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AI-Based Online Feedback Analysis and Opinion Mining System

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Sentiment Analysis, Opinion Mining, Natural Language Processing (NLP), Machine Learning, TF-IDF, Logistic Regression, Lexicon-Based Approach, Spring Boot.

ABSTRACT

The rapid growth of digital platforms and online services has led to a significant increase in user-generated feedback in the form of reviews, comments, and opinions. Analyzing this large volume of textual data manually is time-consuming and inefficient. Therefore, there is a need for an automated system that can effectively analyze feedback and extract meaningful insights. This project proposes an AI-Based Online Feedback Analysis and Opinion Mining System that utilizes machine learning and natural language processing techniques to classify user feedback into different sentiment categories. The system performs text preprocessing steps such as tokenization, stop-word removal, and normalization to prepare the input data for analysis. It uses TF-IDF (Term Frequency–Inverse Document Frequency) for feature extraction and applies Logistic Regression for sentiment classification. In addition, a rule-based sentiment analysis model (lexicon-based approach) is used to enhance the accuracy of predictions. The system classifies feedback into positive, negative, and neutral sentiments. The application is developed using frontend technologies such as HTML, CSS, and JavaScript, and backend technologies including Java and Spring Boot. A MySQL database is used to store user data, feedback records, and analysis results. The system provides a user-friendly interface where users can submit feedback and view sentiment analysis results through an interactive dashboard. The proposed system improves efficiency, reduces manual effort, and provides quick insights into user opinions. It can be effectively used in various domains such as product reviews, customer feedback analysis, and service evaluation. Future enhancements may include real-time data processing, multilingual support, and advanced deep learning techniques for improved sentiment analysis.

1. INTRODUCTION

1.1 OBJECTIVE OF THE PROJECT

1.1.1 INTRODUCTION TO THE PROBLEM

In the modern digital era, the rapid growth of the internet and online platforms has significantly increased the amount of user-generated content. Customers frequently share their opinions, reviews, and feedback about products and services on websites, social media platforms, and online applications. This feedback contains valuable insights that organizations can use to improve their offerings and enhance customer satisfaction.

However, analyzing this massive volume of textual data manually is extremely difficult, time-consuming, and inefficient. Feedback is often unstructured, written in different styles, and may include slang, abbreviations, or mixed sentiments. Traditional analysis methods fail to handle such complexity effectively.

Therefore, there is a strong need for an intelligent system that can automatically analyze user feedback, identify sentiments, and extract meaningful insights. This is where AI-based feedback analysis and opinion mining systems play a crucial role.

In today's competitive environment, organizations must respond quickly to customer needs and preferences. Customer feedback plays a vital role in understanding user expectations and improving product quality. However, due to the exponential growth of data, manual methods are no longer practical. Businesses require automated solutions that can process feedback in real time and provide accurate results.

Another major challenge is the diversity of feedback sources. Users provide feedback through multiple channels such as websites, mobile applications, emails, and social media platforms. This data is highly heterogeneous and requires advanced processing techniques to extract useful information. Without proper analysis, valuable insights may remain hidden within large datasets.

Additionally, feedback often contains ambiguity and mixed opinions. For example, a single review may contain both positive and negative statements. Identifying the overall sentiment in such cases is a complex task. Human analysis may lead to inconsistent results due to subjective interpretation, whereas automated systems can provide consistent and objective analysis.

Language variations also pose a significant challenge. Users may express their opinions using informal language, regional dialects, or abbreviations. Traditional systems struggle to understand such variations, making it difficult to accurately classify sentiment. This highlights the importance of using advanced Natural Language Processing (NLP) techniques in feedback analysis.

Furthermore, organizations need not only sentiment classification but also deeper insights such as identifying key issues, trends, and customer preferences. Simply categorizing feedback as positive or negative is not sufficient. A comprehensive system should be able to extract meaningful patterns and provide actionable insights that can support strategic decision-making.

AI-based feedback analysis systems address these challenges by combining machine learning and NLP techniques. These systems can automatically preprocess text, extract features, and classify sentiment with high accuracy. Machine learning models such as Logistic Regression learn patterns from historical data, while rule-based approaches use predefined sentiment lexicons to enhance classification.

Another important aspect is scalability. Modern systems must handle large volumes of data efficiently without performance degradation. AI-based systems are capable of processing thousands of feedback entries within a short time, making them suitable for real-world applications.

Moreover, real-time analysis has become increasingly important. Organizations need instant insights to respond to customer issues promptly. Automated systems enable real-time processing and visualization of feedback, helping businesses take immediate actions and improve customer satisfaction.

Security and data management are also critical considerations. Feedback data must be stored securely and managed efficiently to ensure privacy and reliability. A well-designed system should include proper database management and secure access mechanisms.

In conclusion, the growing volume and complexity of user-generated feedback present significant challenges for traditional analysis methods. There is a clear need for an intelligent, automated system that can efficiently process and analyze feedback data. AI-based feedback analysis and opinion mining systems provide an effective solution by enabling accurate sentiment classification, extracting valuable insights, and supporting data-driven decision-making. These systems play a crucial role in helping organizations understand customer opinions and improve overall performance.

1.1.2 PROBLEM STATEMENT

The primary problem addressed in this project is the lack of an efficient and automated system to analyze large volumes of online feedback and extract meaningful insights.

The challenges include:

Processing large amounts of unstructured textual data

- Identifying sentiment (positive, negative, neutral) accurately
- Understanding context and user intent
- Reducing manual effort and time consumption

In addition, the system faces challenges in handling diverse language styles, including slang, abbreviations, and informal expressions used by users. There is also a need for real-time analysis to provide quick insights for decision-making. Traditional methods fail to identify patterns, trends, and key issues effectively from large datasets. Therefore, a scalable and efficient automated system is required to process and analyze continuously growing volumes of feedback data.

1.1.3 OBJECTIVE OF THE PROJECT

The main objective of this project is to develop an AI-Based Online Feedback Analysis and Opinion Mining System using Java Full Stack technologies that can automatically analyze user feedback and classify sentiments.

1.1.4The specific objectives include:

- To design an automated feedback analysis system
- To preprocess and analyze textual data efficiently
- To classify sentiments using machine learning techniques
- To provide accurate and real-time analysis results
- To develop a user-friendly web interface

1.1.4 IMPORTANCE OF THE PROJECT

This project is important because:

- It helps organizations understand customer opinions
- Improves product and service quality
- Enhances customer satisfaction
- Supports data-driven decision-making
- Saves time and reduces manual effort
- It helps maintain academic integrity
- Reduces plagiarism in educational institutions
- Encourages original content creation
- Saves time for educators and evaluators
- Provides accurate and fast analysis

1.1.5 PROJECT GOALS

The goals of the system are:

- High accuracy in sentiment classification
- Fast processing of feedback data
- Scalability for handling large datasets
- Easy usability for users and administrators

1.1.6 REAL-WORLD APPLICATIONS

The system can be applied in:

- E-commerce platforms (product review analysis)
- Social media monitoring
- Customer support systems

1.1.7 TARGET USERS

The system is designed for:

- Business organizations
- Product managers
- Customer support teams
- Researchers and analysts.

1.1.8EXAMPLE USAGE SCENARIOS

- A customer submits feedback about a product online
- A company analyzes customer reviews to improve services
- An admin monitors overall sentiment trends
- Businesses identify negative feedback and take corrective actions

1.2 SOFTWARE AND HARDWARE REQUIREMENTS

1.2.1 DEVELOPMENT ENVIRONMENT

The development of this project is carried out using:

- Visual Studio Code
- Eclipse IDE
- Spring Tool Suite (STS)

These tools provide an efficient environment for development, debugging and testing.

1.2.2 PROGRAMMING LANGUAGE

The system uses:

- HTML (for structure)
- CSS (for styling)
- JavaScript (for interactivity)
- Java (for backend logic)

1.2.3FRAMEWORKS AND LIBRARIES

- **Spring Boot Framework**

Spring Boot is used because:

- It simplifies backend development
- Provides built-in server support
- Enables fast API development

1.2.4MACHINE LEARNING AND NLP TECHNIQUES

The system uses:

- Sentiment Analysis
- Tokenization
- Stop-word removal
- TF-IDF (for feature extraction)
- Machine Learning models (Logistic Regression)

these techniques help in analyzing and classifying textual feedback effectively

1.2.5DATABASE

- MySQL

The database is used to:

- Store user data
- Store feedback data
- Maintain analysis results

1.2.6DEPLOYMENT TOOLS

- Embedded Apache Tomcat (Spring Boot)
- Local server hosting

1.2.7HARDWARE REQUIREMENTS

Minimum Requirements:

- Processor: Intel i3 or above
- RAM: 4GB
- Storage: 500GB HDD

Recommended Requirements:

- Processor: Intel i5 or above
- RAM: 8GB or more
- Storage: SSD

1.2.8 JUSTIFICATION OF TECHNOLOGY SELECTION

- Java → Secure and platform-independent
- Spring Boot → Fast and scalable backend
- MySQL → Efficient data storage
- NLP Techniques → Accurate text processing
- HTML/CSS/JS → Simple and responsive UI

1.3 MODULES DESCRIPTIOMN

1.3.1 OVERVIEW OF SYSTEM MODULES

The AI-Based Online Feedback Analysis and Opinion Mining System is designed using a modular architecture to ensure efficient processing, scalability, and easy maintenance. The system is divided into different functional modules, each responsible for a specific task in the feedback analysis pipeline. These modules work together to collect, process, analyze, and present user feedback in a structured and meaningful way.

1.3.2 SYSTEM MODULES

The system consists of several integrated modules, each performing a specific function:

- **User Authentication Module:**
  - Handles user registration, login, and logout
  - Ensures secure access to the system
  - Maintains user data and access control
- **Feedback Submission Module:**
  - Allows users to submit feedback, reviews, and comments
  - Acts as the entry point of the system
  - Stores feedback data in the database
- **Text Processing Module:**
  - Cleans raw input data
  - Removes unwanted characters and symbols
  - Converts text into a consistent format
- **Preprocessing Module:**
  - Performs tokenization
  - Removes stop words
  - Applies text normalization
- **Feature Extraction Module:**
  - Converts text into numerical format
  - Uses TF-IDF technique
  - Identifies important words
- **Sentiment Analysis Module:**
  - Classifies feedback into positive, negative, or neutral
  - Uses machine learning algorithms

- Analyzes patterns and context
- **Report Generation Module:**
  - Displays analysis results
  - Shows sentiment trends
  - Provides insights for decision-making

All these modules work together in a structured flow, starting from user input and ending with result visualization, ensuring accurate and efficient feedback analysis.

1.4 Predictive Analysis and Decision Support

Predictive analysis is an important aspect of modern AI-based systems, including feedback analysis and opinion mining applications. It involves analyzing historical data using machine learning techniques to identify patterns, trends, and potential future outcomes. In the context of feedback analysis, predictive techniques help in understanding user behavior and anticipating changes in customer sentiment over time.

By examining previously collected feedback, organizations can detect recurring patterns and identify areas that may require improvement. For example, a consistent increase in negative feedback related to a particular feature may indicate an underlying issue. Predictive analysis helps in identifying such trends early, allowing organizations to take proactive measures rather than reacting after problems escalate.

Decision support systems play a crucial role in utilizing the results obtained from feedback analysis. These systems assist organizations in making informed and data-

systems assist organizations in making informed and data-driven decisions by transforming raw feedback into meaningful insights. By combining predictive analysis with visualization tools such as dashboards and reports, decision-makers can easily interpret trends and patterns in customer opinions.

The integration of predictive analytics with feedback analysis enables organizations to not only understand current sentiment but also forecast future behavior. For instance, if customer satisfaction is gradually decreasing over time, the system can alert administrators and suggest areas that need immediate attention. This proactive approach helps in improving service quality, enhancing customer experience, and maintaining a competitive advantage.

Furthermore, predictive models such as Logistic Regression and other machine learning algorithms can classify feedback and estimate the likelihood of future outcomes. These models continuously improve as more data is collected, making the system more accurate and reliable over time. The ability to adapt to new data ensures that the system remains effective in dynamic environments where user preferences and opinions frequently change.

2. LITERATURE SURVEY

2.1 OVERVIEW OF AI-BASED FEEDBACK ANALYSIS AND OPINION MINING

With the rapid growth of digital platforms and online services, organizations are continuously receiving large volumes of user-generated content in the form of feedback, reviews, ratings, and comments. This feedback contains valuable information regarding customer satisfaction, product quality, and service performance. However, manually analyzing such large and unstructured datasets is extremely difficult, time-consuming, and prone to human errors.

AI-based feedback analysis systems address this challenge by automatically processing textual data and extracting meaningful insights. These systems use **Artificial Intelligence (AI)** and **Natural Language Processing (NLP)** techniques to understand and analyze human language. Opinion mining, also known as sentiment analysis, is a key component of NLP that focuses on identifying subjective information such as opinions, emotions, and attitudes expressed in text.

According to Cambria et al. (2017), sentiment analysis enables organizations to better understand customer behavior, preferences, and expectations. Similarly, Liu (2012) highlighted that automated sentiment analysis systems are essential for handling large-scale unstructured data efficiently while reducing manual effort and improving decision-making.

2.2 TECHNIQUES FOR FEEDBACK ANALYSIS AND OPINION MINING

AI-based feedback analysis relies on multiple techniques to process, analyze, and extract meaningful insights from user-generated textual data. These techniques work together to convert raw, unstructured feedback into useful information.

Text Preprocessing

Text preprocessing is the first step in feedback analysis. Raw data often contains noise such as special characters, punctuation, and unnecessary words.

The preprocessing steps include:

- Removal of special characters and punctuation
- Conversion of text into lowercase
- Removal of stop words (e.g., "is", "the", "and")
- Tokenization (splitting text into words)
- Stemming and lemmatization (reducing words to root form)

These steps improve the quality of data and increase the accuracy of analysis.

Feature Extraction: After preprocessing, the text is converted into numerical form so that machine learning models can process it.Common techniques include:

- TF-IDF (Term Frequency–Inverse Document Frequency)
- Bag of Words (BoW)
- Word embeddings such as Word2Vec, GloVe, and BERT

Feature extraction helps represent text data in a meaningful way for better prediction.

Sentiment Analysis

Sentiment analysis classifies feedback into categories such as positive, negative, and neutral.

Approaches include:

- Machine Learning models like Logistic Regression, Naïve Bayes, and SVM
- Deep Learning models like LSTM, GRU, and BERT
- Rule-based methods using predefined sentiment words

Combining these methods improves overall accuracy.

Opinion Mining

Opinion mining extracts deeper insights from feedback beyond simple sentiment.

It includes:

- Aspect-based sentiment analysis (e.g., product quality, service)
- Emotion detection (happy, angry, sad)
- Context understanding using semantic analysis

This helps organizations understand user opinions in detail.

Visualization and Reporting

The analyzed results are presented using:

- Bar charts and pie charts
- Line graphs for trends
- Dashboards for monitoring
- Word clouds for keywords

Visualization helps in easy interpretation of results.

Data Ingestion and Storage

Data ingestion involves collecting feedback from:

- User input forms
- CSV file uploads
- Online platforms

The data is stored in databases like MySQL for further processing and analysis.

Model Training and Evaluation

Machine learning models are trained and tested to ensure accuracy.

- Training uses labeled datasets
- Testing evaluates model performance
- Metrics include accuracy, precision, recall, and F1-score

Continuous evaluation improves system performance.

Hybrid Approach

The system uses a hybrid approach by combining:

- Logistic Regression (machine learning)
- Rule-based sentiment analysis

This improves accuracy, speed, and reliability.

2.2.1 Advantages of AI-Based Feedback Analysis

AI-based feedback analysis systems offer several advantages over traditional methods. These systems automate the process of analyzing large volumes of textual data, reducing the need for manual effort. One of the major advantages is speed, as the system can process and classify feedback within seconds. This enables organizations to make quick decisions based on real-time insights.

Another important advantage is accuracy. Machine learning models such as Logistic Regression improve prediction accuracy by learning patterns from data. The inclusion of rule-based sentiment analysis further enhances reliability by handling known sentiment words effectively.These systems are also highly scalable, meaning they can handle increasing amounts of data without affecting performance. They can process feedback from multiple sources such as websites, applications, and social media platforms. Additionally, AI-based systems help in identifying hidden patterns, trends, and customer preferences, which are difficult to detect manually.Overall, AI-based feedback analysis improves efficiency, reduces operational costs, and supports data-driven decision-making in organizations.

2.2.2 Limitations of Feedback Analysis Techniques

Despite their advantages, AI-based feedback analysis techniques also have some limitations. One of the major challenges is handling complex language structures such as sarcasm, irony, and ambiguous statements. These can lead to incorrect sentiment classification.

Another limitation is the dependency on quality data. Machine learning models require properly labeled and clean datasets for training. Poor-quality data can reduce the accuracy of predictions. Similarly, rule-based approaches rely on predefined lexicons, which may not cover all possible words or expressions.

Language diversity is another challenge, as feedback may be written in different languages or mixed languages. This requires additional processing and multilingual support. Context understanding is also difficult, as the same word may have different meanings in different situations.

Furthermore, advanced techniques such as deep learning require high computational resources and longer training time. Maintaining and updating the system with new data and trends is also necessary to ensure consistent performance.

Despite these limitations, continuous improvements in AI and NLP techniques are helping to overcome these challenges and enhance the effectiveness of feedback analysis systems.

2.2.3 Applications of Feedback Analysis and Opinion Mining

AI-based feedback analysis and opinion mining systems are widely used across various domains to extract valuable insights from user-generated data. These systems help organizations understand customer opinions, improve services, and make informed decisions.

- **Customer Feedback Analysis:** Businesses use sentiment analysis to understand customer satisfaction from reviews and feedback, helping them improve products and services.
- **Product Review Analysis:** E-commerce platforms analyze user reviews to identify strengths and weaknesses of products, assisting both customers and companies in decision-making.
- **Social Media Monitoring:** Organizations monitor platforms like Twitter, Facebook, and Instagram to analyze public opinion, brand reputation, and trending topics.

2.3 Challenges and Issues in Feedback Analysis

Despite advances in AI, several challenges remain in analyzing online feedback effectively:

- Unstructured and Noisy Data: Feedback often includes slang, abbreviations, spelling errors, and emojis, complicating preprocessing (Feldman, 2013).
- Context Understanding: Detecting sarcasm, irony, or context-dependent sentiments is difficult for traditional models.
- Multilingual Feedback: Users may submit feedback in multiple languages, requiring translation and language-specific NLP models.
- Aspect Detection: Identifying feedback about specific product or service features requires accurate segmentation and analysis.
- Scalability: Large volumes of feedback necessitate efficient, fast, and scalable processing pipelines (Medhat et al., 2014).

These challenges highlight the need for hybrid models that combine machine learning, deep learning, and semantic understanding.

2.4 Tools, Techniques, and Best Practices

Several tools, frameworks, and best practices are used to implement AI-based feedback analysis systems:

- NLP Libraries: NLTK, SpaCy, and Hugging Face Transformers for text preprocessing and embedding generation.
- Machine Learning Frameworks: Scikit-learn, TensorFlow, and PyTorch for building classifiers and neural network models.
- Visualization Tools: Matplotlib, Seaborn, Tableau, and Power BI for generating insights and reports.
- Preprocessing Techniques: Tokenization, stop-word removal, stemming, lemmatization, and handling multilingual data.

Best practices include:

- Continuously updating models to reflect evolving language patterns and user behavior
- Combining machine learning and deep learning approaches for improved accuracy
- Automating preprocessing pipelines to efficiently handle large-scale feedback
- Using aspect-based and sentiment analysis together for more detailed insights

By integrating these tools and strategies, AI-based feedback analysis systems can accurately monitor sentiment trends, extract meaningful insights, and support data-driven decision-making.

3 PROPOSED METHODOLOGY

The proposed AI-Based Online Feedback Analysis and Opinion Mining System aims to automate the extraction and interpretation of user opinions from large volumes of textual feedback such as reviews, comments, and surveys. The system applies natural language processing techniques to clean and normalize text through tokenization, stop-word removal, and normalization, then converts the processed text into numerical features using TF-IDF for effective representation. A Logistic Regression model performs supervised sentiment classification into positive, negative, and neutral categories, while a rule-based lexicon-driven analyzer enhances accuracy by scoring sentiment-bearing words and phrases. The backend, built using Java and Spring Boot, manages requests, stores user data and feedback records in a MySQL database, and returns analyzed results to a frontend dashboard developed with HTML, CSS, and JavaScript. This integrated approach enables quick, scalable opinion mining for domains like product reviews, customer feedback analysis, and service evaluation, reducing manual effort and providing actionable insights through real-time or near-real-time sentiment reporting.

3.1 SYSTEM ARCHITECTURE

The proposed system follows a layered architecture consisting of four main components: frontend, backend, analysis engine, and database, where each layer performs a specific function to ensure modularity and efficiency. The frontend, built using HTML, CSS, and JavaScript, provides interfaces for user registration, login, feedback submission, and sentiment result visualization through dashboards. The backend, developed with Java and Spring Boot, handles REST API communication, authentication, and business logic, acting as a bridge between the user interface and the analysis engine. The analysis engine performs NLP preprocessing steps such as tokenization, stop-word removal, normalization, and TF-IDF feature extraction, and applies Logistic Regression along with a lexicon-based approach to classify feedback into positive, negative, or neutral sentiments. All user data, feedback records, and sentiment results are securely stored and managed in a MySQL database, ensuring reliable data persistence and efficient retrieval.

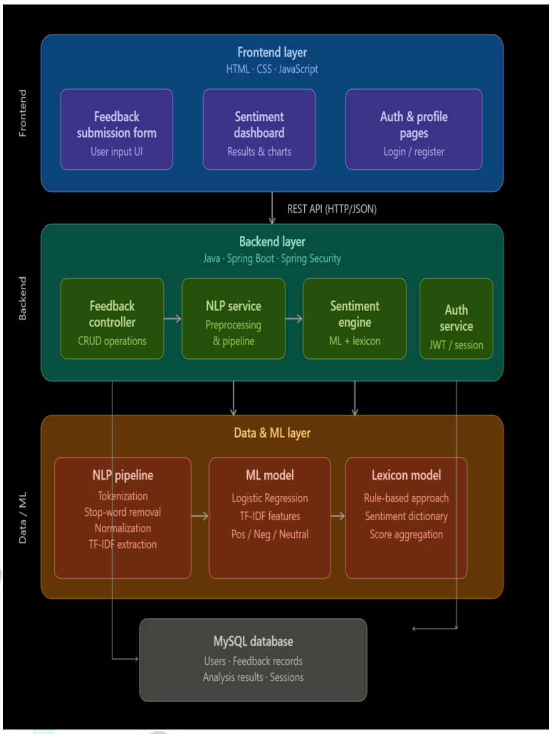


Fig 3.1 Proposed System Architecture

The diagram represents a **four-layer architecture** of the AI-Based Online Feedback Analysis and Opinion Mining System. At the top is the **Frontend layer** (HTML, CSS, JavaScript), which includes the feedback submission form, sentiment dashboard, and authentication/profile pages. Users interact with this layer to submit feedback and view analysis results. The frontend communicates with the backend through REST APIs using HTTP/JSON. The second layer is the **Backend layer** built with Java, Spring Boot, and Spring Security. It contains modules such as the Feedback Controller (handling CRUD operations), NLP Service (managing preprocessing tasks), Sentiment Engine (combining machine learning and lexicon-based analysis), and Auth Service (handling JWT/session authentication). This layer processes incoming requests and coordinates with the analysis components.

The third layer is the **Data & ML layer**, which performs the core analysis. The NLP pipeline carries out tokenization, stop-word removal, normalization, and TF-IDF feature extraction. The ML model (Logistic Regression) classifies feedback into positive, negative, or neutral categories, while the lexicon model applies a rule-based sentiment dictionary and score aggregation to improve accuracy.

At the bottom is the **MySQL database**, which stores user details, feedback records, sentiment analysis results, and session data. The arrows in the diagram show the flow of data from the frontend to the backend, through the analysis engine, and finally to the database for storage and retrieval, ensuring a structured and efficient workflow.

3.2 USE CASE DIAGRAM

The main actor of the system is the **User**, because the system is primarily designed to collect feedback from users and analyze their opinions automatically. In a use case model, actors represent external roles that interact with the system, and the primary actor is the one whose goal is fulfilled by the system.

- **User as primary actor:** The user submits reviews, comments, or opinions, requests sentiment analysis, and views the result generated by the system.
- **Admin as secondary actor:** The admin is an optional supporting actor who monitors stored feedback, checks analysis reports, and supervises overall system usage.
- **Reason for two actors:** This separation makes the system easier to model because the user handles operational activities, while the admin handles management and monitoring functions.
- **System interaction:** Both actors remain outside the system boundary and interact with its use cases such as login, feedback submission, viewing results, and report monitoring.

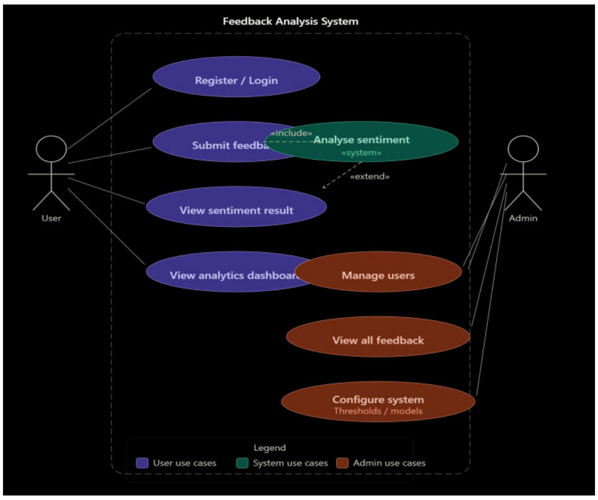


Fig 3.2 Use Case Diagram

The diagram represents the Use Case Diagram of the Feedback Analysis System, showing the interactions between two main actors: User and Admin. The system boundary (dashed rectangle) defines the functionalities provided by the application. On the user side, the main use cases include *Register/Login*, *Submit Feedback*, *View Sentiment Result*, and *View Analytics Dashboard*. When a user submits feedback, the system automatically performs the *Analyze Sentiment* use case (shown with an «include» relationship), meaning sentiment analysis is a mandatory internal process triggered during feedback submission. The «extend» relationship indicates that viewing sentiment results depends on the sentiment analysis process.

On the admin side, additional administrative use cases are provided, such as *Manage Users*, *View All Feedback*, and *Configure System* (e.g., setting thresholds or selecting models). These functionalities allow the admin to monitor system activity, control user access, and adjust analysis settings. The color legend differentiates between user use cases, system processes, and admin use cases, clearly illustrating role-based responsibilities and how both users and administrators interact with the system.

3.3 CLASS DIAGRAM

This class diagram is designed to match a typical Spring Boot + MySQL implementation, where the system is organized into clearly separated layers: entities, controllers, services, repositories, and analyzer components. The **entity classes** (such as User, Feedback, and SentimentResult) represent the data model and map directly to database tables in MySQL. These entities define the structure of the data, including primary keys, attributes, and relationships (for example, one User can have many Feedback entries, and each Feedback produces one SentimentResult), which helps in enforcing data integrity and simplifying object-relational mapping using JPA or Hibernate.

The **controllers and services** implement the application logic in a layered way. Controllers like FeedbackController and UserController handle HTTP requests, validate inputs, and call corresponding service classes such as SentimentAnalysisService and DashboardService. These services orchestrate the flow of data, including fetching or saving records from repositories, initiating sentiment analysis, and preparing response objects. The separation between controllers and services keeps the web layer lightweight and the business logic centralized, which improves maintainability and makes it easier to test individual components using unit tests.

Finally, the **repository and analyzer classes** complete the backend architecture. Repository interfaces such as UserRepository, FeedbackRepository,and SentimentResultRepository extend Spring Data JPA and provide CRUD operations and custom queries against the MySQL database. Alongside them, the analyzer classes (TextPreprocessor, TFIDFVectorizer, LogisticRegressionModel, and LexiconAnalyzer) encapsulate the NLP and machine-learning logic for preprocessing text, extracting features, classifying sentiment, and combining rule-based and statistical scores. The entire class diagram thus reflects a clean, modular Spring Boot design where entities manage data, controllers manage interaction, services manage business flow, repositories manage persistence, and analyzer classes handle opinion mining and sentiment analysis.

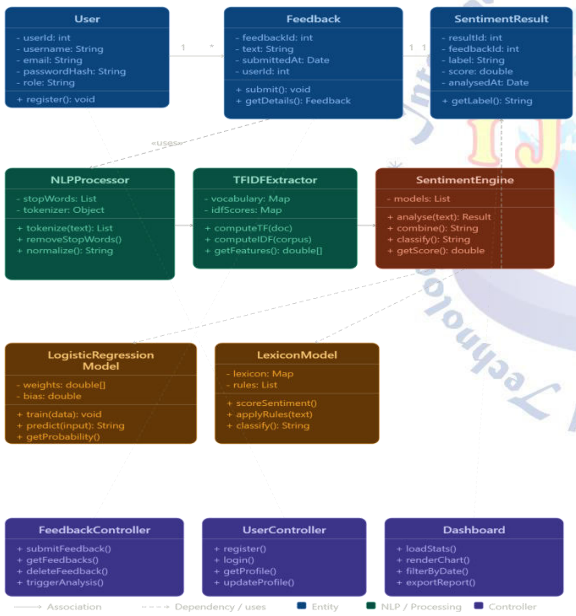


Fig 3.3 Sequence Diagram

The diagram represents the **Class Diagram** of the Feedback Analysis System, showing the structure of classes, their attributes, methods, and relationships. The system is divided into four main sections: **Entities**, **NLP/Processing components**, **Machine Learning models**, and **Controllers**. In the Entity layer, the User class contains user details such as userId, username, email, passwordHash, and role, and is associated with the Feedback class in a one-to-many relationship (one user can submit multiple feedbacks). The Feedback class stores feedbackId, text, submitted date, and userId, and has a one-to-one relationship with the SentimentResult class, which stores the sentiment label, score, and analysis date.

The NLP/Processing layer includes the NLPProcessor, TFIDFExtractor, and SentimentEngine classes. The NLPProcessor performs tokenization, stop-word removal, and normalization. The TFIDFExtractor computes term frequency (TF), inverse document frequency (IDF), and generates feature vectors. The SentimentEngine acts as the core analysis component that combines results and classifies sentiment by using two models: the LogisticRegressionModel (machine learning-based, with weights and bias for prediction) and the LexiconModel (rule-based, using a sentiment dictionary and scoring rules).

At the bottom, the Controller layer includes FeedbackController, UserController, and Dashboard. These controllers handle application logic such as submitting feedback, triggering analysis, user registration/login, profile management, loading statistics, rendering charts, and exporting reports. The solid arrows represent associations (relationships between entities), while the dashed arrows indicate dependencies or usage between processing components and controllers. Overall, the diagram illustrates how user input flows from controllers to processing components, through ML models, and finally stores the analyzed sentiment results in the system.

4. RESULTS

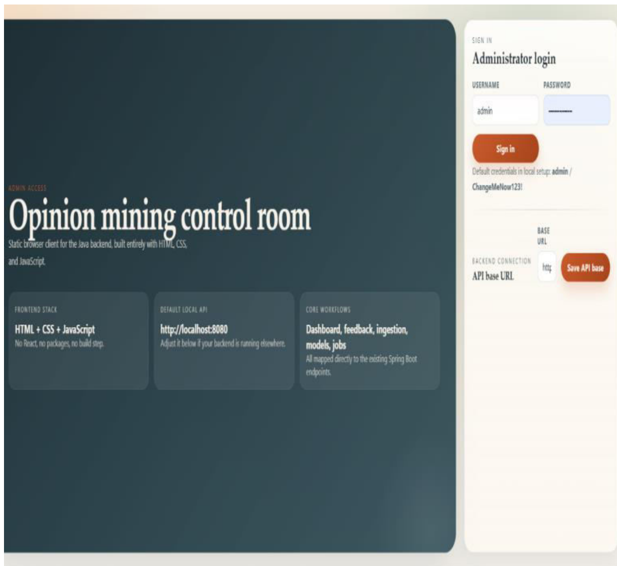
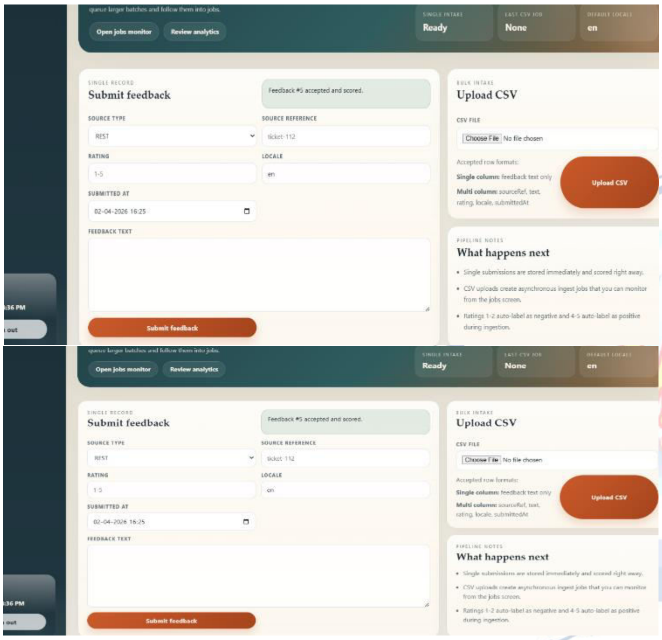


Fig 4.1: System Login Interface(Before Prediction)

The image shows the Administrator Login Page of the system. Users enter their username and password to access the application.

It also includes API configuration to connect the frontend with the backend (localhost:8080). The page provides an overview of system modules like dashboard, feedback, and model management.

This screen acts as the entry point and ensures secure access to the system.



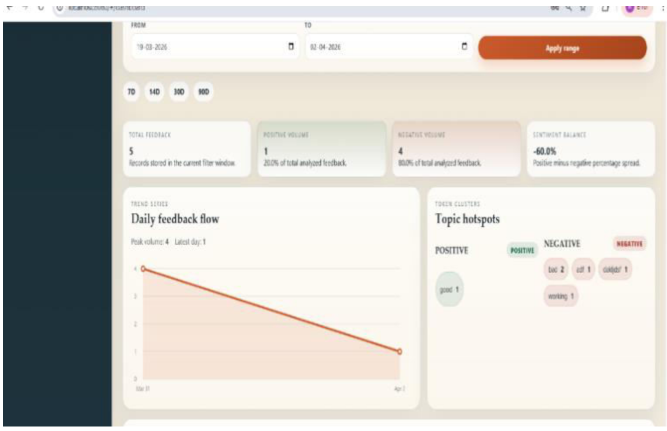


Fig 4.2.1: DashBoard Overview

This figure represents the student prediction dashboard where users input academic details such as assignment marks, attendance percentage, and mid-exam scores.

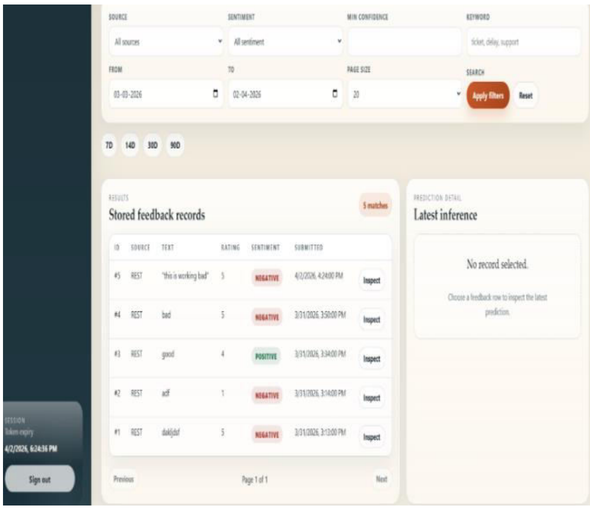


Fig 4.2.2: Feedback Records Display

4.2 BEFORE PREDICTION

The following images represent the system interface before performing sentiment prediction. The system provides a dashboard view and input modules for collecting user feedback.

4.2.1 DashBoard Overview

- The first image shows the Feedback Analytics Dashboard, which provides a summary of system activity.
- It displays key metrics such as:
  - Total feedback count
  - Positive and negative sentiment distribution
  - Topic clusters and keyword analysis
- The dashboard helps in monitoring overall feedback trends and system performance.

4.2.2 Feedback Records Display

- The system stores previously submitted feedback records.
- Each record contains:
  - Feedback text
  - Sentiment label (Positive/Negative)
  - Submission time
- This allows users to review historical data before performing new predictions.

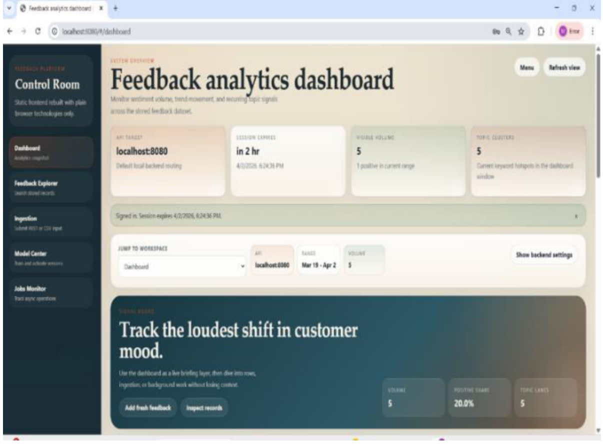


Fig 4.2.3: Ingestion Module

4.2.3 Ingestion Modules

The system provides a user-friendly interface for submitting feedback data. Users can enter:

- Feedback text
- Source type
- Rating (1–5)

A "Submit Feedback" button is used to send the data into the system for analysis. This module ensures easy data entry and smooth ingestion of feedback.

4.2.4 CSV Upload module

- The system also supports **bulk data upload** using CSV files.
- Users can upload multiple feedback entries at once.
- This feature is useful for analyzing large datasets efficiently.

4.3 After Prediction

The following images show the system after performing sentiment analysis and displaying results.

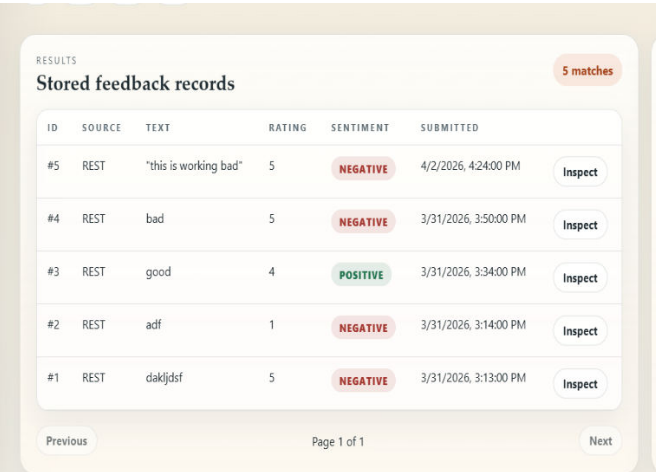


Fig 4.3.1: Sentiment Analysis Result

4.3.1 Sentiment Analysis Result

- After submitting feedback, the system processes the input using:
  - **Logistic Regression (Machine Learning)**
  - **Rule-Based Sentiment Analysis**
- The system classifies feedback into:
  - Positive
  - Negative
  - Neutral
- The results are displayed clearly in the dashboard and records table.

4.3.2 Uploading Dashboard Metrics

- The dashboard updates dynamically after prediction.
- It shows:
  - Total feedback count
  - Positive sentiment percentage
  - Negative sentiment percentage
  - Sentiment balance
- These metrics help in understanding overall user opinion.

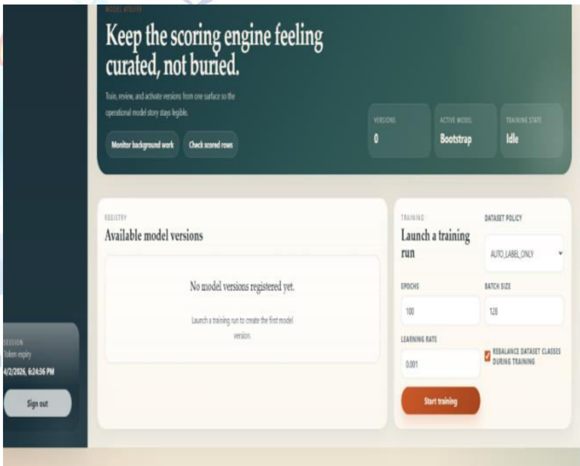


Fig 4.4: Model Training Interface

4.4 Model Training Interface

- The system includes a **Model Center** for training the model.
- Users can configure:
  - Epochs
  - Batch size
  - Learning rate

5. CONCLUSION

The AI-Based Online Feedback Analysis and Opinion Mining System provides an efficient solution for analyzing user feedback and identifying sentiment automatically. The system integrates machine learning (Logistic Regression) and rule-based sentiment analysis (lexicon-based NLP) to classify feedback into positive, negative, and neutral categories.

The system processes user feedback data through preprocessing and analysis to generate meaningful insights. The dashboard visualizes sentiment distribution, trends, and keyword patterns, helping organizations understand customer opinions effectively.

The combination of Logistic Regression and rule-based methods improves the overall accuracy and reliability of the system. The results demonstrate that the system can reduce manual effort, provide quick analysis, and support better decision-making based on user feedback.

Overall, this project highlights the importance of AI in opinion mining and shows how automated sentiment analysis can be used in real-world applications such as customer feedback analysis, product reviews, and service improvement.

FUTURE ENHANCEMENT

The system can be further enhanced by incorporating real-time feedback analysis to process user opinions instantly. The accuracy of sentiment classification can be improved by integrating advanced machine learning and deep learning models such as LSTM or BERT. Additionally, adding multilingual support will enable the system to analyze feedback in different languages, making it more versatile. The system can also be extended to include emotion detection, allowing it to identify feelings such as happiness, anger, or sadness along with sentiment. Improved data visualization techniques and more interactive dashboards can provide better insights for users. Furthermore, integrating the system with social media platforms will allow large-scale data collection and analysis. Finally, implementing explainable AI techniques will help users understand how predictions are made, increasing transparency and trust in the system.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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