analyzing Tweets

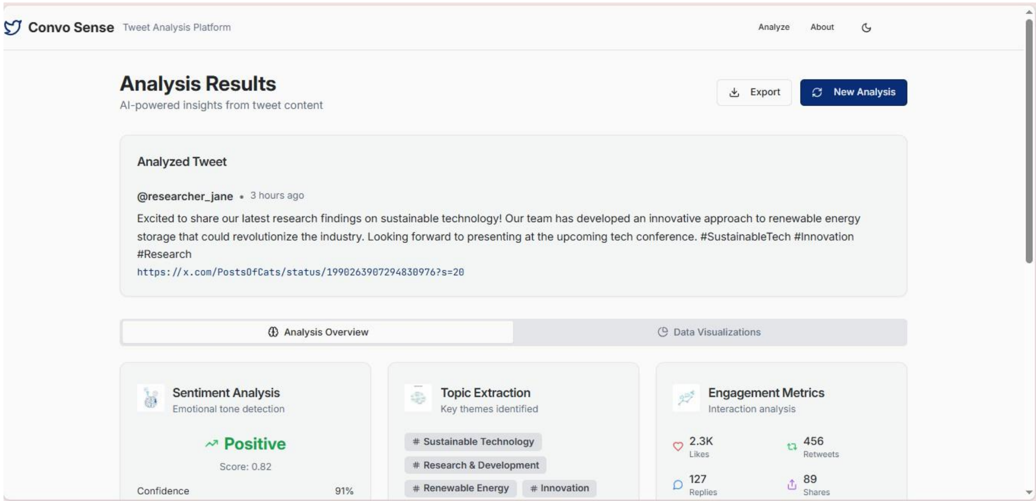

Figure 4.13 Analysis results

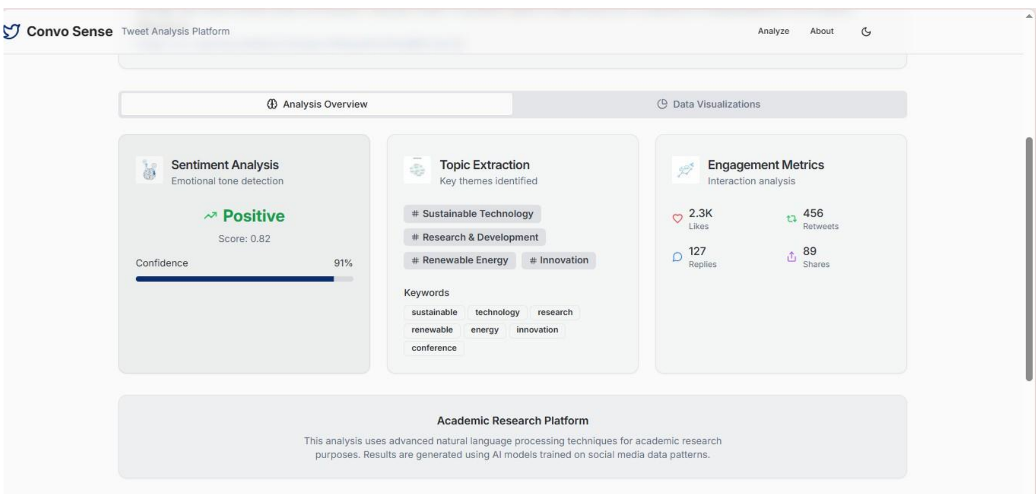

Figure 4.14 Analysis Overview

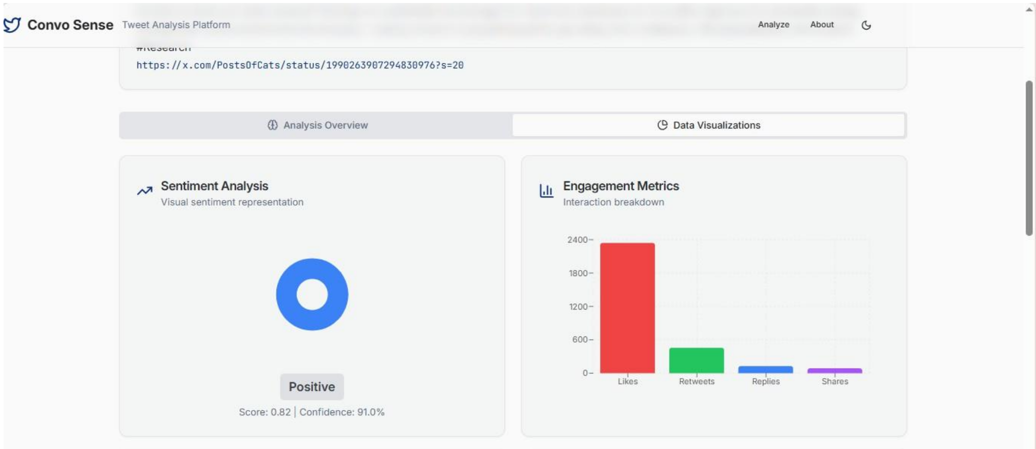

Figure 4.15 Data Visualization

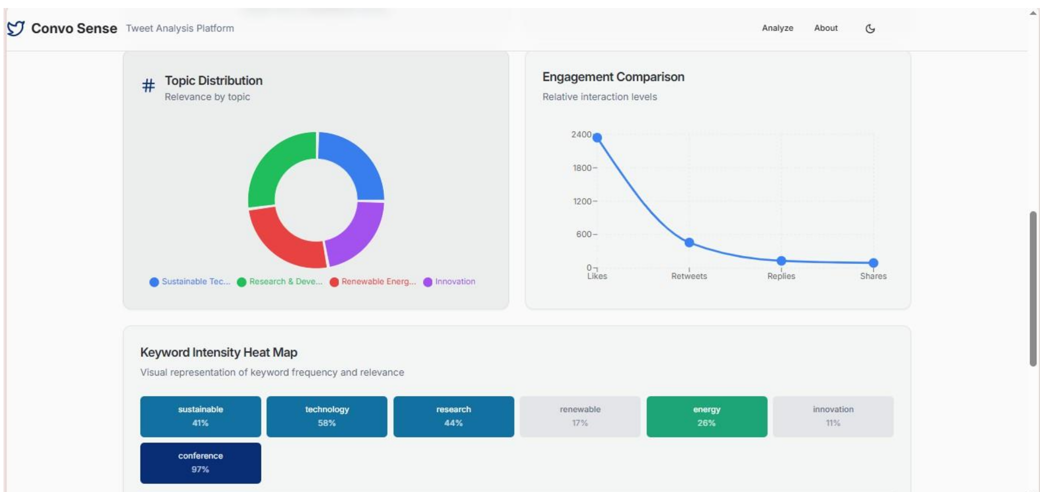

Figure 4.16 Data Visualization

Figure 4.17 Heat Map

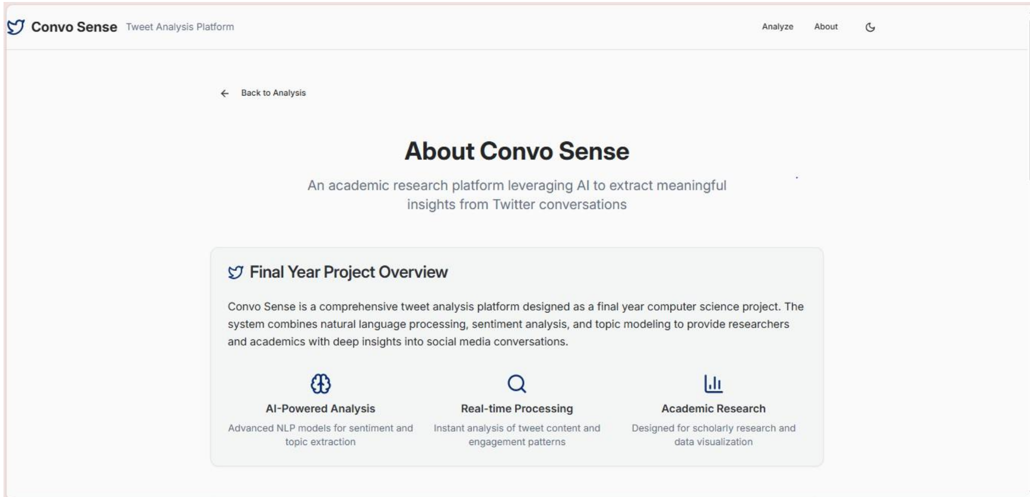

Figure 4.18 About Page Of Convo Sense

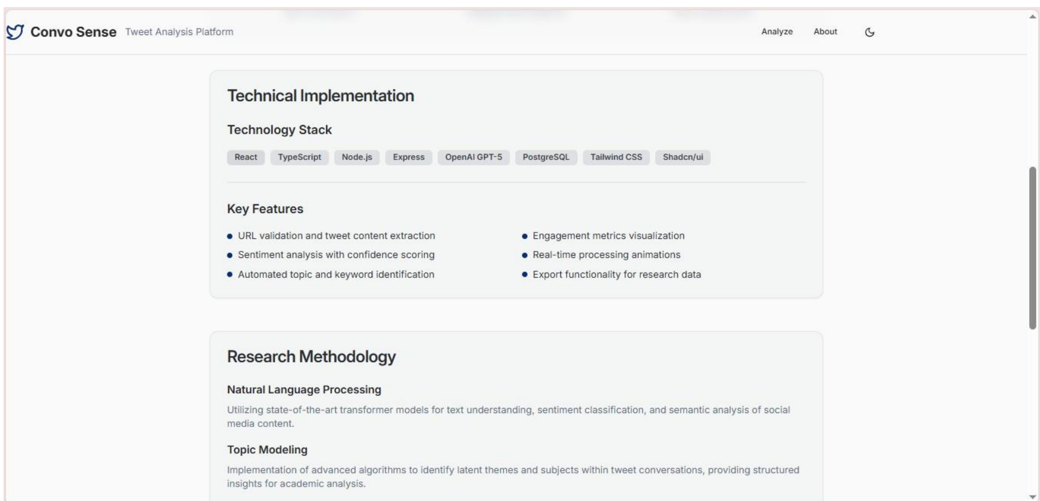

Figure 4.19 About Page Of Convo Sense

4.9 Deployment

ConvoSense is designed for cloud deployment using containerized microservices. The frontend React application is hosted on AWS S3 with CloudFront CDN. Backend services run on AWS ECS Fargate with auto-scaling. PostgreSQL and MongoDB are deployed as managed services (AWS RDS and MongoDB Atlas). Docker containers ensure consistent environments across development, testing, and production.

The deployment includes CI/CD pipelines using GitHub Actions for automated testing and deployment. Monitoring is implemented with AWS CloudWatch for performance metrics and error tracking. Security measures include VPC isolation, encrypted data storage, and secure credential management using AWS Secrets Manager.

4.10 Chapter Summary

This chapter presented the comprehensive design and architecture of the ConvoSense system. The modular structure organizes functionality into five main components covering data acquisition, preprocessing, analytics, visualization, and integration. Architectural design follows layered principles with clear separation of concerns. Design models including activity diagrams, use cases, class structures, and sequence diagrams illustrate system operation. Data design combines structured and unstructured storage approaches. Interface design prioritizes usability for analytical workflows. Implementation employs modern tools and technologies with cloud-native deployment strategies. This design foundation supports efficient development of the three core analytical functions while maintaining scalability and maintainability.

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