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MULTILINGUAL SENTIMENT ANALYSIS FOR E-COMMERCE PLATFORM

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ABSTRACT
The rapid growth of global e-commerce has generated large volumes of customer reviews written in multiple languages, making multilingual feedback analysis increasingly important. Traditional sentiment analysis systems are often optimized for English and may lose contextual information when processing reviews in other languages. This paper presents a multilingual sentiment analysis system for e-commerce platforms that automatically detects the language of customer reviews and classifies them into Positive, Neutral, and Negative categories. The proposed methodology combines language detection using LangID, translation of non-English reviews using Deep Translator, contextual representation using multilingual BERT (mBERT), and Random Forest for final sentiment classification. TextBlob is additionally used to calculate polarity and subjectivity scores. A Flask-based web application integrates these components into a unified workflow that displays the original review, detected language, translated text, predicted sentiment, confidence, polarity, and subjectivity. The system was evaluated on 300 test instances, achieving F1-scores of 0.92 for both Positive and Negative classes and 0.90 for the Neutral class. The results demonstrate that the proposed hybrid approach provides reliable multilingual sentiment predictions and supports practical e-commerce customer-feedback analysis.

Keywords:
Multilingual Sentiment Analysis, E-Commerce Reviews, mBERT, Random Forest, Natural Language Processing, TextBlob

INTRODUCTION
Global e-commerce platforms receive customer feedback from users with different linguistic backgrounds. Product reviews may be written in English, Hindi, Tamil, Telugu, French, Spanish, and other languages, and the same product may receive feedback in several languages. For businesses, these reviews are valuable sources of information about customer satisfaction, product quality, delivery experience, and service performance. However, manually examining multilingual feedback is time-consuming and makes it difficult to obtain a consistent view of customer opinion. Therefore, this study focuses on automatically classifying multilingual product reviews as **Positive, Neutral, or Negative** while providing additional information about the review language and sentiment characteristics.

Traditional sentiment analysis systems commonly rely on lexicons, machine-learning classifiers, or language-specific preprocessing. Such systems can perform well for a single language but may not generalize across languages because vocabulary, grammar, expressions, and cultural context vary. Translation-based approaches can make multilingual processing easier, but translation itself may introduce semantic or contextual changes. Recent transformer-based methods have improved contextual representation for sentiment analysis. Multilingual models such as **mBERT** and **XLM-R** make it possible to transfer language representations across multiple languages, motivating hybrid approaches that combine multilingual contextual representations with conventional classifiers.

The literature reviewed in this study provides the foundation for the proposed approach. Liu established sentiment analysis as an important area of opinion mining, while Jurafsky and Martin provided a broader foundation for natural language processing and contextual language modelling. Devlin et al. introduced **BERT**, demonstrating the importance of bidirectional transformer representations for language understanding.

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Mąbökela, Celik, and Rabie reviewed multilingual sentiment analysis for under-resourced languages and highlighted the challenges caused by limited linguistic resources. Breiman introduced **Random Forest** as an ensemble learning method based on multiple decision trees, and Bahrawi demonstrated its application to sentiment classification. Wolf et al. described the Transformers ecosystem for modern NLP applications, while Junczys-Dowmunt et al. introduced Marian for efficient neural machine translation.

Despite these developments, a practical research gap remains in integrating the complete multilingual sentiment-analysis process into a single application-oriented workflow. Many sentiment-analysis implementations focus on English or evaluate individual models without connecting language detection, translation, sentiment prediction, and user-facing analysis. The present work addresses this gap by combining **LangID** for language detection, translation for non-English reviews, **multilingual BERT (mBERT)** for contextual feature representation, and **Random Forest** for final three-class sentiment classification. **TextBlob** is additionally used to obtain polarity and subjectivity measures, providing users with further information about the characteristics of each review.

The significance of the study lies in its practical integration of multilingual NLP techniques with an accessible web application. The proposed workflow connects **user review → language detection → translation of non-English text → preprocessing → feature representation → Random Forest classification → sentiment and additional score analysis**. This integrated approach can reduce the effort required to interpret multilingual customer feedback and provide businesses with a consistent way to examine customer opinions. The system can also be extended to additional languages, code-mixed reviews, fine-grained emotions, and real-time feedback streams, making it a useful foundation for future multilingual e-commerce sentiment-analysis applications.

METHODOLOGY

The methodology of this study is designed to develop a practical multilingual sentiment-analysis system for e-commerce customer reviews. The research follows an **application-oriented system design**, in which multilingual review processing, language detection, translation, text preprocessing, feature representation, sentiment classification, and result presentation are integrated into a single workflow. The system accepts a customer review as input and produces a structured output containing the original review, detected language, translated text when required, predicted sentiment, confidence, polarity, and subjectivity. This design is intended to make multilingual customer-feedback analysis more consistent and accessible.

A. Research Design

The study adopts a hybrid machine-learning and natural language processing design. Rather than depending on a single sentiment-analysis algorithm, the proposed workflow combines multiple stages. First, the submitted review is processed and its language is automatically identified using LangID. If the review is not in English, it is translated into English using Deep Translator. The processed text is then represented using contextual features through multilingual BERT (mBERT) and/or TF-IDF vectors. Finally, Random Forest is used as the three-class sentiment classifier to predict Positive, Neutral, or Negative sentiment. TextBlob is also incorporated to calculate polarity and subjectivity scores.

B. Study Area and Data Source

The study is focused on the domain of **multilingual e-commerce customer-review analysis**. The dataset used in the project contains review-related fields such as **Review ID, Language, Product Category, Review Text, and Sentiment**. The reviews are intended to represent multilingual customer feedback, including languages such as English, Spanish, French, Hindi, and Tamil. The research therefore concentrates on analysing textual customer feedback rather than restricting the study to a single product category or language.

B. Participants/Sample

In this study, the sample consists of customer-review records rather than human participants directly involved in an experimental survey. The project reports evaluation using 300 test instances. These review records are processed through the proposed multilingual workflow and classified into three sentiment categories: Positive, Neutral, and Negative. The use of multiple languages allows the system to evaluate its ability to handle multilingual customer feedback in an e-commerce environment.

D. Data Collection

The data collection component is based on multilingual e-commerce review records. Each review is associated with information such as its review identifier, language, product category, review text, and sentiment label. Before analysis, the review text undergoes preprocessing to remove unnecessary noise, normalize text, handle punctuation and stop words where applicable, and tokenize the input. This preprocessing creates a cleaner textual representation for subsequent language detection, translation, and feature extraction.

E. Instruments and Technologies

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Several software libraries and NLP technologies are used as instruments for implementing the proposed system. **Python** serves as the core implementation language, while **Flask** provides the web application, routing, and backend functionality. **LangID** is used for automatic language detection, and **Deep Translator** handles translation of non-English reviews. **Hugging Face Transformers** supports loading and using mBERT for multilingual contextual representations. **Random Forest** performs the final three-class sentiment classification, while **TextBlob** calculates polarity and subjectivity. **PyTorch** supports model execution and related utilities.

F. Data Analysis

The analysis begins with language identification and preprocessing of each review. Non-English reviews are translated into English before downstream sentiment processing. Feature representation is then generated using mBERT contextual embeddings and/or TF-IDF vectors. These representations are supplied to the Random Forest classifier, which predicts one of the three sentiment categories. In addition to the primary sentiment prediction, TextBlob is used to calculate polarity and subjectivity, providing supplementary information about the review. The application presents these results through a Flask-based interface.

User Review	Language Detection	Translation	Preprocessing	mBERT/TF-IDF	Random Forest	Sentiment + Scores

LITERATURE SURVEY

Liu established sentiment analysis as a major area of opinion mining and described methods for identifying and summarizing subjective information from text [1]. Jurafsky and Martin provide a broad foundation for modern natural language processing and contextual language modeling [2].

Devlin et al. introduced BERT, demonstrating the value of bidirectional transformer representations for language understanding [3]. The project applies the same contextual-representation principle through multilingual BERT so that review text can be represented using multilingual contextual information.

Mąbökela, Celik, and Rabie reviewed multilingual sentiment analysis for under-resourced languages and emphasized the difficulties associated with limited linguistic resources [4]. This is particularly relevant to multilingual e-commerce settings where language distributions are uneven and language-specific resources may be limited.

Breiman introduced Random Forest as an ensemble learning method based on multiple decision trees [5]. Bahrawi demonstrated the use of Random Forest for sentiment classification [6]. In the present project, Random Forest is used as the final classifier after feature representation.

Wolf et al. described the Transformers ecosystem that made modern transformer models broadly accessible to NLP applications [7]. Junczys-Dowmunt et al. introduced Marian for fast neural machine translation, illustrating the role of efficient translation systems in multilingual NLP pipelines [8].

Recent work continues to investigate transformer-based sentiment analysis for e-commerce. Studies have reported the effectiveness of transformer architectures on product reviews and multilingual settings, while also highlighting issues such as class imbalance, translation effects, and computational cost. These findings support the project's hybrid, application-oriented design and its future scope for stronger multilingual models.

OBJECTIVES

- **Detect** the language of customer reviews automatically.
- **Process** multilingual review text using NLP preprocessing and normalization.
- **Classify** product reviews as **Positive, Negative, or Neutral**.
- **Provide** confidence, polarity, and subjectivity information along with the prediction.
- **Provide** a simple web-based interface for multilingual sentiment prediction.
- **Support** e-commerce businesses in understanding customer feedback and product perception.

SYSTEM ARCHITECTURE

The proposed architecture connects the user interface, multilingual language-processing stages, feature representation, classifier, and result presentation into a single workflow.

1) User Review: The user enters a product review through the Prediction page.
2) Language Detection: LangID identifies the language of the submitted review.
3) Translation: Non-English text is translated into English using the implemented translation process.
4) Preprocessing: The review text is cleaned, normalized, and prepared for feature representation.
5) Feature Representation: mBERT contextual embeddings and/or TF-IDF vectors are used to represent the review.
6) Classification: Random Forest predicts the review as Positive, Neutral, or Negative.

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7) Analysis Output: The application displays the sentiment, confidence, polarity, subjectivity, and related information to the user.

TECHNOLOGIES USED

Technology/Library	Role in the System
Python	Core implementation language
Flask	Web application, routing, and backend
LangID	Web application, routing, and backend
Deep Translator	Translation of non-English reviews
Random Forest	Final three-class sentiment classification
TextBlob	Polarity and subjectivity calculation
Pytorch	Model execution and supporting utilities

TESTING AND EVALUATION

The project includes functional tests covering **normal, multilingual, invalid-input, performance, and deployment-related conditions**. The following table presents the reported test scenarios from the project.

TestID	Scenario	Expected Result	Status
TC01	English review	Positive	Pass
TC02	Non-English review	Translated&positive	Pass
TC03	Empty review	Input cannot be empty	Pass
TC04	Special Character	Neutral/Invalid	Pass
TC05	Mixed- Language review	Positive	Pass
TC06	Prediction response time	Within 2 Seconds	Pass
TC07	French review	Translated & Positive	Pass
TC08	Negative review	Negative	Pass
TC09	Translation fallback	Fallback to untranslated input	Pass
TC10	Model/Vectorizer loading	Loads without error	Pass

RESULTS AND DISCUSSION

The implemented system was tested using the project test cases and a reported evaluation set of **300 instances**. The testing scenarios covered English reviews, non-English reviews, empty input, special characters, mixed-language reviews, response time, French reviews, translation fallback, and model/vectorizer loading. The prediction workflow was therefore evaluated at both the classifier level and through the web application.

Table 2. Classification Report

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.91	0.92	0.92	100
Neutral	0.89	0.90	0.90	80
Positive	0.91	0.92	0.92	120
Total	-	-	-	300

A. Classification Performance

The classification report shows strong and relatively balanced performance across the three sentiment classes. The Negative class records a precision of 0.91, recall of 0.92, and F1-score of 0.92 for 100 instances. The Neutral class records a precision of 0.89, recall of 0.90, and F1-score of 0.90 for 80 instances. The Positive class records a precision of 0.91, recall of 0.92, and F1-score of 0.92 for 120 instances. Thus, the reported F1-score ranges from 0.90 to 0.92.

B. Interpretation of the Results

The similarity between the Negative and Positive F1-scores indicates that the classifier does not show a large performance difference between the two larger sentiment groups. The Neutral class is slightly lower, which is reasonable because neutral reviews can contain mixed or less explicitly emotional language. The results support the practical use of the hybrid representation-and-classification workflow for three-class sentiment prediction.

C. Multilingual Processing Output

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The application preserves the original review while also displaying the **detected language and translated text**. This is useful for multilingual e-commerce because a user or analyst can inspect the original input and the translated representation used during processing.

APPLICATION INTERFACE / OUTPUT SCREENS

The developed **Flask-based application** provides separate interfaces for navigation, project information, user registration and authentication, dataset viewing, and sentiment prediction. The following screenshots represent the application interfaces documented in the project.

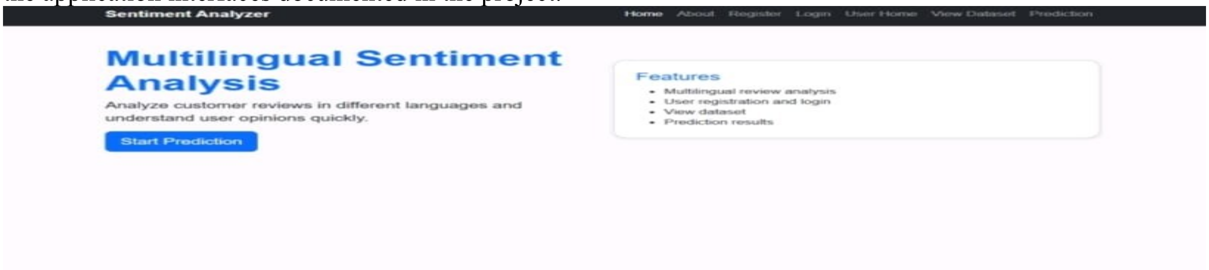

FIG 1. HOME PAGE

The Home page acts as the landing page and provides navigation to the main functions of the application.

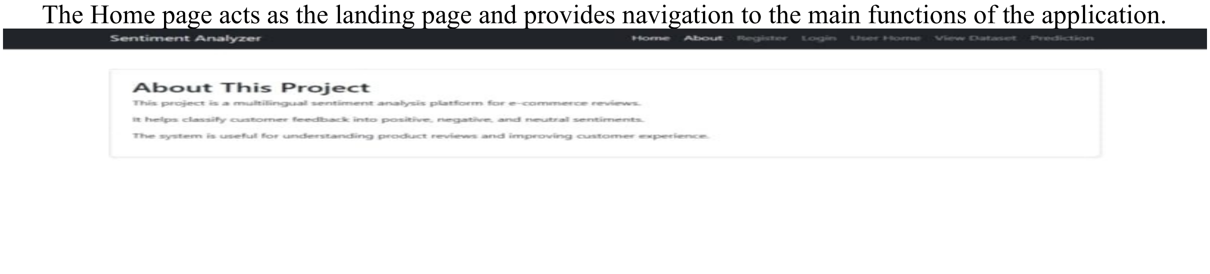

FIG 2. ABOUT PAGE

The About page summarizes the purpose of the multilingual sentiment-analysis platform and its role in e-commerce review analysis.

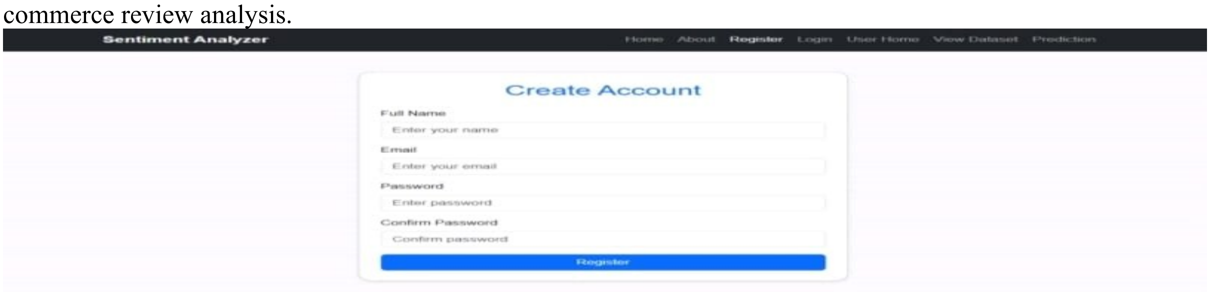

FIG 3. REGISTRATION PAGE

The Registration page allows a new user to create an account using name, email, password, and confirmation fields.

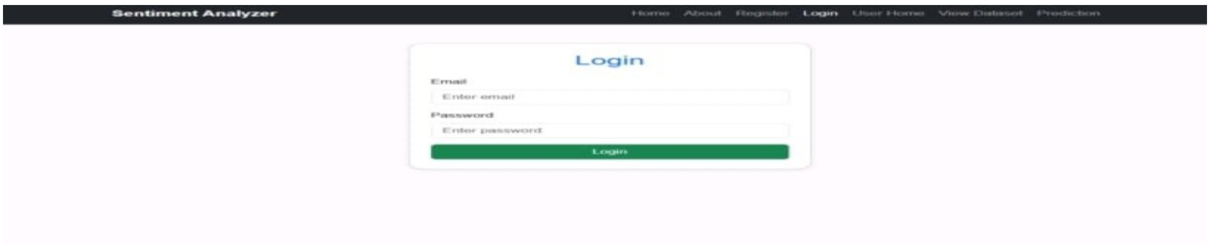

FIG 4. LOGIN PAGE

The Login page provides authenticated access using email and password.

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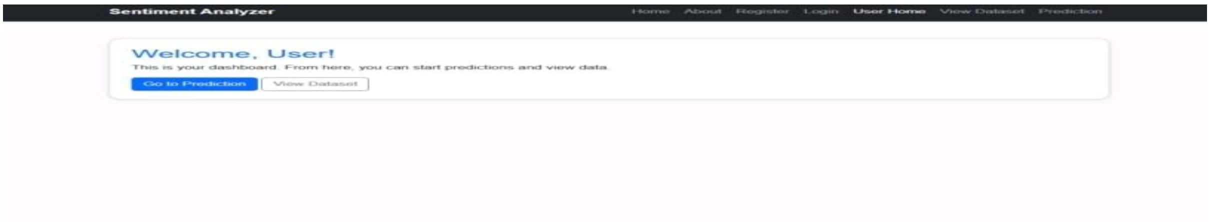

FIG 5. USER HOME PAGE

The User Home page provides dashboard access to prediction and dataset functions.

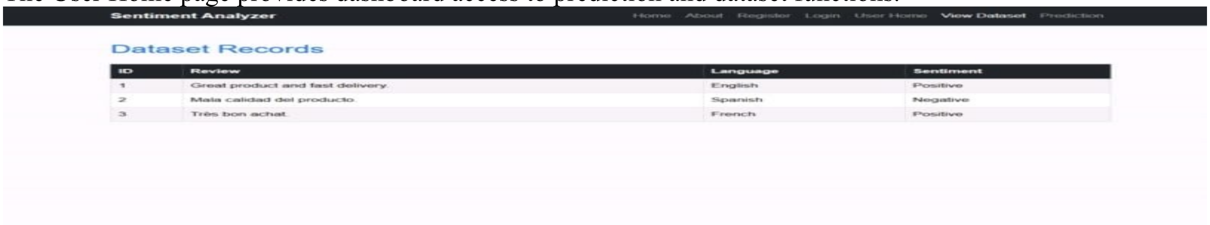

FIG 6. VIEW DATASET PAGE

The View Dataset page displays sample review records together with language and sentiment information.

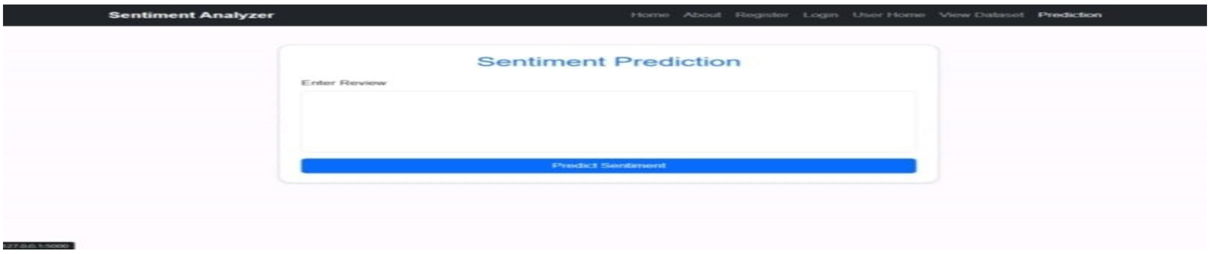

FIG 7. PREDICTION PAGE

The Prediction page accepts review text and submits it for sentiment analysis.

LIMITATIONS AND FUTURE SCOPE

The implemented multilingual sentiment-analysis workflow has several practical limitations. Translation is used for non-English reviews, so errors in machine translation may affect sentiment prediction, while transformer-based representations require greater computational resources. The reported evaluation covers 300 test instances and therefore may not establish performance across all languages, product categories, cultural expressions, and e-commerce platforms. Neutral and code-mixed reviews may also be difficult to classify because their sentiment can be implicit or expressed through multiple languages. In the future, the system can be improved by using stronger multilingual models such as XLM-RoBERTa, larger and more diverse datasets, additional languages, and better support for code-mixed and transliterated Indian-language reviews. The system can also be extended to fine-grained emotion classification, real-time review streams, explainable AI methods, voice and video review analysis, and feedback-driven model retraining.

CONCLUSION

The proposed **Multilingual Sentiment Analysis for E-Commerce Platform** demonstrates an integrated approach for analysing customer reviews written in different languages. The system combines language detection, translation, NLP preprocessing, multilingual contextual representation using mBERT, Random Forest classification, TextBlob-based polarity and subjectivity analysis, and a Flask web interface. The reported evaluation contains **300 test instances**, achieving F1-scores of **0.92 for Negative, 0.90 for Neutral, and 0.92 for Positive**. The application-level testing also reports all specified test cases as **Pass**. These results indicate that the implemented workflow can provide consistent three-class sentiment predictions while presenting useful supporting information to the user. The main contribution of the project is the integration of multilingual processing and sentiment prediction into a single practical e-commerce workflow rather than treating classification as an isolated task.

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