Fusion-Based Sentiment Analysis for Evaluating E-Commerce Product Experience

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Abstract
As e-commerce continues to grow, customer-generated reviews have become a valuable source of insight into product satisfaction and user experience. This project presents a Fusion Sentiment Analysis Method that integrates natural language processing with machine learning to analyze customer reviews effectively. The methodology involves two key stages: sentiment feature extraction using an extended sentiment dictionary and polarity classification (positive or negative) through machine learning algorithms such as Logistic Regression, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). To improve sentiment detection accuracy, the sentiment dictionary is expanded using semantic similarity measures, and a custom weighting mechanism is applied to emphasize emotionally significant words an element often underutilized in previous studies. The proposed model is applied to reviews from a major e-commerce platform, with findings intended to help businesses improve product quality and refine marketing strategies using data-driven insights.
Keywords: Fusion based sentiment analysis, E- commerce product, LR, SVM, KNN

Introduction
Online product reviews have become a crucial source of customer feedback in the growing world of e-commerce. However, extracting meaningful insights from large volumes of unstructured reviews is a challenge. This project aims to tackle that challenge using a Fusion-Based Sentiment Analysis approach, which combines advanced NLP techniques and machine learning models to interpret and analyze customer sentiments more accurately.
This project is significant because understanding customer sentiment helps businesses enhance product quality, improve user satisfaction, and make informed marketing decisions. By integrating sentiment feature extraction, polarity classification through such as machine learning algorithms are Logistic Regression, Support Vector Machines (SVM), K-Nearest Neighbors (KNN). It also introduces an extended sentiment dictionary and a custom weighting mechanism for improved precision.
In the following sections, we will explore how this model works, how it is trained and applied to real e-commerce review data. This project strives to transform raw customer feedback into actionable insights, empowering businesses to respond effectively to user experiences and market demands.

Motivation
In a highly competitive market, customer satisfaction and feedback play a significant role in the success of any product or service. E-commerce businesses rely heavily on customer reviews to understand user expectations, measure product quality, and identify problem areas. Traditional analytics tools often focus only on numerical ratings or simple keyword analysis, which fail to capture the true sentiment and emotion expressed in natural language.
Moreover, customers express their thoughts in diverse ways, sometimes using sarcasm, idioms, or complex sentence structures that are hard to interpret without context-aware systems. The need for a more nuanced understanding of such expressions has pushed researchers toward developing more advanced sentiment analysis

models that go beyond basic polarity detection. There's also a need to identify which specific product features are being discussed positively or negatively

NLP

Natural Language Processing (NLP) is a branch of Artificial Intelligence (AI) that focuses on the interaction between computers and human (natural) languages. It enables machines to read, interpret, and understand human language in a meaningful way. NLP combines computational linguistics with machine learning and deep learning techniques to process and analyze large volumes of textual or spoken language data.

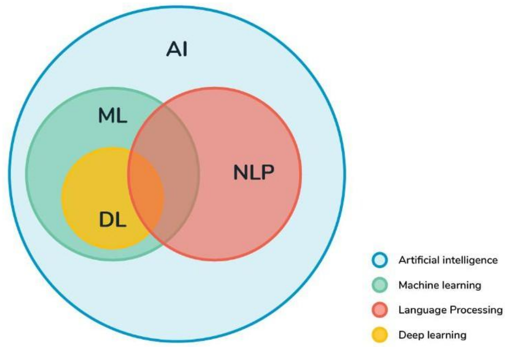


Fig.1. Natural language Processing – A part of AI

Objective

The primary objective of this project is to design and implement a fusion-based sentiment analysis model that accurately interprets customer opinions from e-commerce product reviews. The model aims to integrate dictionary-based sentiment scoring with machine learning techniques to leverage the advantages of both approaches. By incorporating sentiment dictionaries, semantic expansion, machine learning algorithms like Logistic Regression, SVM, KNN and contextual representation through word embeddings (Word2Vec), the system aims to provide highly accurate sentiment predictions. Ultimately, the goal is to develop a scalable and reliable sentiment analysis framework that helps businesses gain deeper insights into customer feedback, optimize product offerings, enhance marketing strategies, and improve customer satisfaction.

Literature Review

In this chapter will review some key research papers to understand existing techniques for sentiment analysis in e-commerce product reviews. These studies aim to accurately classify customer sentiments to improve business insights. As Archimedes said, "Man has always learned from the past," highlighting the importance of learning from prior work. Selected studies are discussed to showcase significant contributions and methodologies that support the development of the proposed fusion-based sentiment analysis model.

SURVEYS

Sentiment analysis on social network data and its marketing strategies: A review:

"P. Dash, J. Mishra, and S. Dara"

This study explores the effectiveness of influencer marketing through sentiment analysis to help brands make informed decisions when selecting influencers. It emphasizes creating sticky and viral content, encouraging user-generated content like reviews and comments, and highlights the challenges of tracking influencer campaigns. Using secondary data, the research identifies the ideal conditions for influencer marketing, examines audience reactions, and assesses the impact of social media campaigns on brand awareness and business growth. Sentiment analysis helps determine public opinion and the polarity of sentiments from online sources to guide marketing strategies.

Use of sentiment analysis in social media campaign design and analysis:

"S. Gupta and R. Sandhane"

This research proposes Sentiment Analysis (SA) categorizes opinions in text as positive, neutral, or negative, helping businesses understand the emotions behind social media posts. It is essential for tracking and shaping social media strategies. This paper systematically reviews existing literature on SA in social media campaigns using PRISMA guidelines. It highlights methods and techniques used, identifies trends, challenges, and implications, and offers insights for researchers and academics. The study also suggests future research directions for applying SA in campaign design and analysis.

A study of the application of weight distributing method combining sentiment dictionary and TF-IDF for text sentiment analysis:

"H. Liu, X. Chen, and X. Liu"

This study explores the most common methods in text sentiment analysis are rule-based sentiment dictionaries and machine learning, which involve vectorizing text and classifying it. However, both have limitations, such as rigid rules and weak emphasis on sentiment words. This paper proposes a weight-distributing method that combines both approaches, enhancing sentence vectors to highlight sentiment words while preserving overall text information. Empirical results demonstrate the method's effectiveness compared to traditional approaches.

Cross-domain sentiment aware word embeddings for review sentiment analysis:

"J. Liu, S. Zheng, G. Xu, and M. Lin"

This research proposes Learning low-dimensional word vectors is a core NLP task, but traditional models often miss sentiment information. Existing methods may capture sentiment in reviews but fail to account for domain-specific word meanings, affecting sentiment classification when emotions vary. To address this, the paper extends the Continuous Bag of Words model and proposes a cross-domain sentiment-aware word embedding model that captures both sentiment and domain relevance. Experiments on Amazon review data across domains demonstrate that incorporating sentiment and domain information significantly improves performance over existing embeddings.

Constructing domain-dependent sentiment dictionary for sentiment analysis:

"M. Ahmed, Q. Chen, and Z. Li"

This paper introduces SentiDomain, a domain-dependent sentiment dictionary built using a weakly supervised neural model that learns sentiment cluster embeddings from sentence representations. Trained on unlabeled data, it reconstructs sentence representations and enhances aspect-level sentiment analysis using an attention-based LSTM that downweights non-sentiment parts. Experiments on English and Chinese datasets show improved polarity detection over existing methods.

This study explores the application of artificial intelligence (AI) and Machine Learning (ML) techniques, particularly Random Forest classification, to predict car insurance risks using publicly available datasets from Kaggle [14] [15]. By implementing feature extraction and classification methodologies, this research demonstrates the effectiveness of AI-driven predictive models in enhancing risk assessment accuracy and operational efficiency in the insurance sector.

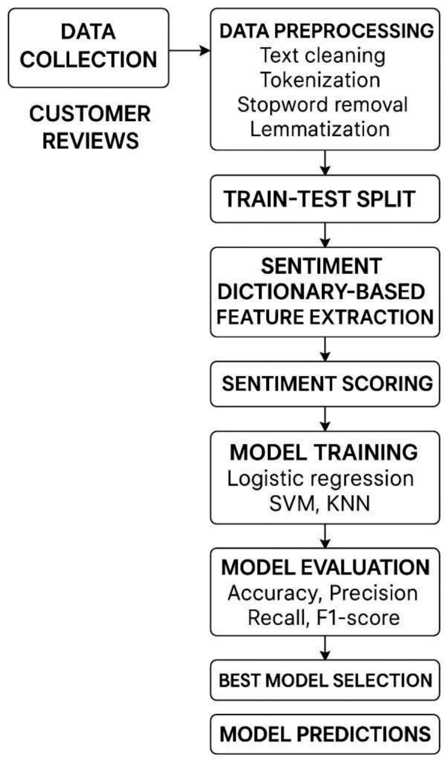
Proposed Model

In this project, we propose a Fusion-Based Sentiment Analysis Model that combines techniques in Natural Language Processing (NLP) and Machine Learning to analyze and classify customer sentiments from e-commerce product reviews.

This model integrates Sentiment Dictionary-Based Feature Extraction, semantic dictionary expansion, and word embedding techniques such as TF-IDF and Word2Vec to perform comprehensive sentiment analysis. It extracts detailed insights from customer reviews with deep contextual understanding. This Fusion-Based Sentiment Analysis approach enables accurate identification of sentiment polarity and contextual relevance in user opinions.

The system intelligently captures not just explicit emotions but also the subtle tone of consumer feedback. This makes it capable of providing sentiment interpretation with high precision and relevance.
The model is trained on real-world datasets containing thousands of labeled reviews, enabling it to learn from actual consumer experiences across various product categories. By addressing the limitations of traditional models. To enhance prediction performance, we incorporated multiple machine learning algorithms including Logistic Regression, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Among all the evaluated models, K-Nearest Neighbors (KNN) demonstrated the best algorithm, making it the most effective model in the fusion-based sentiment analysis framework.
By employing this fusion-based sentiment analysis model, we aim to enhance the accuracy, precision, and reliability of sentiment analysis in e-commerce. The ultimate goal is to provide platforms and product developers with actionable insights that improve customer experience, product design, and marketing strategies.

SYSTEM ARCHITECTURE



DATA COLLECTION (CUSTOMER REVIEWS):

Customer review data was collected from a variety of e-commerce platforms, including Amazon, containing 4,000 reviews annotated with sentiment labels (0 for negative, 1 for positive). Each review includes metadata such as product name, brand, review date, and categories, which are instrumental in supporting aspect-based sentiment analysis.

DATA PREPROCESSING:

Data preprocessing is crucial in sentiment analysis to clean, transform, and standardize textual data for model compatibility. This phase was executed in two broad parts: general data cleaning and NLP-based text processing.

Initial Data Checks & Basic Cleaning:

1. Converted all textual data to lowercase for consistency.
2. Removed null, empty, or unlabeled reviews.
3. Standardized and renamed feature columns for ease of access.
4. Verified correct data types and schema alignment.

NLP-Based Text Preprocessing:

1. **Tokenization:** Reviews were broken down into individual tokens (words).
2. **Stopword Removal:** Common but non-informative words like "is", "the", "and" were removed.
3. **Lemmatization:** Words were reduced to their root form using WordNet lemmatizer (e.g., "running" → "run").
4. **Noise Removal:** Special characters, emojis, and punctuation were filtered out.

TRAIN-TEST SPLIT

The dataset is divided into training and testing subsets. This separation is crucial for evaluating the model's performance on unseen data and avoiding overfitting.

SENTIMENT DICTIONARY-BASED FEATURE EXTRACTION

In this stage, where sentiment scores are assigned to words using a predefined sentiment dictionary. This step helps convert unstructured text into structured sentiment feature vectors, which are crucial for further model training.

Each word is assigned a score based on its polarity (positive or negative).

These individual scores are aggregated to derive an overall sentiment value for the entire review.

SENTIMENT SCORE COMPUTATION:

Once the individual sentiment values are identified, a cumulative score is calculated to represent the review's sentiment intensity and direction.

1. Positive scores are summed for words with favourable sentiment.
2. Negative scores are similarly aggregated for unfavourable expressions.

These scores are then combined to produce a final sentiment score, generally normalized to fall with of 0 or 1.

Interpretation of the Final Score:

Positive sentiment → 1.

Negative sentiment → 0.

MODEL TRAINING

Machine Learning Algorithms Used:

1. Logistic Regression:

Logistic Regression is a widely used supervised learning algorithm that is particularly effective for binary and multi-class classification problems. In the context of this project, it is employed to classify customer reviews into sentiment categories such as positive or negative. Logistic Regression models the probability that a given input belongs to a specific class using a logistic function, making it suitable for sentiment analysis where the outcome is probabilistic in nature. It is computationally efficient and interpretable, offering insight into the influence of various textual features on the final sentiment classification.

2. Support Vector Machine (SVM):

Support Vector Machine (SVM) is a robust machine learning algorithm that constructs an optimal hyperplane in a high-dimensional space to distinguish between sentiment classes. In this project, SVM is utilized due to its effectiveness in handling sparse and high-dimensional text data. It maximizes the margin between classes, which enhances generalization and accuracy in sentiment prediction. By applying kernel tricks, SVM can handle non-linearly separable data, making it ideal for capturing subtle nuances in customer reviews that influence sentiment.

3. K-Nearest Neighbour (KNN):

K-Nearest Neighbour (KNN) is a non-parametric, instance-based learning algorithm that classifies a given review based on the majority sentiment of its 'k' closest training samples in the feature space. For this project, KNN is leveraged to provide an intuitive and straightforward baseline for sentiment classification. It operates under the assumption that reviews with similar textual patterns or structures are likely to share the same sentiment. While it can be computationally intensive for large datasets, KNN is valuable for its simplicity and effectiveness in capturing local structure in the data. Among the three models evaluated, KNN demonstrated the highest performance on test data, making it the optimal choice for fusion-based sentiment analysis.

Evaluation Matrix

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform. The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).

Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$= \frac{+}{+ \quad + \quad +} \qquad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$= \frac{}{+} \qquad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$= \frac{}{+} \qquad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

$$1 \quad = \frac{2 * Pcso * ca}{+} \qquad (4)$$

SYSTEM IMPLEMENTATION

SYSTEM MODULES

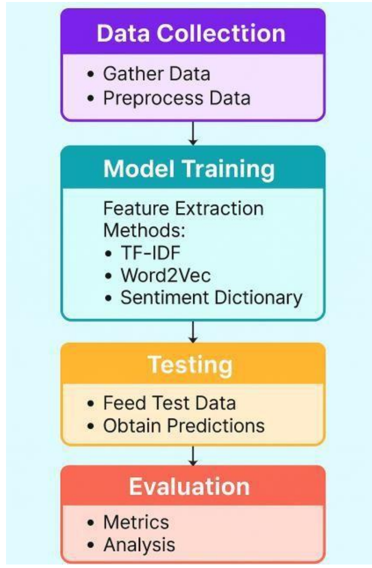


Fig.2. System Modules

Data Collection:

Gather Data: Collect diverse product reviews from platforms like Amazon, including text reviews, ratings, and product categories.

Preprocess Data: Apply NLP techniques (tokenization, stopword removal, stemming, noise removal). Convert text into structured formats like TF-IDF or word embeddings for model input.

2. Model Training:

Feature Extraction Modules:

1. TF-IDF: Captures term importance in reviews.
2. Word2Vec: Used Google News Word2Vec to convert words into numerical vectors.
3. Sentiment Dictionary: Assigns sentiment scores, extended via semantic similarity.

ML-Based Classification: Transform reviews into feature vectors and use models (Logistic Regression, SVM, KNN) to classify sentiment as positive or negative **3. Testing:**

Feed Test Data: Input unseen and real-time review data into the trained sentiment analysis system.

Obtain Predictions: For each review, obtain sentiment scores from machine learning models. Apply the algorithm to arrive at a final sentiment label (Positive or Negative).

Thresholding: For numerical sentiment scores, apply thresholds (e.g., Positive = 1, Negative = 0) to convert continuous scores into discrete sentiment labels.

Evaluation:

Metrics: Assess performance using accuracy, precision, recall, and F1-score.

Analysis: Study misclassifications to refine model settings and improve overall accuracy.

Results

The execution of the process will be explained clearly with the help of continuous screenshots.

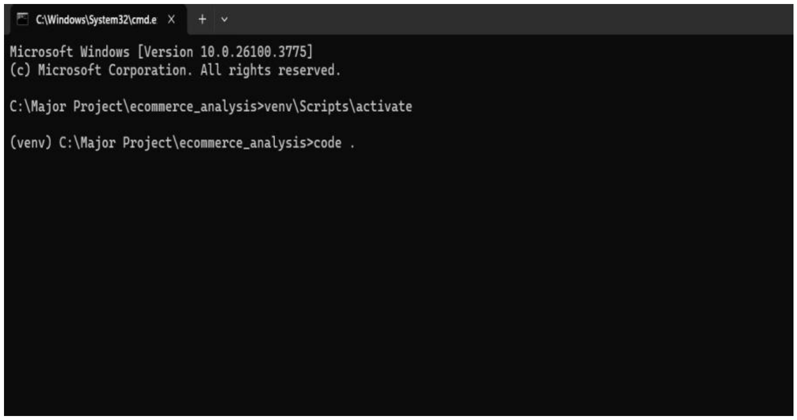


Fig.3. These are the commands to run the project.

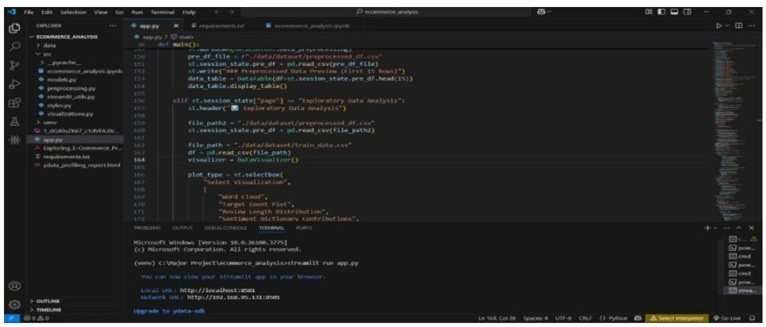


Fig.4. Launching Stream lit application.

Fig.5. This interfaced is plays the title, problem statement, and objective.

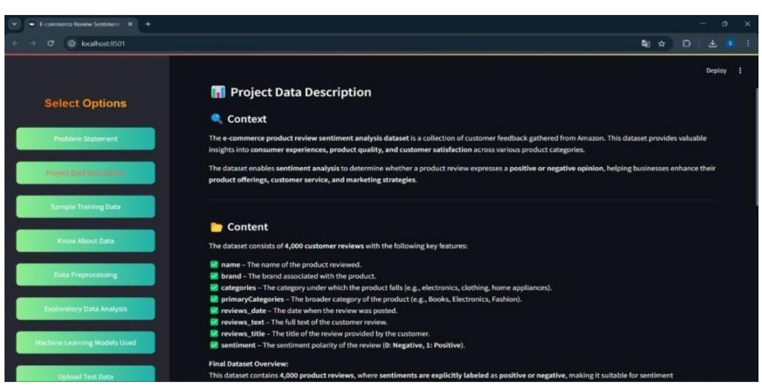


Fig 9.4: This interface displays the project data description, including the dataset context and source.

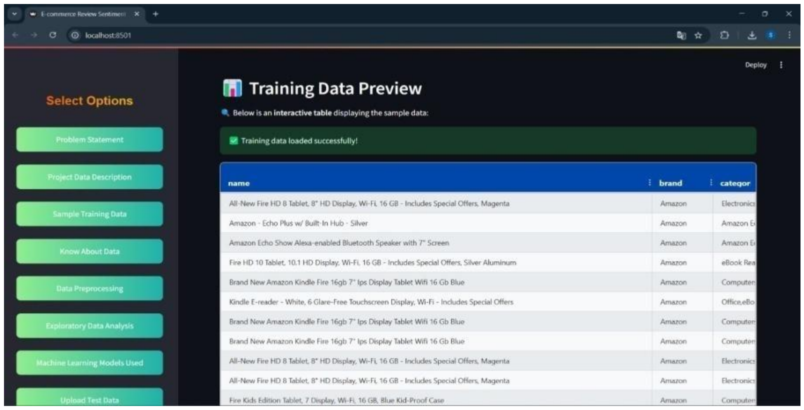


Fig 9.5: The preview of first 25 rows of dataset was displayed.

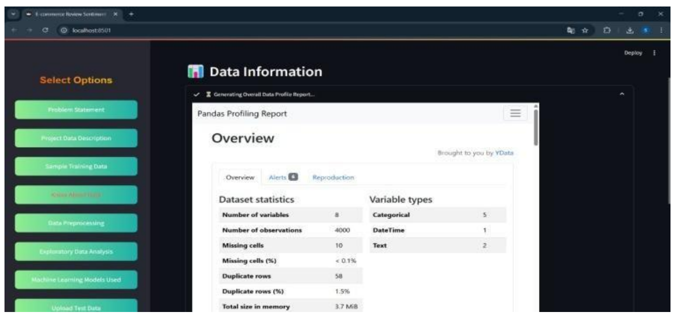


Fig 9.6: This interface presents overall profiling report of the dataset.

Fig 9.7: Using Exploratory Data Analysis, this interface visualizes the keywords from the processed reviews.

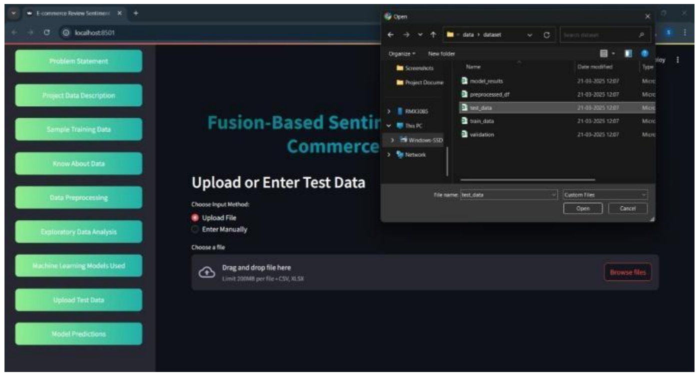


Fig 9.8: In this interface we have to upload the test data.

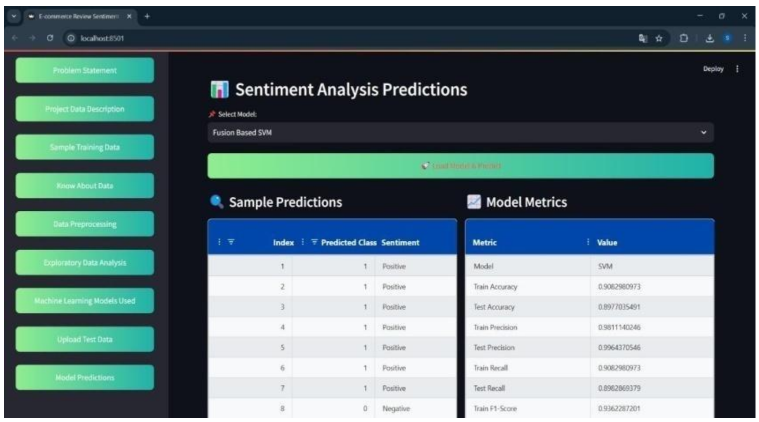


Fig 9.9: This interface presents model predictions of given test dataset using SVM algorithm

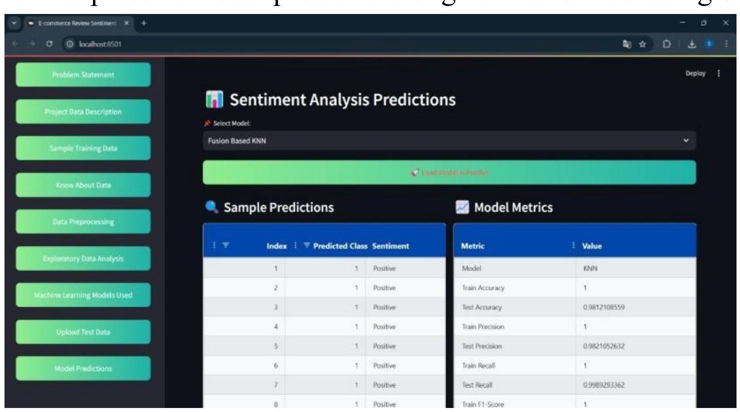


Fig 9.10: In this interface presents the model predictions of given test dataset using KNN algorithm.

Conclusion

The fusion-based sentiment analysis system for evaluating e-commerce product experience integrates machine learning and natural language processing algorithms to improve the accuracy of sentiment classification. By combining structured product review data with features and polarity scores from sentiment dictionaries, the system captures both contextual and emotional nuances of customer feedback. Models like Logistic Regression, SVM, and KNN are used to classify sentiments. The fusion approach of outputs enhances prediction reliability, especially in handling ambiguous or mixed sentiments. This method provides valuable insights into customer opinions, enabling better product recommendations and strategic improvements. It proves technically, economically, and operationally feasible for real-time applications in e-commerce environments. Overall, the system supports enhanced user satisfaction, business performance, and marketing strategies.

Future Scope

The fusion-based sentiment analysis system presents a strong foundation for understanding customer feedback in the e-commerce domain. In the future, the system can be extended to support real-time sentiment tracking by integrating streaming data pipelines, enabling businesses to react instantly to customer opinions. Incorporating multilingual sentiment analysis would allow the platform to cater to a wider global audience. Additionally, the system could evolve to handle multi-modal data, such as voice reviews, images, emojis or video feedback, offering richer sentiment interpretation. Integration with e-commerce recommendation engines could enhance personalization by aligning product suggestions with sentiment trends. Finally, a user-friendly dashboard with visual analytics could help business users make data-driven decisions efficiently. These advancements would significantly improve the impact and usability of the system in real-world e-commerce applications.

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