PREDICTING CUSTOMER SATISFACTION USING MLOPS

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE




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ABSTRACT

This paper presents the design and implementation of a sentiment analysis system for customer reviews, integrating machine learning with MLOps for real-time performance and automation. The system classifies customer sentiments into positive, neutral, or negative categories using Natural Language Processing (NLP) techniques such as tokenization and TF-IDF vectorization. A Random Forest Classifier is employed for its ensemble-based robustness and interpretability in sentiment prediction. The architecture follows a modular approach, comprising key components such as Data Collection, Preprocessing, Feature Extraction, Sentiment Prediction, MLOps Pipeline, and an Alert Notification Module. Customer reviews are processed and labeled in real time, with sentiment results and confidence scores stored in MongoDB. In cases of negative sentiment, automated email alerts are sent to customer support teams, enabling prompt response and issue resolution. MLOps integration enables automated model training, deployment, and monitoring, supporting continuous improvement and scalability. Model performance is evaluated using standard metrics including accuracy, precision, recall, and F1-score, confirming the system's reliability and effectiveness. The proposed system demonstrates how combining NLP and automated ML workflows can enhance customer engagement, reduce feedback response time, and support proactive business decisions. This solution offers a scalable, maintainable, and intelligent framework for real-time sentiment analysis in modern customer-centric applications.

ABSTRACT(TAMIL)

(MLOPS ஐப் பயன்படுத்தி வாடிக்கையாளர் திருப்தியைக் கணிப்பது)

இந்த ஆய்வுக் கட்டுரை, வாடிக்கையாளர் விமர்சனங்களை உணர்வுப்பூர்வமாக வகைப்படுத்தும் ஒரு இயந்திரக் கற்றல் அமைப்பின் வடிவமைப்பு மற்றும் செயல்படுத்தலை விவரிக்கிறது. இந்த அமைப்பில், வாடிக்கையாளர் கருத்துகள் நல்லது, சாதாரணம், மோசமானது என மூன்று வகைகளில் வகைப்படுத்தப்படுகின்றன. TF-IDF மற்றும் tokenization போன்ற இயற்கை மொழி செயலாக்க (NLP) நுட்பங்கள் மூலம் உரை தரவுகள் செயலாக்கப்படுகின்றன. வகைப்படுத்தலுக்காக Random Forest வகைப்படுத்தி பயன்படுத்தப்படுகிறது. அமைப்பு Data Collection, Preprocessing, Feature Extraction, Sentiment Prediction, MLOps Pipeline மற்றும் Alert Notification எனும் தொகுதிகளால் அமைக்கப்பட்டுள்ளது. MongoDB மூலம் ஒவ்வொரு விமர்சனமும் அதன் உணர்வுப் புள்ளிகள் மற்றும் நம்பகத்தன்மை மதிப்புகளுடன் சேமிக்கப்படுகிறது. மோசமான உணர்வுகள் பதிவானால், தொடர்புடைய குழுவிற்கு தானியங்கி மின்னஞ்சல் எச்சரிக்கை அனுப்பப்படுகிறது. MLOps ஒருங்கிணைப்பு தொடர்ந்து மாதிரி பயிற்சி, வெளியீடு மற்றும் கண்காணிப்பை எளிமைப்படுத்துகிறது. துல்லியம், precision, recall மற்றும் F1-score ஆகியவற்றைப் பயன்படுத்தி மாதிரியின் செயல்திறன் மதிப்பீடு செய்யப்படுகிறது. இவ்வமைப்பு, உணர்வுபூர்வ பகுப்பாய்வு மற்றும் தானியங்கி செயலாக்கம் இணைந்து, வாடிக்கையாளர் திருப்தியை நேரடி நேரத்தில் மேம்படுத்தும் திறன் கொண்டதாக நிரூபிக்கிறது.

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CHAPTER – 1

1. INTRODUCTION

In the modern digital era, vast volumes of user-generated content—particularly customer reviews—are available across e-commerce platforms, social media, and service-based applications. These reviews serve as rich sources of customer feedback, revealing valuable insights into user satisfaction, product quality, and service efficiency. However, manually analysing such massive and diverse datasets is impractical, making automated sentiment analysis an essential tool in understanding customer perceptions.

This project focuses on building an intelligent **Sentiment Analysis System** using **Machine Learning (ML)** techniques. The primary objective is to classify customer opinions into distinct sentiment categories such as positive, negative, or neutral. By doing so, organizations can proactively address concerns, enhance product offerings, and improve overall customer satisfaction.

The proposed system employs a structured workflow, beginning with data collection and preprocessing to eliminate noise and standardize textual inputs. This is followed by feature engineering and selection to extract meaningful indicators of sentiment. A machine learning model is then trained on labeled datasets to accurately predict the sentiment of unseen customer reviews. The system also integrates real-time inference endpoints, allowing live sentiment prediction for ongoing feedback streams.

Incorporating Natural Language Processing (NLP) and ML algorithms, the system ensures both scalability and adaptability across domains. The deployment of such a model not only reduces human effort but also enhances decision-making processes in business analytics and customer relationship management.

This project demonstrates the powerful intersection of data science, linguistics, and artificial intelligence to automate and refine the process of sentiment interpretation in customer reviews. It paves the way for more responsive, informed, and customer-centric business strategies

CHAPTER – 2

2. LITERATURE SURVEY

In recent years, sentiment analysis has emerged as a pivotal tool in understanding customer opinions across digital platforms. Traditional approaches to sentiment classification relied heavily on manual annotation and lexicon-based models, which, while interpretable, struggled with scalability and contextual understanding. With the advancement of **Machine Learning (ML) and Natural Language Processing (NLP)**, sentiment analysis has transitioned to more automated and intelligent systems capable of handling large volumes of unstructured text data.

Research by **Pang and Lee (2008)** laid the foundation for supervised learning approaches in sentiment classification, emphasizing the effectiveness of Naïve Bayes and Support Vector Machines in analyzing movie reviews. Later**, Cambria et al. (2014)** introduced concept-level sentiment analysis, highlighting the need for semantic understanding and contextual polarity in interpreting nuanced sentiments within customer feedback.

Deep learning models have further transformed the sentiment analysis landscape. **Socher et al. (2013)** introduced Recursive Neural Tensor Networks, enabling hierarchical analysis of sentence structure and sentiment. Similarly, **Liu (2015)** highlighted the integration of **Long Short-Term Memory (LSTM)** networks to capture sequential dependencies in textual data, significantly improving sentiment prediction accuracy over traditional bag-of-words methods.

Recent studies have emphasized the use of pre-trained language models like **BERT and RoBERTa** in customer sentiment classification. Research by **Sun et al. (2019)** showed how fine-tuned BERT models outperform traditional ML techniques by understanding bidirectional context and subtle emotional cues in reviews. The transformer architecture's success has popularized transfer learning in NLP tasks, offering high performance with reduced training time.

The adoption of domain-specific sentiment scoring systems, such as **SentiWordNet** and **VADER**, has also enhanced the interpretability of sentiment models in e-commerce and service feedback systems. Furthermore, works by **Zhang et al. (2020)** emphasized the integration of **emotion detection** and **sarcasm identification** to improve model robustness in real-world applications.

Recent innovations in model deployment have also played a vital role. Tools like **TensorFlow** Serving and **PyTorch** Serve, alongside **MLOps** practices, enable real-time inference, scalability, and monitoring of sentiment models. Studies in model explainability, such as by **Ribeiro et al. (2016)**, have explored SHAP and LIME to provide transparent and accountable sentiment classification systems, particularly in customer-focused applications.

These developments collectively establish a strong foundation for building scalable, intelligent, and explainable sentiment analysis systems. By combining feature engineering, contextual modeling, and real-time inference, modern frameworks ensure a holistic approach to understanding customer sentiment in both academic and industrial domains.

CHAPTER – 3

3. OBJECTIVE

3.1 Primary Objectives

▪ Develop a robust sentiment analysis system capable of understanding customer opinions from product reviews.

▪ Accurately predict customer satisfaction levels based on textual feedback using machine learning techniques.

▪ Enhance business decision-making by providing insights into customer behaviour and expectations.

3.2 Secondary Objectives

▪ Design a modular and scalable pipeline for sentiment extraction and satisfaction score prediction.

▪ Support multi-lingual and domain-specific sentiment analysis to widen applicability.

▪ Enable real-time feedback analysis for e-commerce platforms.

▪ Improve user experience by incorporating explainable AI to interpret model predictions.

3.3 Technical Objectives

▪ Implement natural language processing (NLP) techniques for preprocessing, tokenization, and tagging.

▪ Integrate Senti-CS scoring and feature vector generation for high-accuracy classification.

▪ Apply feature selection algorithms to reduce dimensionality and improve model efficiency.

▪ Use state-of-the-art classifiers (e.g., SVM, LSTM, or BERT) for sentiment classification and score prediction.

▪ Ensure seamless deployment using MLOps practices including continuous integration, monitoring, and version control.

CHAPTER – 4

4. SYSTEM ANALYSIS

4.1 EXISTING SYSTEM

In the domain of customer feedback analysis, traditional systems have primarily relied on basic keyword-based sentiment detection and manual review methods. These systems often utilize static lexicons or rule-based techniques to classify sentiments as positive, negative, or neutral. While such approaches offer simplicity, they lack contextual understanding, leading to inaccurate predictions in cases involving sarcasm, ambiguity, or domain-specific language.

Many existing models operate with pre-labeled datasets like the Brazilian E-Commerce Public Dataset or IMDb Reviews, which may not generalize well across different industries or dynamic user behaviors. Additionally, these systems tend to focus only on sentiment classification without quantifying customer satisfaction levels or providing interpretability.

Another major limitation lies in the absence of real-time analytics and MLOps integration, which restricts scalability, continuous improvement, and deployment automation. Furthermore, most platforms do not offer personalized insights or adaptive learning based on new user data, thereby failing to meet modern commercial demands.

While platforms like TextBlob, VADER, and pre-trained transformers like BERT offer improved accuracy over traditional techniques, they are often used as standalone models without a holistic pipeline. The lack of modularity, explainability, and customization in current systems underlines the need for an enhanced architecture that combines sentiment detection with predictive analytics in a scalable and explainable manner.

4.2. PROPOSED SYSTEM

To address the limitations of existing sentiment analysis frameworks, we propose a robust, AI-integrated system designed to accurately detect sentiment, analyze emotion intensity, predict customer satisfaction scores, and provide actionable insights in real-time. This next-generation system leverages advanced machine learning techniques and modern MLOps pipelines to ensure continuous improvement, scalability, and high adaptability across diverse domains.

Emotion-Aware Sentiment Detection:

Unlike traditional polarity-based sentiment systems, our proposed model incorporates emotion detection and intensity analysis. This enables a deeper understanding of user sentiment by classifying emotions such as anger, joy, sadness, or surprise, along with their intensity levels. This granularity provides richer context for decision-making and helps businesses address customer concerns more effectively.

Contextual and Sarcasm-Resistant NLP:

The system employs transformer-based models like BERT and RoBERTa fine-tuned for contextual understanding. These models can capture nuances such as sarcasm, idioms, and domain-specific language, which often confuse conventional algorithms. This results in higher classification accuracy and minimizes misinterpretation of complex expressions.

Aspect-Based Sentiment Analysis(ABSA):

To isolate sentiments across multiple features of a product or service, our system incorporates ABSA. For example, reviews mentioning delivery, product quality, or customer service will be individually scored and interpreted. This component enables targeted improvements across specific business areas, driving strategic refinement.

Customer Satisfaction Score Prediction

Beyond sentiment detection, the system forecasts a numerical satisfaction score (0–5 scale) using regression models trained on historical feedback and behavioral indicators. This feature helps businesses prioritize high-risk customer segments and proactively improve service delivery.

Real-Time Feedback Dashboard

A dynamic, user-friendly dashboard will display sentiment trends, satisfaction scores, and emotional insights in real-time. Built with modular UI components and integrated via MLOps pipelines, this dashboard will serve both technical and non-technical stakeholders with intuitive data visualizations and alerts.

Automated Feedback Summary Generation

The system will employ natural language generation (NLG) techniques to summarize lengthy customer feedback into concise reports, making them easier to process for customer support teams. Summaries will include sentiment orientation, key concerns, and suggested actions.

MLOps Pipeline for Continuous Deployment

The entire system will be deployed using MLOps tools like ZenML or MLflow, ensuring modular development, versioning, automated testing, and CI/CD integration. This will support model retraining on new data, maintaining performance over time.

4.3. ALGORITHM

This project utilizes the **Random Forest** algorithm for sentiment classification due to its robustness, interpretability, and high performance on textual datasets transformed via vectorization techniques.

Random Forest is an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and reduce the risk of overfitting. Each tree is trained on a random subset of the data, and the final output is determined by majority voting across all trees. This method works particularly well for high-dimensional data such as TF-IDF vectors, which are used to represent the textual customer feedback in this project.

The entire classification pipeline is illustrated in **Figure 4.3.1**, which outlines the major phases in the model's operational flow:

4.3.1 Random Forest Workflow

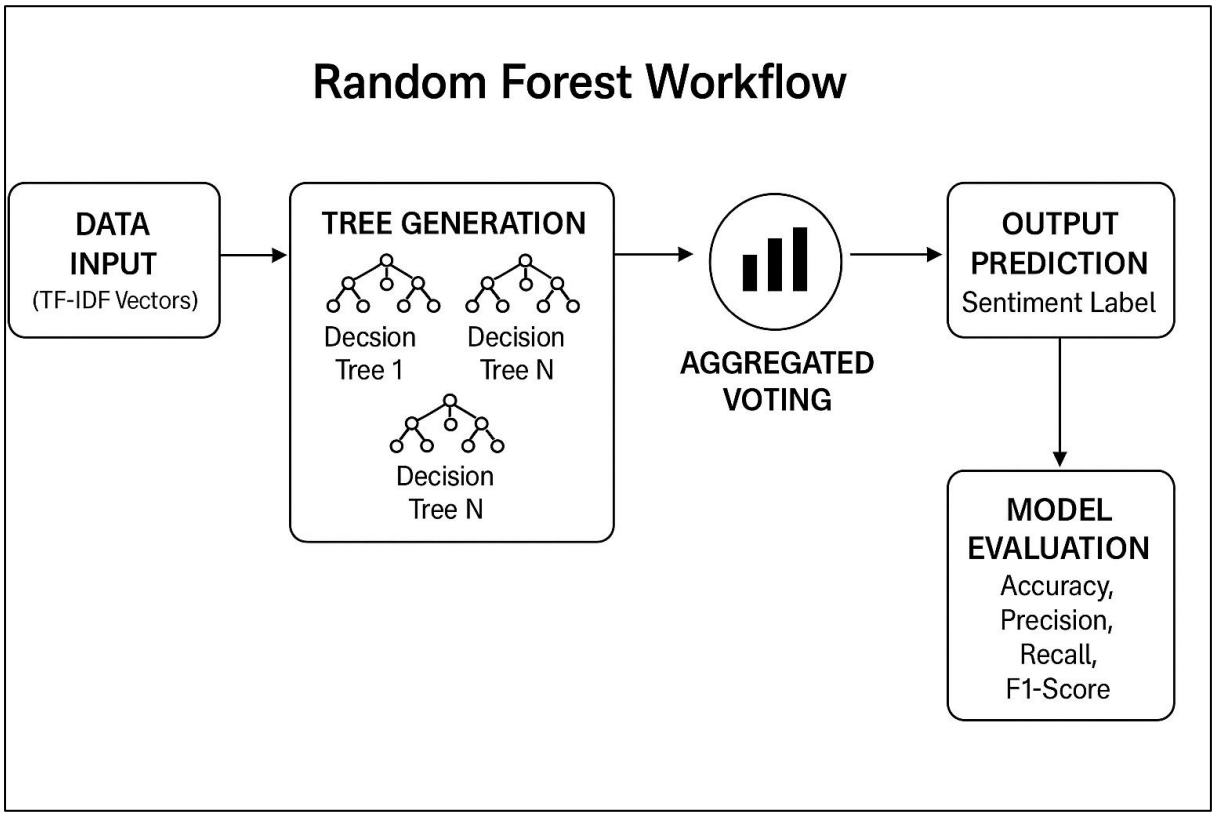

Figure 4.3.1: ***Random Forest-based Sentiment Classification Process***

Explanation of Workflow:

- **Data Input:** The raw customer feedback undergoes preprocessing and vectorization using **TF-IDF (Term Frequency-Inverse Document Frequency)** to convert textual data into numerical form.
- **Tree Generation:** A multitude of decision trees are trained on different bootstrap samples of the TF-IDF input vectors. Each tree makes an independent prediction.
- **Aggregated Voting:** The individual outputs from the decision trees are combined through a majority voting mechanism to produce the final sentiment prediction — categorized as *positive*, *neutral*, or *negative*.
- **Output Prediction:** The aggregated result is presented as the final sentiment label for the given review.
- **Model Evaluation:** The predicted results are validated using key performance metrics such as:
    - **Accuracy** – Proportion of correct predictions over total instances.
    - **Precision** – Correctly predicted positive observations over total predicted positive.
    - **Recall** – Correctly predicted positive observations over all actual positives.
    - **F1-Score** – Harmonic mean of precision and recall for balanced assessment.

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5. EXTERNAL INTERFACES

5.1 USER INTERFACE (FRONTEND)

The user interface (UI) serves as the primary access point for both administrators and end-users to interact with the sentiment analysis and customer satisfaction prediction platform. The frontend is designed with a focus on usability, clarity, and responsiveness to ensure an optimal experience across devices.

Features:

- **Feedback Submission Portal:** Allows customers to input feedback through forms or voice-to-text options.
- **Real-Time Sentiment Display:** Provides instant sentiment classification (Positive, Neutral, Negative) and satisfaction scores.
- **Dashboard for Admins and Analysts:**
    - Visual representation of feedback trends.
    - Confidence Score for satisfaction prediction.
    - Alert system for negative trends.
    - Personalized mail system for customer reviews
- **Model Performance Overview:** Displays current deployed model version, accuracy, drift metrics, and retraining status.
- **Authentication System:** Role-based access control for Admin, ML Engineer, and Analyst roles.

Technologies Used:

- HTML for component-based UI architecture.
- CSS for responsive and modern styling.
- Jinja2 template engine to connect Backend to Frontend
- Axios for API calls and real-time updates

5.2 BACKEND INTERFACE

The backend acts as the core processing layer, managing business logic, API endpoints, and communication between the frontend, model services, and database.

Features:

- **RESTful APIs:** Exposes endpoints for feedback submission, prediction requests, model performance data, and admin configurations.
- **Model Serving Endpoint:** Integrates with MLflow or BentoML to serve trained models via API.
- **Feedback Routing:** Handles the queuing and processing of incoming customer feedback using asynchronous workers (e.g., Celery).
- **Notification System:** Sends alerts to admins when sentiment thresholds or model drift thresholds are breached.

Technologies Used:

- FastAPI (or Flask) for building scalable API services.
- uvicorn as a production WSGI server.
- Python for backend logic and ML inference orchestration.

5.3 MACHINE LEARNING MODEL INTERFACE

This interface defines how ML models are trained, served, monitored, and retrained through the MLOps pipeline.

Features:

- **Model Training Interface:** Accepts training data from preprocessing pipeline, supports hyperparameter tuning.
- **Model Registry:** Version-controlled model storage and metadata management using MLflow or Weights & Biases.

- **Deployment API:** Model served through Dockerized containers using FastAPI or TorchServe.
- **Monitoring Interface:** Integrates Prometheus and Grafana for monitoring model latency, accuracy, and input drift.

Key Tools:

- Scikit-learn, XGBoost for baseline and production models.
- MLflow for model tracking, logging, and registry.
- GitHub Actions for CI/CD workflows

5.4 DATABASE INTERFACE

The database stores structured and unstructured data essential for analytics, model training, and user management.

Components:

- **Feedback Database:** Stores raw and preprocessed customer feedback with associated metadata (timestamp, sentiment, score).
- **Model Metadata Store:** Holds model performance logs, hyperparameters, training metrics.
- **User Activity Logs:** Tracks usage patterns, predictions accessed, retraining triggers.
- **Audit Trail System:** Maintains records of modifications, model deployments, and retraining events for governance.

Technologies Used:

- MongoDB or Elasticsearch for unstructured logs and sentiment indexes.
- SQLAlchemy for ORM-based interaction with relational DBs.

CHAPTER – 6

6. NON-FUNCTIONAL REQUIREMENTS

The non-functional requirements of the proposed system define the quality attributes and constraints that influence the user experience, performance, security, and maintainability of the platform. These requirements ensure that the system not only meets functional expectations but also delivers a robust and scalable user-centric solution.

6.1 PERFORMANCE REQUIREMENTS

- **Real-Time Feedback Processing:**
    - The system must process and return sentiment classification and satisfaction predictions within 2 seconds for each customer input.
- **High Throughput Model Serving:**
    - The deployed model should handle at least 100 concurrent prediction requests without noticeable degradation in response time.
- **Asynchronous Task Handling:**
    - Background processes like retraining, data ingestion, and feedback logging should not affect the responsiveness of the UI/API.

6.2 SCALABILITY

- **Horizontal Scaling:**
    - The backend and model-serving components shall support container-based horizontal scaling via Docker and Kubernetes.
- **Data Volume Scalability:**
    - The platform must handle growth from thousands to millions of feedback entries without restructuring the underlying storage or retraining logic.

- **Modular Component Design:**
    - Each module (UI, API, model, monitoring) shall function independently to facilitate scaling and upgrading without system-wide disruption.

6.3 RELIABILITY & AVAILABILITY

- **Uptime Guarantee:**
    - The system shall maintain at least 99.5% uptime during production usage, with redundancy in model servers and database clusters.
- **Fault Tolerance:**
    - Auto-restart mechanisms shall be in place for critical services. All logs and metrics must be preserved across system crashes for diagnostics.
- **Data Backup:**
    - Incremental and full backups will be scheduled daily and weekly, respectively, ensuring no data loss in the event of failure.

6.4 USABILITY

- **User-Friendly Interface:**
    - The interface will follow modern design principles with intuitive navigation, minimal learning curve, and responsive design for cross-device compatibility.
- **Accessibility Standards:**
    - The system shall comply with WCAG 2.1 accessibility standards, enabling support for screen readers and keyboard navigation.
- **Role-Based Views:**
    - Different user roles (e.g., Customer, Analyst, Admin) will receive contextual dashboards and controls tailored to their permissions and needs.

6.5 MAINTAINABILITY

- **Code Modularity and Documentation:**
    - All components will follow modular design principles with complete in-line documentation and API specifications using tools like Swagger.

- **CI/CD Integration:**
    - GitHub Actions will ensure continuous integration and automated testing on each pull request. Code coverage must exceed 80% for core modules.

- **Model Lifecycle Management:**
    - ML models will be versioned via MLflow and subject to monitoring, retraining, and rollback through defined lifecycle hooks.

6.6 SECURITY

- **Data Privacy:**
    - All personally identifiable information (PII) will be encrypted at rest and in transit using AES-256 and TLS protocols.

- **Authentication & Authorization:**
    - Secure OAuth2.0 or JWT-based authentication will control access, and RBAC (Role-Based Access Control) will restrict operations based on user roles.

- **Input Validation:**
    - All user inputs will undergo strict sanitization and validation to prevent injection attacks and XSS vulnerabilities.

6.7 PORTABILITY & COMPATIBILITY

- **Cross-Browser Support:**
  - The system will be compatible with major browsers (Chrome, Firefox, Edge, Safari) and responsive on mobile and tablet devices.

- **Cloud-Agnostic Deployment:**
  - The entire system will be containerized and deployable on AWS, GCP, Azure, or any on-premise Kubernetes cluster

- **API Compatibility:**
  - APIs will conform to REST standards, allowing integration with third-party systems and external business intelligence tools.

6.8 LEGAL AND ETHICAL COMPLIANCE

- **GDPR and Data Protection:**
  - The platform will comply with GDPR and other relevant data protection laws for handling user feedback and model training data.
- **Model Bias & Explainability:**
  - The models will undergo fairness evaluations, and predictions will include explainability reports using SHAP or LIME, ensuring transparency and auditability.

CHAPTER – 7

7. SOFTWARE SYSTEM ATTRIBUTES

This section outlines the quality characteristics that define the operational effectiveness and technical soundness of the proposed system. These attributes ensure that the solution is not only functionally complete but also adaptable, robust, and future-ready.

7.1 MODULARITY

- The system will be composed of clearly defined, independent modules such as:
  - Data Ingestion Module
  - Preprocessing and Feature Engineering Pipeline
  - Sentiment Analysis & Emotion Detection Model
  - Customer Satisfaction Score Predictor
  - Monitoring and Retraining Pipeline
- Each module will follow a separation of concerns to enable independent development, testing, and deployment.
- ZenML pipelines will be used to enforce modular design and seamless integration across machine learning stages.

7.2 REUSABILITY

- Code components will be written as reusable functions and classes, with configurations abstracted using YAML and JSON files.
- Pre-trained models, transformation pipelines, and tokenizers will be stored and versioned using MLflow and DVC, allowing for reuse across iterations and datasets.
- The MLOps design will support deployment of multiple ML models in different environments (e.g., staging, production) without reengineering core logic.

7.3 MAINTAINABILITY

- The entire codebase will follow **PEP8 standards** and include inline documentation using docstrings and auto-generated API docs with tools like Swagger or Sphinx.
- GitHub Actions will automate code testing, linting, and deployment, enabling continuous delivery and easy debugging.
- All dependencies will be managed through 'requirements.txt' and environment files (conda.yaml), ensuring easy reproduction and minimal conflicts.

7.4 ADAPTABILITY

- The platform will support integration of new sentiment models or scoring techniques with minimal changes to the pipeline.
- Feature flags and dynamic configurations will allow tuning model parameters, switching between APIs (e.g., HuggingFace vs. local models), or adding new metrics.
- The architecture will support plug-and-play style improvements to any model stage, facilitating adaptation to client-specific domains or languages.

7.5 INTEROPERABILITY

- RESTful APIs will expose all critical services for interaction with external CRM systems, chatbots, or feedback forms.
- The system will export feedback results, analytics, and summaries in standard formats like JSON, CSV, and PDF.
- The database will be designed for integration with external dashboards or BI tools like Tableau, Power BI, or Grafana via ODBC/JDBC connectors.

7.6 SECURITY

- JWT-based secure login mechanisms will be used to protect API endpoints and user dashboards.
- End-to-end encryption for data transmission (TLS 1.3) and secure cloud storage (e.g., S3 with SSE) will be implemented.
- The system will incorporate rate limiting and anomaly detection to prevent abuse or denial-of-service attacks.
- Sensitive user information, including feedback content, will be anonymized or tokenized before storage.

7.7 SCALABILITY

- System components will be containerized using Docker and orchestrated via Kubernetes to ensure horizontal scalability.
- The sentiment analysis and satisfaction prediction models will be deployed using TorchServe or FastAPI-based model servers for low-latency, high-throughput inference.
- Redis and Kafka will be used for queuing and caching in high-traffic environments to ensure minimal processing delays.

7.8 USABILITY

- A clean and responsive UI with real-time updates, visualizations, and feedback explanations will be provided to both users and analysts.
- Interactive dashboards will present insights on sentiment trends, customer satisfaction scores, and engagement metrics.
- The user interface will include onboarding walkthroughs, tooltips, and help menus to reduce training time and improve overall accessibility.

7.9 RELIABILITY

- Regular health checks, heartbeat mechanisms, and fallback procedures will ensure system resilience in case of model or API failure.
- The system will support automatic failover between multiple instances of the model and API servers.
- Logging and alerting through tools like Prometheus and Grafana will help detect and resolve failures proactively.

7.10 TESTABILITY

- Unit, integration, and end-to-end tests will be written using pytest, unittest, and Postman collections for API testing.
- ML model performance will be validated using metrics such as accuracy, F1-score, and AUC-ROC during every CI/CD run.
- Model drift detection will be incorporated to alert when input data distribution or output predictions deviate from historical patterns.

CHAPTER - 8

8. DESIGN CONSTRAINTS

Design constraints are the limitations and conditions that influence how the system is designed, developed, and deployed. These constraints ensure the system adheres to specified standards, performance expectations, and operational requirements. The following subsections outline the critical constraints that guide the system's architecture, development environment, and deployment strategy.

8.1. HARDWARE CONSTRAINTS

The system is designed to operate efficiently on mid-tier computing infrastructure, with the following minimum hardware requirements:

- **Processor**: Quad-core CPU (Intel i5 or equivalent)
- **Memory**: Minimum 8GB RAM for model training and real-time inference
- **Storage**: Minimum 20GB of free disk space for datasets, model files, and logs
- **GPU**: Optional (for training deep learning models); inference is optimized for CPU-only environments

The deployment server, whether on-premises or in the cloud, must meet these specifications to ensure consistent performance without latency in prediction and analysis.

8.2. SOFTWARE AND PLATFORM CONSTRAINTS

The system relies on a well-defined software stack and libraries. Changes or incompatibilities in these can significantly affect the operation:

- **Programming Languages**: Python (v3.8 or above) for backend and machine learning logic; HTML, CSS, JavaScript for frontend development
- **Frameworks**: Flask or Django for web services; scikit-learn, pandas, NLTK/TextBlob for data processing and sentiment analysis

- **Database**: MySQL or PostgreSQL as the primary relational database for storing user data, feedback, and sentiment scores
- **Operating System**: Ubuntu Linux (preferred), compatible with most Python-based ML tools

Strict adherence to version control and dependency management (e.g., using pip freeze or requirements.txt) is mandatory to avoid runtime errors.

8.3. FUNCTIONAL CONSTRAINTS

- The system must classify text feedback in real-time or near real-time (<2 seconds).
- Sentiment prediction must include polarity (positive, negative, neutral) and optionally, emotion classification.
- Users should only access data and features based on their role (admin vs. general user).
- The model should support input feedback lengths up to 1000 characters.

These functional limitations ensure predictable system behavior and maintain usability across various usage scenarios.

8.4. DATA CONSTRAINTS

- **Input Format**: Accepts textual reviews only in UTF-8 encoded strings.
- **Language Support**: The system is optimized for English-language feedback. Non-English inputs may yield inaccurate results unless additional multilingual preprocessing is added.
- **Data Source**: All datasets used for training must be legally sourced and cleaned to remove personally identifiable information (PII).
- **Training Dataset Size**: The model is tuned to handle datasets of up to 100,000 samples without performance degradation.

CHAPTER – 9

9. MODULE DESCRIPTION

The system is divided into modular components to ensure scalability, maintainability, and efficient processing of user input for sentiment analysis and satisfaction prediction. Each module is responsible for a distinct function in the data pipeline, from raw review ingestion to result generation and evaluation. The following sections provide an in-depth description of each module in the system.

9.1. USER MODULE

Purpose:
Handles all user-related interactions, including review submission and result visualization.

Responsibilities:

- Allow users to input review text through the frontend interface.
- Send data securely to the server for processing.
- Display analysis results including sentiment classification and satisfaction score.

Technologies:
HTML/CSS/JavaScript (Frontend), REST API (Backend communication)

9.2. SYSTEM CONTROLLER MODULE

Purpose:
Acts as the core orchestrator, coordinating the interaction between other modules.

Responsibilities:

- Accept input from the User Module.
- Call the respective modules in the correct order: Pre-processing → Feature Extraction → Classification → Sentiment Analysis → Evaluation → Result Display.
- Return the final output to the user interface.

Technologies:

Python Flask/Django (API), JSON (Data Format)

9.3. REVIEW DATASET MODULE

Purpose:

Handles the storage and retrieval of historical review data used for training and evaluation.

Responsibilities:

- Load labelled review datasets for training and testing.
- Support importing new datasets for model retraining.
- Provide data integrity checks and version control.

Technologies:

Pandas, CSV/JSON file format, SQL for long-term storage

9.4. PRE-PROCESSING MODULE

Purpose:

Cleans and standardizes raw text to ensure consistent feature representation.

Responsibilities:

- Remove stop words, punctuations, and irrelevant characters.
- Apply tokenization and lowercasing.
- Perform stemming or lemmatization.
- Handle null, empty, or malformed inputs gracefully.

Technologies:

NLTK, SpaCy, RegEx, custom text cleaning functions

9.5. FEATURE EXTRACTION MODULE

Purpose:

Transforms cleaned text into structured features suitable for machine learning.

Responsibilities:

- Convert text into vector format using techniques like TF-IDF or Word2Vec.
- Normalize feature vectors if required.
- Store feature matrices temporarily for training or classification.

Technologies:

scikit-learn (TF-IDF Vectorizer), Gensim (Word2Vec), NumPy

9.6. CLASSIFICATION MODULE

Purpose:

Assigns a predicted category to the user review using trained machine learning models.

Responsibilities:

- Load the trained model from disk (e.g., .pkl file).
- Predict the sentiment category (e.g., positive, negative, neutral).
- Optionally output class probabilities for confidence estimation.

Technologies:

scikit-learn (Logistic Regression, SVM, etc.), joblib/pickle

9.7. SENTIMENT ANALYSIS MODULE

Purpose:

Performs fine-grained analysis of textual tone and emotional cues.

Responsibilities:

- Use polarity scores to assess sentiment intensity.
- Detect emotional tone (happy, angry, disappointed) using custom lexicons or pretrained models.
- Integrate with classification results for enhanced sentiment accuracy.

Technologies:

TextBlob, VADER, Transformers (optional)

9.8. RESULTS DISPLAY MODULE

Purpose:

Delivers the final output in a user-readable format.

Responsibilities:

- Show sentiment polarity, emotion tag, and satisfaction prediction.
- Display analytics like rating (1–5 stars), graph views, or explanation (via LIME/SHAP if enabled).
- Support multilingual output (future scope).

Technologies:

Frontend rendering via JavaScript or dynamic templates (Jinja2)

9.9. NOTIFICATION & FEEDBACK MODULE

Purpose:

Provides feedback to customers or internal teams based on prediction outcomes.

Responsibilities:

- Notify users of sentiment classification (e.g., thank you messages or support follow-up).
- Generate reports for business insights.
- Collect user feedback to improve accuracy.

Technologies:

SMTP (Email alerts), ReportLab (PDF), API integrations (Slack, Teams)

CHAPTER – 10

10. APPENDICES

A. PROJECT FOLDER STRUCTURE

```
project-root/
│
├── app.py                # Main application script (Flask server)
├── pipeline.py           # Pipeline entry point integrating preprocessing, training, and prediction
├── templates/
│   ├── index.html        # Frontend UI for sentiment input
│   └── reviews.html      # Dashboard for stored feedback
├── src/
│   ├── data_loader.py    # Loads dataset and splits it into train/test
│   ├── preprocessor.py   # Performs text cleaning, tokenization, and vectorization
│   ├── trainer.py        # Contains training routines and model saving
│   └── evaluator.py      # Evaluates the model's accuracy and performance metrics
└── models/
    └── sentiment_model.pkl  # Serialized trained sentiment classification model
```

B. TECHNOLOGIES USED

Component	Technology Used
Frontend	HTML, CSS
Backend	Flask (Python)
Database	MongoDB

Component	Technology Used
Machine Learning	Scikit-learn, NLTK
CI/CD & MLOps	MLflow, GitHub Actions
Deployment	Localhost / Cloud-Ready

C. MONGODB DOCUMENT STRUCTURE

Each customer feedback is stored in the following JSON-like document format:

json

CopyEdit

```
{
  "customer_name": "John Doe",
  "email": "john@example.com",
  "review": "The service was disappointing.",
  "sentiment": "negative",
  "confidence": 0.91,
}
```

D. SAMPLE SENTIMENT CLASSIFICATION OUTPUT

Review	Sentiment	Confidence
“Absolutely loved the product!”	Positive	0.95
“It was okay, not great.”	Neutral	0.78
“Terrible experience. Never again.”	Negative	0.89

CHAPTER – 11

11. SYSTEM DESIGN

The Customer Satisfaction Prediction System adopts a modular, service-oriented architecture that integrates a web-based user interface, backend model services, and an MLOps pipeline. Major components include User Feedback Module for capturing customer reviews, Sentiment Analysis Module to classify textual feedback using trained NLP models, and Satisfaction Scoring Module to quantify satisfaction levels. Additionally, the Admin Panel enables user and data management, while the MLOps Pipeline automates model training, evaluation, deployment, and monitoring. The system uses structured data storage with relational databases (e.g., PostgreSQL) for managing users, feedback logs, and model metrics. Secure login and role-based access are enforced via authentication protocols. Frontend technologies include HTML, CSS, and JavaScript (with React or Vue), while the backend is built with Python (Flask/Django) and MLflow for model lifecycle management. The interface is optimized for ease of use across customers, admins, and data scientists, ensuring efficient interaction and system reliability.

11.1 ARCHITECTURE DESIGN

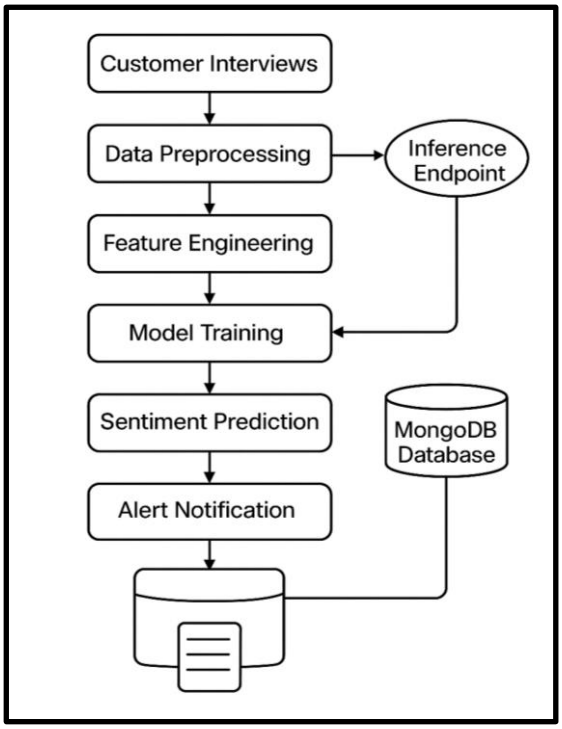
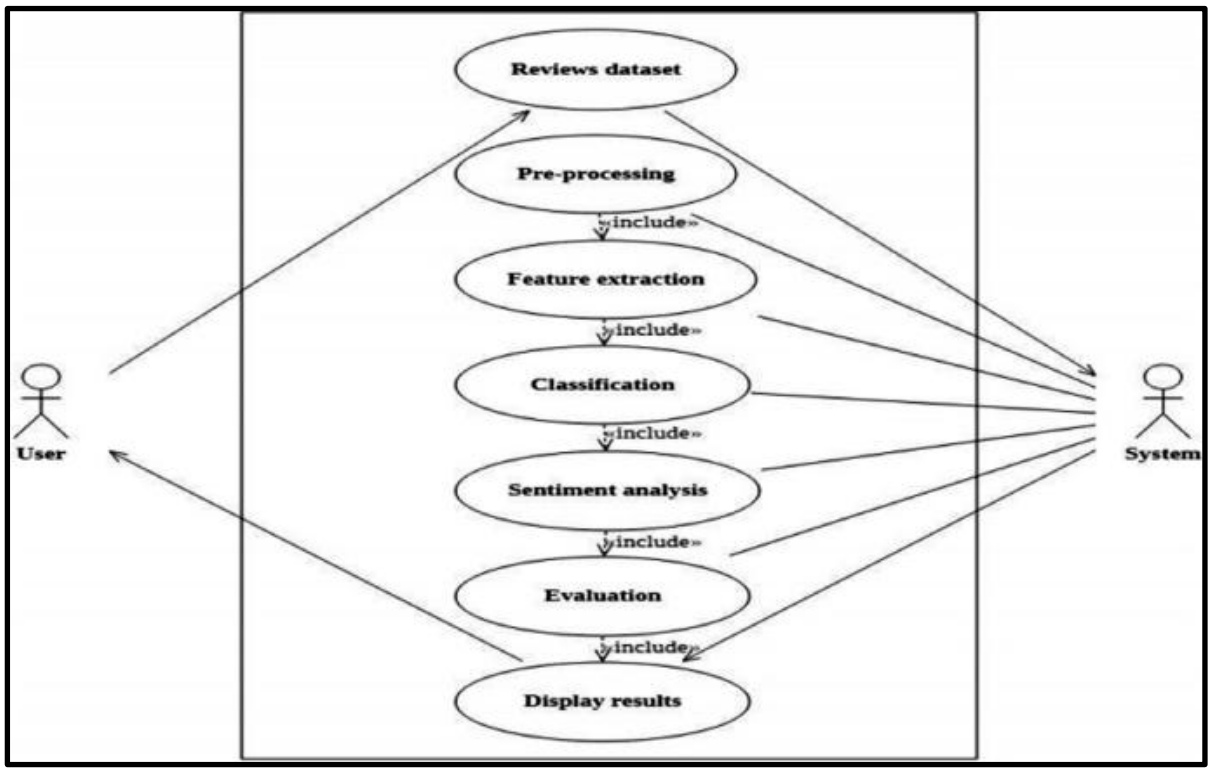


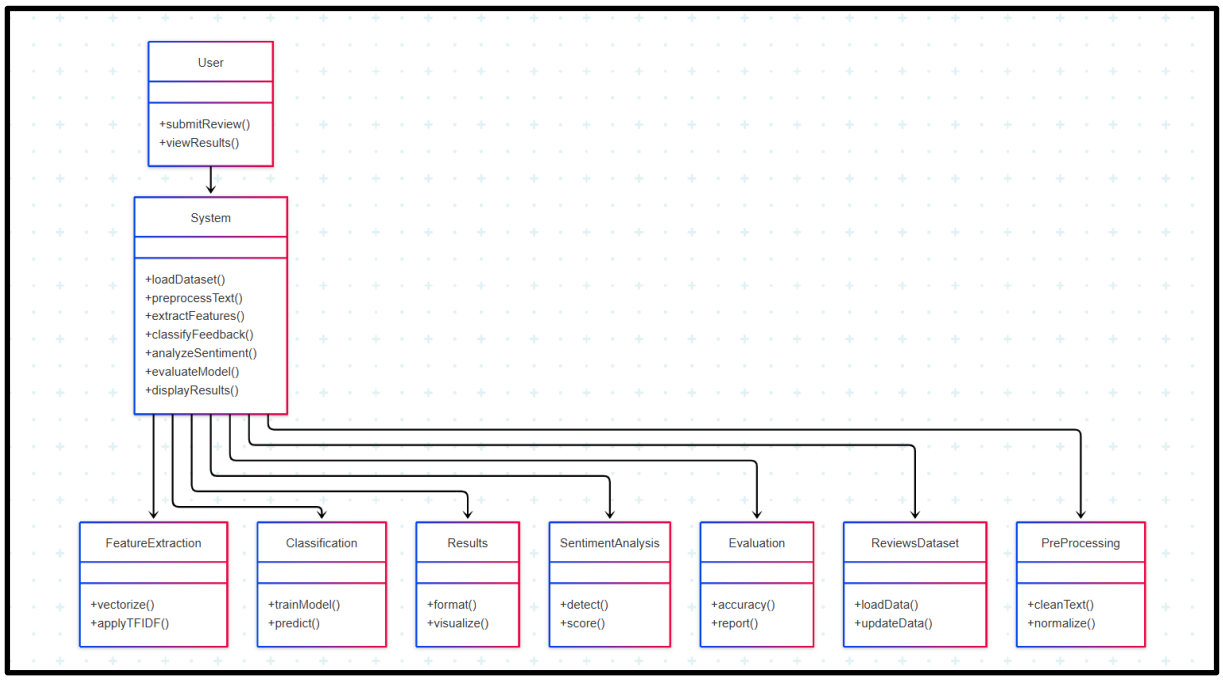
Figure 11.1: ***Architecture Design***

11.2 DIAGRAMS IN UML

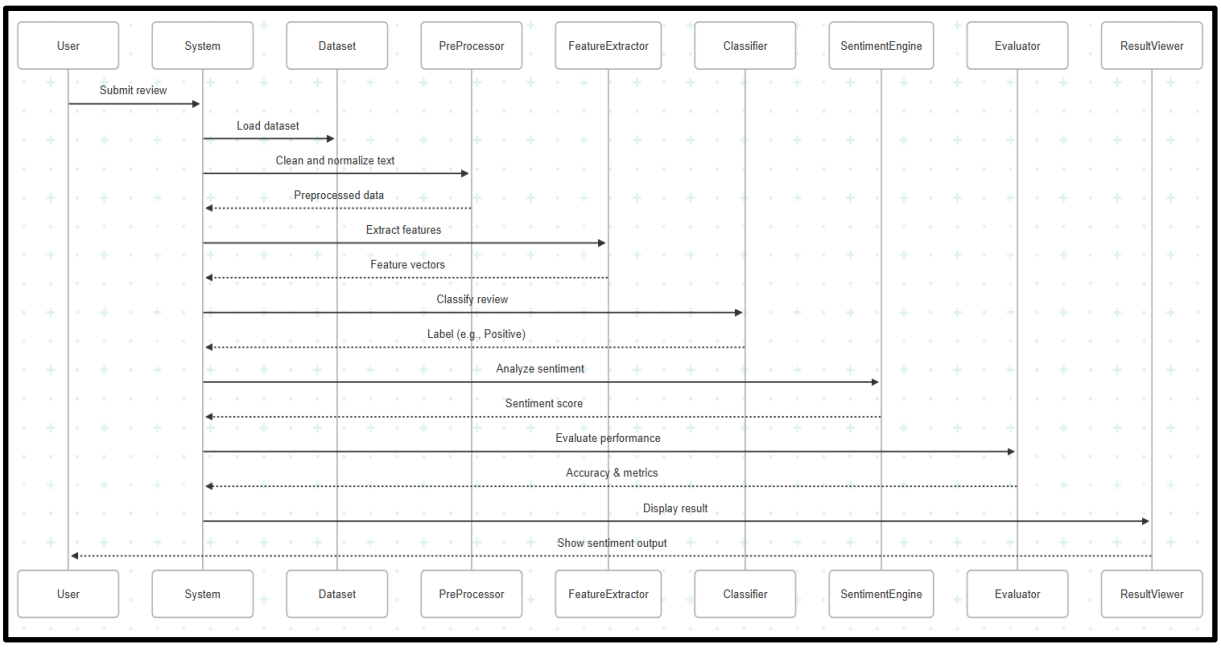
USECASE DIAGRAM



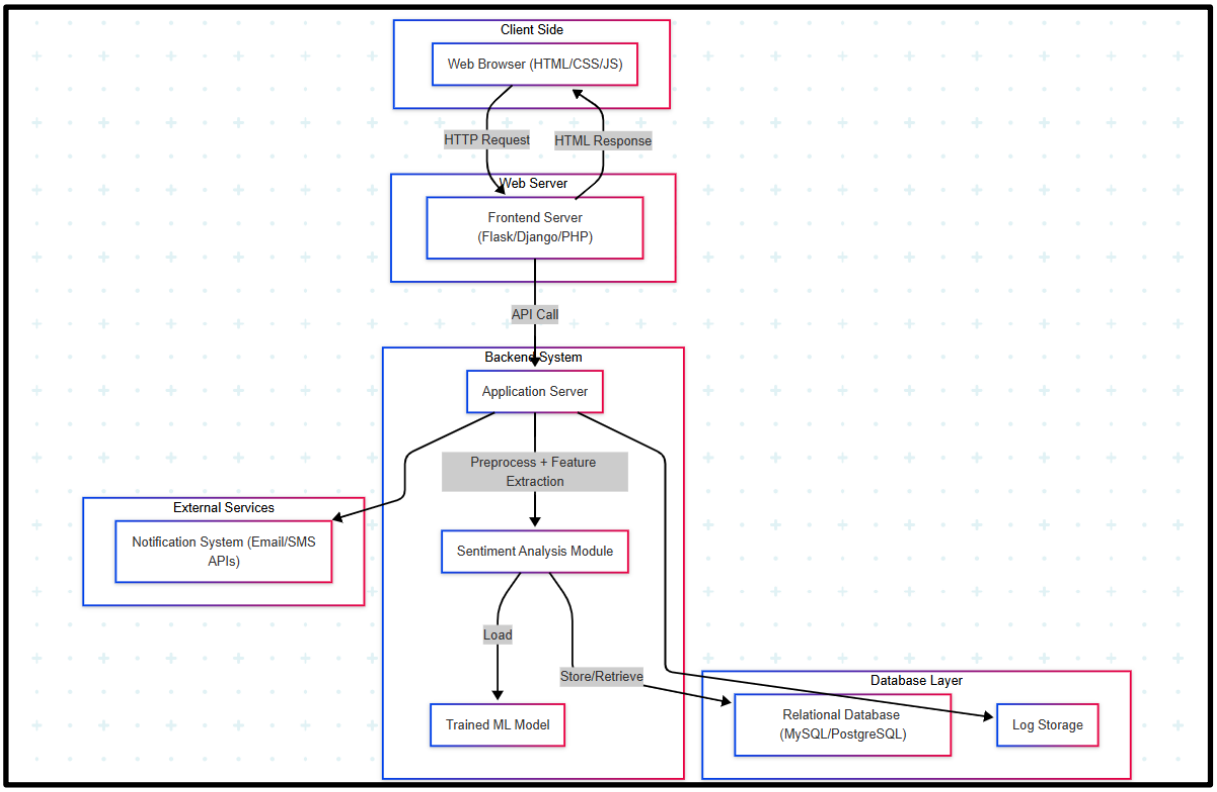
CLASS DIAGRAM



SEQUENCE DIAGRAM



DEPLOYMENT DIAGRAM



CHAPTER – 12

12. IMPLEMENTATION

The implementation of the proposed system integrates Natural Language Processing (NLP), machine learning models, and a production-grade MLOps pipeline to provide a robust and scalable solution for real-time sentiment analysis and customer satisfaction prediction. The system was developed using modular components with clear responsibilities, ensuring ease of maintenance, deployment, and future scalability.

Real-time Sentiment Prediction

The core functionality of the system revolves around its ability to predict sentiment in real time. As customer reviews are submitted via the web-based interface, they are immediately passed through a pre-processing pipeline, feature extractor, and classification model. The sentiment classifier—trained using techniques such as TF-IDF and Support Vector Machines or Logistic Regression—assigns the review a label: Positive, Neutral, or Negative. This real-time classification ensures that feedback is processed and interpreted without delay, enabling organizations to stay attuned to customer opinions.

Negative Sentiment Alert System

An essential component of the system is the automated **Negative Sentiment Alert System**. When a review is classified as "Negative," the backend triggers an alert mechanism that sends a **personalized email** to the designated customer support team. The email contains the original feedback, customer ID (if available), and sentiment confidence score, enabling swift follow-up. This real-time notification system is crucial for minimizing customer dissatisfaction and allows businesses to proactively resolve issues before they escalate.

MongoDB Integration

To manage storage and retrieval efficiently, the system employs **MongoDB**, a scalable NoSQL database. Each customer review is stored as a document, containing the original text, sentiment label, prediction confidence, and timestamp. MongoDB's flexible schema design supports dynamic document storage, which is ideal for text-based data. This integration not only supports efficient querying but also aids in historical analysis and model auditing.

Scalable MLOps Pipeline

A major strength of the implementation is the integration of a **Scalable MLOps Pipeline**. Using tools like **MLflow**, **DVC**, and **GitHub Actions**, the pipeline supports:

- Continuous integration and deployment (CI/CD) of new model versions.
- Automated retraining when new labeled data is ingested.
- Model performance monitoring with real-time feedback loops.

12.1 FRONTEND IMPLEMENTATION

Real-Time Sentimental Prediction: index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <title>Sentiment Analyzer</title>
 <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/bootstrap.min.css" rel="stylesheet">
  <style>
    body {
      background: linear-gradient(to right, #e0f7fa, #f1f8e9);
      font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
      background: url('static/image/s2.jpg');
    }
    .container {
      max-width: 700px;
      margin-top: 60px;
      background-color: white;
      padding: 40px;
      border-radius: 15px;
      box-shadow: 0 0 20px rgba(0,0,0,0.1);
    }
    .emoji {
      font-size: 1.4rem;
      vertical-align: middle;
    }
    textarea {
      resize: none;
    }
    .char-counter {
      font-size: 0.9em;
      color: gray;
```

```
    text-align: right;
   }
  </style>
</head>
<body>
  <div class="container">
       <h2 class="text-center text-primary mb-4">🤗 PREDICTING CUSTOMER SATISFACTION USING MLOPS</h2>
   <form method="post" action="/predict" onsubmit="clearTextArea()">
    <div class="mb-3">
     <label for="feedback" class="form-label">Enter Feedback:</label>
      <textarea class="form-control" id="feedback" name="feedback" rows="4" required oninput="countChars(this)"></textarea>
     <div class="char-counter" id="charCount">0 characters</div>
    </div>
    <button type="submit" class="btn btn-success w-100">Analyze Sentiment</button>
   </form>
   {% if prediction %}
<div class="alert alert-{{ color }} text-center mt-4" role="alert">
  <strong>Prediction:</strong> {{ prediction }}<br>
  <strong>Confidence:</strong> {{ confidence }}<br>
</div>
{% endif %}
   {% if history %}
   <div class="mt-4">
    <h5 class="text-muted">📝 Recent Predictions:</h5>
    <ul class="list-group">
     {% for item in history %}
     <li class="list-group-item list-group-item-{{ item.color }}">
      <strong>{{ item.review }}</strong><br>
      <small>{{ item.result }} – Confidence: {{ item.confidence }}</small>
     </li>
     {% endfor %}
    </ul>
   </div>
```

```
    {% endif %}
  </div>
  <script>
    function countChars(textarea) {
      const count = textarea.value.length;
      document.getElementById('charCount').innerText = `${count} character${count !== 1 ? 's' : ''}`;
    }
    function clearTextArea() {
      setTimeout(() => {
        document.getElementById('feedback').value = '';
        document.getElementById('charCount').innerText = '0 characters';
      }, 100);
    }
  </script>
</body>
</html>



<script>
function predictSentiment(reviewText, resultId, email) {
    const formData = new FormData();
    formData.append("review", reviewText);
    formData.append("email", email);

    fetch("/predict-review", {
        method: "POST",
        body: formData
    })
    .then(res => res.json())
    .then(data => {
        if (data.error) {
            document.getElementById(resultId).innerText = "Prediction failed.";
        } else {
            document.getElementById(resultId).innerText =
```

```
            `Sentiment: ${data.sentiment} (Confidence: ${data.confidence})`;
        }
    })
    .catch(err => {
        document.getElementById(resultId).innerText = "Error occurred.";
        console.error(err);
    });
}
```

Automated Mail Response: reviews.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Customer Reviews - Satisfaction Predictor</title>
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
                                                                    <link
href="https://fonts.googleapis.com/css2?family=Poppins:wght@400;600&display=swap"
rel="stylesheet">

    <style>
        * { margin: 0; padding: 0; box-sizing: border-box; }
        body {
            font-family: 'Poppins', sans-serif;
            background: url('static/image/p1.jpg') no-repeat center center fixed;
            background-size: cover;
            color: #333;
        }
        header {
            background-color: #512da8;
            color: white;
            padding: 20px 0;
            text-align: center;
        }
        .container {
```

```
    max-width: 960px;
    margin: 40px auto;
    background-color: white;
    padding: 30px;
    border-radius: 12px;
    box-shadow: 0 4px 15px rgba(0,0,0,0.1);
}
h2 {
    color: #512da8;
    margin-bottom: 20px;
}
.review-card {
    border: 1px solid #ccc;
    border-radius: 10px;
    padding: 20px;
    margin-bottom: 20px;
    background-color: #f3e5f5;
}
.review-card p { margin: 8px 0; }
.email {
    font-weight: bold;
    color: #3f51b5;
}
.btn {
    padding: 8px 16px;
    border: none;
    border-radius: 6px;
    margin-right: 10px;
    font-weight: bold;
    cursor: pointer;
}
.btn-predict {
    background-color: #4caf50;
    color: white;
}
```

```
        .btn-reply {
            background-color: #ff9800;
            color: white;
        }
        footer {
            background-color: #4527a0;
            color: white;
            text-align: center;
            padding: 15px 0;
            margin-top: 40px;
        }
    </style>
</head>
<body>

<header>
    <h1>Customer Feedback Dashboard</h1>
</header>

<div class="container">
    <h2>Recent Customer Reviews</h2>

    {% for review in reviews %}
    <div class="review-card">
        <p class="email">{{ review.email }}</p>
        <p>"{{ review.review }}"</p>

            <button class="btn btn-predict" onclick="predictSentiment(`{{ review.review }}`, 'res{{ loop.index }}', '{{ review.email }}')">Predict</button>
                    <button class="btn btn-reply" onclick="sendReply(`{{ review.email }}`)">Reply</button>
            <button class="btn btn-reply" onclick="autoReply(`{{ review.email }}`)">Gemini Reply</button>

        <p id="res{{ loop.index }}" style="margin-top: 10px; font-weight: bold;"></p>
    </div>
```

```
    {% endfor %}

    <a href="/" class="btn btn-reply" style="margin-top: 20px;">← Back to Home</a>
</div>

<footer>
    &copy; 2025 Customer Satisfaction Analyzer | Built with care 🧠
</footer>

<script>
function sendReply(email) {
    const message = prompt("Enter your reply to send via email:");
    if (!message) return;

    const formData = new FormData();
    formData.append("email", email);
    formData.append("message", message);

    fetch("/send-reply", {
        method: "POST",
        body: formData
    })
    .then(res => res.json())
    .then(data => {
        alert(data.success ? "Email sent!" : "Failed: " + data.error);
    });
}

function autoReply(email) {
    fetch("/generate-reply", {
        method: "POST",
        body: new URLSearchParams({ email })
    })
    .then(res => res.json())
    .then(data => {
```

```
        if (data.success) {
            alert(`Gemini reply sent successfully.\n\nResponse:\n${data.reply}`);
        } else {
            alert("Error: " + data.error);
        }
    })
    .catch(err => {
        alert("Unexpected error occurred: " + err);
    });
}
</script>
```

12.2 BACKEND IMPLEMENTATION IN PYTHON (FASTAPI)

Create the Flask App and Prediction Models

app.py

```
# Initialize FastAPI
app = FastAPI()

# Mount static directory
app.mount("/static", StaticFiles(directory="static"), name="static")

# Set up Jinja2 template rendering
templates = Jinja2Templates(directory="templates")

# Load model and transformers
tfidf = joblib.load("models/tfidf_vectorizer.pkl")
label_encoder = joblib.load("models/label_encoder.pkl")
model_uri = "runs:/b0e618c550ca4208b216af807d7849e2/sentiment_model"
model = mlflow.sklearn.load_model(model_uri)

# History for display
history = []

@app.get("/", response_class=HTMLResponse)
```

```
async def home(request: Request):
    return templates.TemplateResponse("home.html", {"request": request})

@app.get("/index", response_class=HTMLResponse)
async def sentiment_page(request: Request):
    return templates.TemplateResponse("index.html", {"request": request})

@app.post("/predict", response_class=HTMLResponse)
async def predict_sentiment(request: Request, feedback: str = Form(...)):
    # Vectorize input
    review_vector = tfidf.transform([feedback])

    # Predict encoded label
    prediction_encoded = model.predict(review_vector)
    prediction_label = label_encoder.inverse_transform(prediction_encoded)[0]

    # Predict probability
    prediction_proba = model.predict_proba(review_vector)

    # Get confidence of predicted class
    confidence = prediction_proba[0][prediction_encoded[0]] * 100  # As percentage

    # Set Bootstrap color
        color = "success" if prediction_label.lower() == "positive" else "danger" if
prediction_label.lower() == "negative" else "warning"

    # Store feedback history
    history.insert(0, {
        "review": feedback,
        "result": prediction_label,
        "confidence": f"{confidence:.2f}%",  # Round nicely
        "color": color
    })
    if len(history) > 5:
        history.pop()
```

```
    return templates.TemplateResponse("index.html", {
        "request": request,
        "prediction": prediction_label,
        "confidence": f"{confidence:.2f}%",  # Pass to template
        "color": color,
        "history": history
    })

@app.get("/reviews", response_class=HTMLResponse)
async def get_reviews(request: Request):
    mongo_uri = os.getenv("MONGO_URI")
    client = MongoClient(mongo_uri)
    db = client["Review-mlops"]
    collection = db["reviews"]

    # Fetch reviews, assuming each review has 'email' and 'review' keys
    cursor = collection.find({}, {"_id": 0})
    reviews = list(cursor)

    return templates.TemplateResponse("reviews.html", {
        "request": request,
        "reviews": reviews
    })

from fastapi.responses import JSONResponse
@app.post("/predict-review")
async def predict_review(review: str = Form(...), email: str = Form(...)):
    # Predict
    review_vector = tfidf.transform([review])
    prediction_encoded = model.predict(review_vector)
    prediction_label = label_encoder.inverse_transform(prediction_encoded)[0]
    prediction_proba = model.predict_proba(review_vector)
    confidence = prediction_proba[0][prediction_encoded[0]] * 100
    confidence_str = f"{confidence:.2f}%"
```

```
sentiment_with_conf = f"{prediction_label} ({confidence_str})"
```

Database Connection

```
# MongoDB connection
mongo_uri = os.getenv("MONGO_URI")
client = MongoClient(mongo_uri)
db = client["Review-mlops"]
collection = db["reviews"]

# Update by both email and review
result = collection.update_one(
    {"email": email, "review": review},
    {"$set": {"sentiment": sentiment_with_conf}}
)

if result.matched_count == 0:
    # Insert new if not found
    collection.insert_one({
        "email": email,
        "review": review,
        "sentiment": sentiment_with_conf
    })

    # print(prediction_label)
    # print(confidence_str)

return JSONResponse({
    "sentiment": prediction_label,
    "confidence": confidence_str
})
```

Setup Automated Mail Response

```
# Set Gemini API Key (make sure it's in your environment variables or .env file)
@app.post("/generate-reply")
async def generate_and_send_reply(email: str = Form(...)):
    # Connect to MongoDB
    mongo_uri = os.getenv("MONGO_URI")
    client = MongoClient(mongo_uri)
    db = client["Review-mlops"]
    collection = db["reviews"]

    # Fetch review and sentiment
     review_data = collection.find_one({"email": email}, {"_id": 0, "review": 1, "sentiment": 1})
    if not review_data:
        return {"success": False, "error": "Email not found in database."}

    review = review_data["review"]
    sentiment = review_data["sentiment"]

    # Generate content using Gemini
    prompt = f"""The customer gave the following review: "{review}" which was classified as "{sentiment}".
Write a professional, polite email reply to the customer that reflects
this sentiment and addresses their concern or appreciation accordingly."""

    try:
        model = GenerativeModel("gemini-1.5-pro-latest")
        response = model.generate_content(prompt)
        reply = response.text

        # Send email using your existing send_reply logic
        sender_email = "vmmbaskaran@gmail.com"
        sender_password = os.getenv("SENDER_PASS")  # App Password for Gmail

        msg = EmailMessage()
```

```
        msg.set_content(reply)
        msg["Subject"] = "Response to Your Feedback"
        msg["From"] = sender_email
        msg["To"] = email

        with smtplib.SMTP_SSL("smtp.gmail.com", 465) as smtp:
            smtp.login(sender_email, sender_password)
            smtp.send_message(msg)

        return {"success": True, "reply": reply}

    except Exception as e:
        return {"success": False, "error": str(e)}
```

12.3 MLOps INTEGRATION

Data Collection Module: data_loader.py

```
import pandas as pd

def load_data(filepath="data/Reviews.csv"):
    """Load review data from Excel dynamically."""
    df = pd.read_csv(filepath)
    return df
```

Data Preprocessing Module: preprocessor.py

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
import joblib
import os

def preprocess_data(df, save_path="models/"):
    """Preprocess text data and encode labels."""
    tfidf = TfidfVectorizer(max_features=5000)
    X = tfidf.fit_transform(df['review'])  # Assuming 'review' column
```

```
    # Encode labels
    label_encoder = LabelEncoder()
     y = label_encoder.fit_transform(df['sentiment'])  # Convert positive/negative/neutral to numbers

    # Save TF-IDF vectorizer and Label Encoder
    os.makedirs(save_path, exist_ok=True)
    joblib.dump(tfidf, os.path.join(save_path, "tfidf_vectorizer.pkl"))
    joblib.dump(label_encoder, os.path.join(save_path, "label_encoder.pkl"))

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    return X_train, X_test, y_train, y_test
```

Data Training Module: trainer.py

```
from sklearn.ensemble import RandomForestClassifier
import mlflow
import mlflow.sklearn

def train_model(X_train, y_train):
    """Train Random Forest model and log with MLflow."""
    with mlflow.start_run():
        model = RandomForestClassifier(n_estimators=100)
        model.fit(X_train, y_train)

        mlflow.sklearn.log_model(model, "sentiment_model")
        mlflow.log_param("n_estimators", 100)

    return model
```

Data Evaluation Module: evaluator.py

```
from sklearn.metrics import accuracy_score
import mlflow

def evaluate_model(model, X_test, y_test):
```

```
    """Evaluate model and log accuracy to MLflow."""
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    print(f"Test Accuracy: {acc:.4f}")
    mlflow.log_metric("accuracy", acc)
```

Pipeline Deployement: pipeline.py

```
import os
import mlflow
from src.data_loader import load_data
from src.preprocessor import preprocess_data
from src.trainer import train_model
from src.evaluator import evaluate_model

def run_pipeline(data_path="data/Reviews.csv", model_dir="models/"):
    # 1. Load Data
    print("📥 Loading data...")
    df = load_data(data_path)
    if 'review' not in df.columns or 'sentiment' not in df.columns:
        raise ValueError("Dataset must contain 'review' and 'sentiment' columns.")
    # 2. Preprocess Data
    print("Preprocessing data...")
    X_train, X_test, y_train, y_test = preprocess_data(df, save_path=model_dir)
    # 3. Train Model
    print("Training model...")
    model = train_model(X_train, y_train)

    # 4. Evaluate Model
    print("Evaluating model...")
    evaluate_model(model, X_test, y_test)
    print("Pipeline complete.")

if __name__ == "__main__":
    mlflow.set_experiment("SentimentAnalysisPipeline")
    run_pipeline()
```

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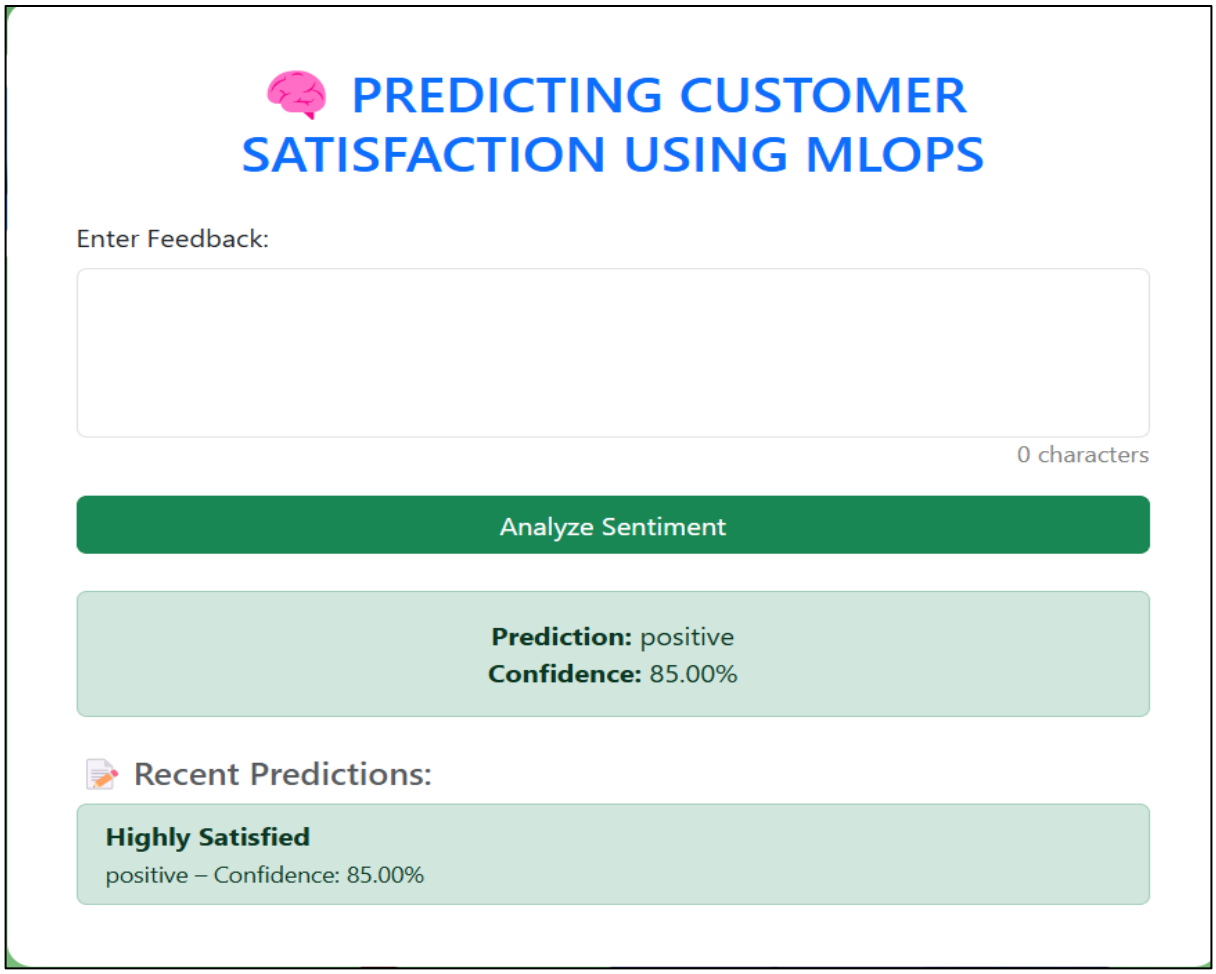
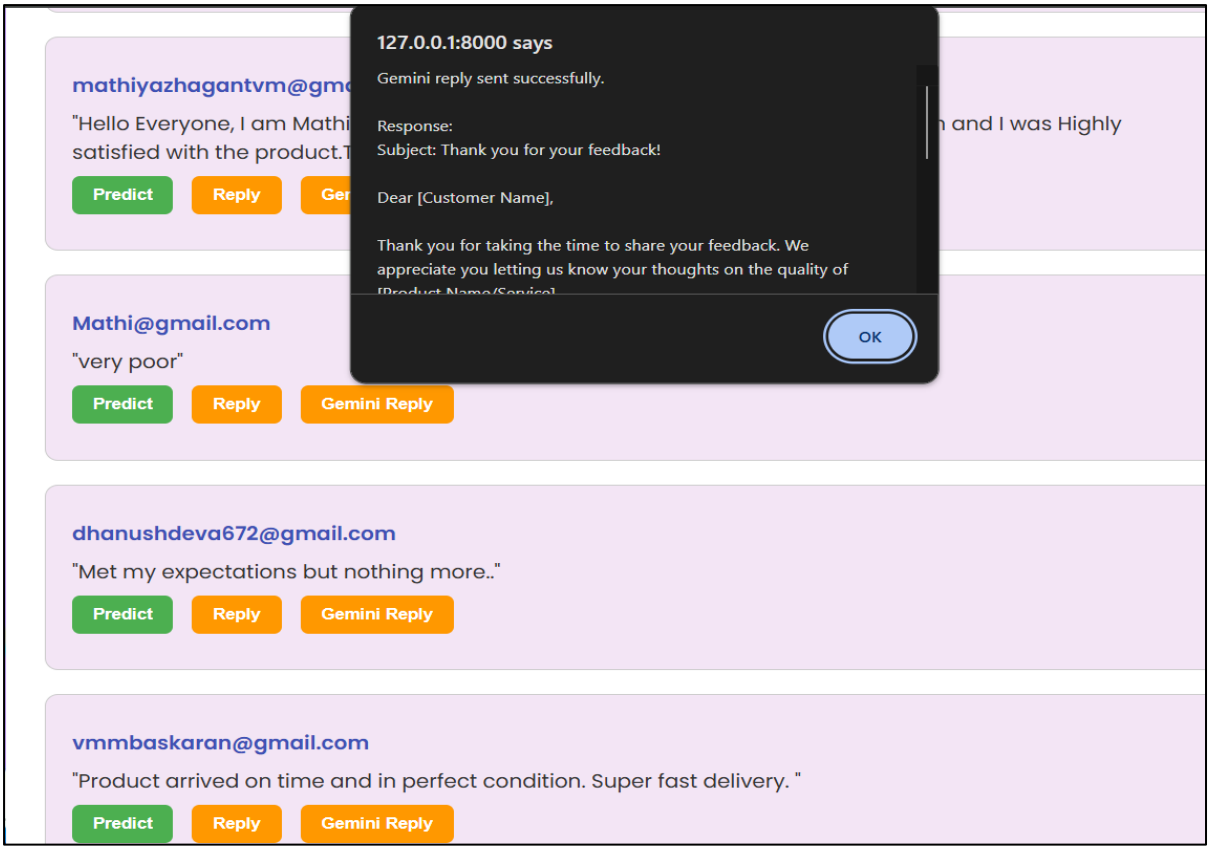
13. OUTPUTS

Real-Time Sentimental Prediction:



Personalized Mail Response System:



Response to Your Feedback

1 message

<vmmbaskaran@gmail.com> Sat, May 3, 2025 at 8:57 PM
To: vmmbaskaran@gmail.com

Subject: Thank you for your Super Feedback!

Dear [Customer Name],

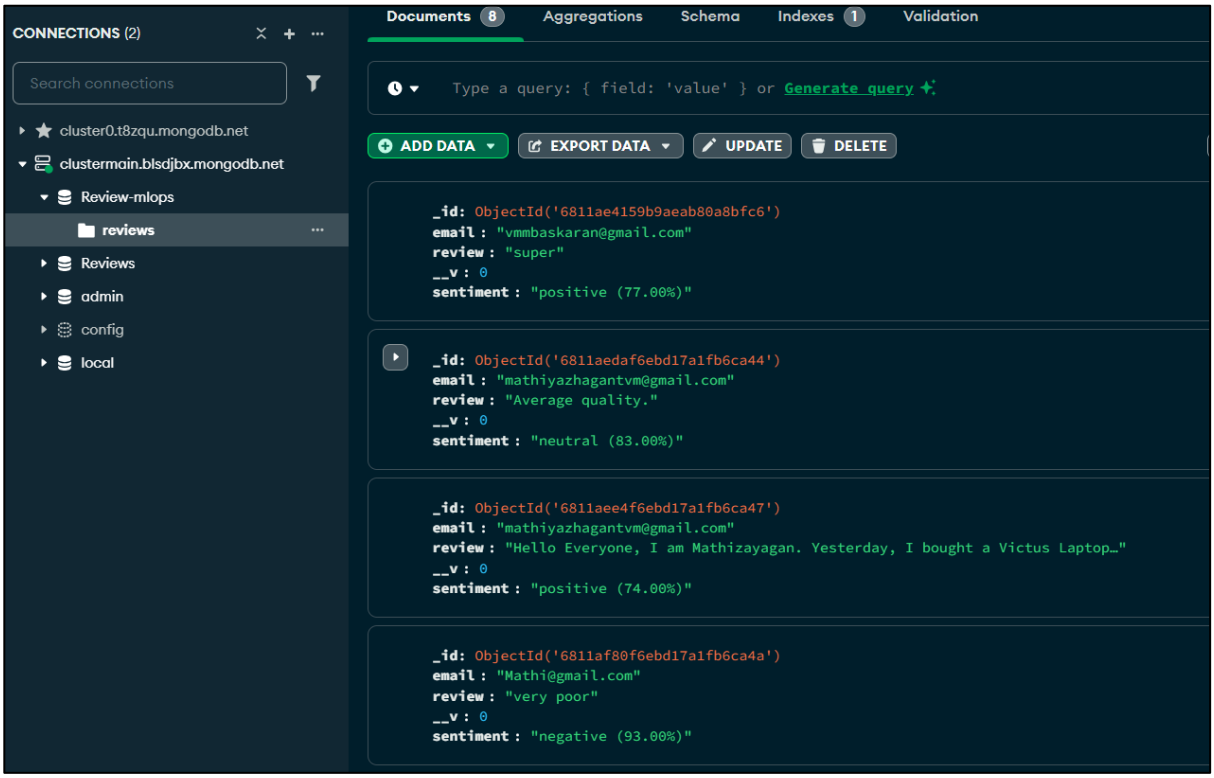
Thank you for taking the time to leave us a review. We're thrilled you had a positive experience and described it as "super"! We appreciate your feedback and are always striving to deliver outstanding service and products.

We're glad you're happy with us. We hope to see you again soon!

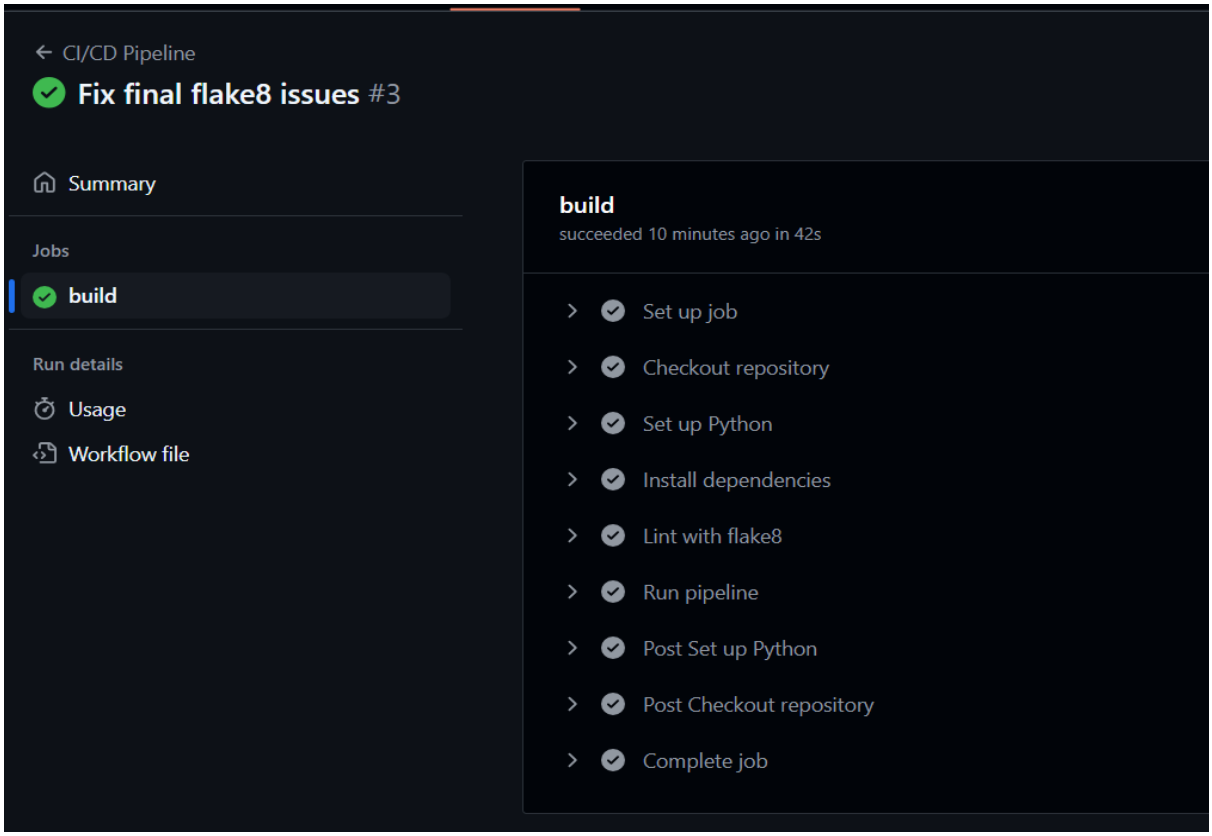
Sincerely,

The [Your Company Name] Team

MongoDB Integration:



Scalable MLOps Pipeline



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14. FUTURE ENHANCEMENTS

To ensure continued relevance, scalability, and accuracy, several future enhancements can be implemented in the customer satisfaction prediction system:

1. Multilingual Sentiment Analysis

Currently, the model processes English-language reviews only. In the future, support for regional and international languages (such as Hindi, Tamil, Spanish, etc.) will be integrated using multilingual transformers like mBERT or XLM-RoBERTa, allowing a more inclusive customer experience.

2. Aspect-Based Sentiment Analysis (ABSA)

Enhance the sentiment analysis by identifying sentiments specific to product aspects (e.g., delivery, packaging, quality). This provides granular insights to businesses, helping them improve targeted areas rather than acting on generic feedback.

3. Sarcasm and Irony Detection

Standard models often fail to capture sarcastic or ironic tones. Implementing specialized sarcasm detection models or fine-tuned transformers can improve sentiment classification accuracy in complex linguistic scenarios.

5. Real-Time Dashboard and Analytics

A live analytics dashboard using tools like **Grafana**, **Plotly Dash**, or **Streamlit** could visualize incoming sentiment trends, customer interaction history, and response effectiveness for business intelligence purposes.

7. Auto-Retraining Pipeline

Integrate full automation for model re-training based on performance degradation or concept drift. Tools like **DVC**, **MLflow**, and **ZenML** can be used to build a closed feedback loop where new labeled data improves the model continuously.

8. Voice Feedback Integration

Allow users to submit audio feedback, which will be transcribed using speech-to-text APIs (e.g., Google Speech, Whisper) and then analyzed for sentiment. This enhances usability for visually impaired or non-typing users.

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15. CONCLUSION

This project presents a comprehensive solution for real-time sentiment analysis aimed at predicting customer satisfaction using cutting-edge MLOps methodologies. With the exponential rise in digital customer interactions, businesses face an overwhelming influx of feedback data that must be processed swiftly and intelligently. The implemented system successfully addresses this need by combining machine learning models with a scalable and automated deployment pipeline to classify customer sentiments in real-time. Through the integration of a robust MLOps pipeline, the solution not only ensures continuous delivery and deployment but also supports model retraining and monitoring, thereby maintaining long-term accuracy and adaptability as user behaviour and language patterns evolve.

A key achievement of this project is the automatic detection of negative sentiments and the proactive alert system that notifies support teams via personalized email notifications. This feature empowers organizations to address customer concerns before they escalate, thereby improving service quality and customer retention. Furthermore, the MongoDB-backed data layer offers a flexible and scalable storage solution for sentiment-labelled feedback, enabling easy access, querying, and analytics. The user-friendly interface ensures accessibility for both technical and non-technical users, enhancing the overall usability and integration of the platform in real business environments.

Additionally, the modular architecture of the system, featuring components such as data loading, preprocessing, training, evaluation, and frontend/backend interfacing, demonstrates a production-ready design aligned with industry best practices. The clear separation of concerns and pipeline automation paves the way for effortless scaling and the inclusion of advanced features in future iterations. By adhering to CI/CD principles, the system remains maintainable and easily upgradable, supporting long-term sustainability and growth.

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16. REFERENCE

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