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Sentiment Analysis on Social Media

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Abstract

The rapid growth of multilingual online reviews has created a rich yet underutilized source of product intelligence, while many existing sentiment analysis tools still depend on static datasets and offline pipelines, limiting their ability to capture evolving consumer trends. This work proposes an "Product" Sentiment Intelligence System that performs real-time extraction and analysis of user feedback, with a focus on YouTube comments as a high-volume, opinion-rich channel. The system automatically scrapes live comments and reviews, supporting multiple languages such as English, Hindi, and Telugu. A unified preprocessing pipeline normalizes code-mixed and transliterated text, followed by vectorization using TF-IDF to capture term importance across diverse linguistic patterns. On top of these representations, Logistic Regression models are trained for aspect-based sentiment classification at the feature level (e.g., camera, battery, performance), enabling fine-grained understanding beyond overall review polarity.

To address the challenge of authenticity in user-generated content, the architecture incorporates a Presentation Attack Detection-inspired anti-spoofing module that flags suspicious or bot-like feedback based on temporal, behavioural, and lexical cues. The system further provides comparative visual analytics across products, highlighting sentiment distributions per aspect, trend lines over time, and side-by-side competitor benchmarking. An integrated recommendation layer leverages these insights to suggest optimal products and key selling points for both consumers and vendors. Experimental evaluation on real-world, multilingual review datasets demonstrates improved accuracy and robustness in feature-level sentiment detection compared to conventional, monolingual or static approaches. Cross-product analysis results validate the effectiveness of the proposed visual and analytical components in supporting transparent, user-centric decision-making. Overall, the system offers a scalable and extensible framework for next-generation e-commerce intelligence, bridging real-time social feedback with explainable AI-driven insights.

Keywords: Sentiment Analysis, Natural Language Processing (NLP), Machine Learning, Data Preprocessing, Text Classification, Logistic Regression, Term Frequency-Inverse Document Frequency, Review Analysis System, Multilingual Analysis, Visualization Dashboard.

1. Introduction

Due to the rapid growth of e-commerce websites and online service providers, a huge number of product reviews are generated on a daily basis. Such reviews carry useful information related to customer opinions, experiences, and satisfaction levels. Analyzing a huge number of reviews manually is a difficult and time-consuming task. Hence, automated sentiment analysis techniques have emerged as a key area of research

in Natural Language Pro cessing (NLP) and machine learning domains. Sentiment analysis techniques are useful in identifying and classifying opinions expressed in textual data as positive, negative, or neutral, thereby helping businesses to better comprehend customer feedback.

Various research studies have contributed significantly to the development of sentiment analysis techniques. Initially, various studies were conducted on sentiment classification techniques, where researchers demonstrated how semantic orientation techniques could be employed to automatically determine the polarity of product reviews [1]. Subsequently, researchers proposed comprehensive techniques related to opinion mining and highlighted the significance of extracting customer opinions from online platforms [2]. Further studies were conducted on various machine learning techniques, including Naïve Bayes, SVM, and Logistic Regression, to improve the accuracy of sentiment classification techniques [3]. Recent research has emphasized the improvement of sentiment analysis through the application of more sophisticated feature extraction techniques and the application of deep learning models. It has been demonstrated through various research contributions that the application of machine learning algorithms along with text representation techniques improves the overall performance of sentiment prediction systems [4],[5]. Thus, the application of sentiment analysis has become a powerful tool to analyze customer sentiments through the analysis of large volumes of customer feedback data.

As a result of the research contributions mentioned above, the proposed project aims to develop a Product Review Sentiment Analysis System based on the application of NLP techniques, TF-IDF feature extraction, and machine learning algorithms to automatically determine the sentiments of customer reviews as positive, negative, and neutral.

Objectives of this study:

- To develop an automated system that classifies reviews into positive, negative, and neutral sentiments.
- To analyze large volumes of reviews quickly and reduce manual effort.
- To present results through visualization dashboards for better understanding.
- To build a scalable and user-friendly system using Python and Django.

2. Literature Survey

As we went through some of the research papers and we have to know more about the sentiment analysis on different ways

The initial research in sentiment analysis was study on the semantic orientation for the unsupervised classification of the product reviews [1] proposed a method to detect the sentiment by measuring the association between the phrases and the positive or negative reference words. The study on the opinion mining and sentiment analysis [2] discussed the methods to extract the opinions from the customer reviews, whereas the Twitter sentiment classification using distant supervision [3] discussed the methods to automatically label the large-scale social media data for the training of the sentiment models.

Then, the sentiment analysis has been further improved by applying machine learning techniques such as Naïve Bayes, SVM, and Logistic Regression [4], [5]. These techniques automatically classify reviews into positive, negative, or neutral categories. The techniques learn patterns from data and examine text-based features such as words to classify sentiments more precisely.

The improvements made to sentiment analysis techniques also included applying deep learning techniques. These techniques utilize neural networks to identify relationships between text. At the same time, applying techniques such as lexicon-based methods [7] and aspect-based sentiment analysis [8] was used to identify sentiments regarding product features. Additionally, applying NLP preprocessing

techniques [9], supervised opinion mining models [10], hybrid learning techniques [11], feature extraction techniques [12] such as TF-IDF and word embeddings, and others were used to further improve sentiment analysis techniques. The recent improvements made to sentiment analysis techniques also included applying deep neural network techniques [13] and NLP-based opinion extraction techniques [14].

The current sentiment analysis systems include unsupervised, lexicon-based, machine learning, and deep learning methods. The unsupervised methods classify reviews using semantic orientation methods such as PMI, whereas the lexicon-based methods utilize predefined sentiment dictionaries to determine the polarity of reviews and, in some cases, perform feature-based analysis of a product. Machine learning methods, such as Naïve Bayes and SVM, enhance review classification accuracy, whereas deep learning methods utilize neural networks to improve review prediction.

However, these techniques have some drawbacks. The unsupervised and lexicon-based techniques have difficulties in understanding context, sarcasm, and domain-specific language. The machine learning techniques require large labeled data sets for training. They are mainly focused on achieving accuracy in classification problems. Moreover, these techniques do not provide in-depth analysis. The deep learning techniques are accurate. However, these techniques require large computational resources. Furthermore, these techniques do not have user-friendly interfaces, comparison analysis, and visualization capabilities. The limitation of these techniques can be addressed by the proposed system, which is "Sentiment Analysis on Social Media," combining NLP techniques with efficient machine learning algorithms in a scalable web-based system. The system not only classifies the reviews into positive, negative, or neutral sentiment, but it also offers comparative analysis of the products, support for multiple languages, and interactive dashboards. Thus, the system can be made more practical, user-friendly, and applicable for real-time decision-making.

3. Methodology

3.1 Natural Language Processing (NLP):

Natural Language Processing(NLP) plays a crucial role in converting raw customer reviews into meaningful insights. Since product reviews are unstructured text data, NLP techniques are used to clean, process, and transform this data into a format that machine learning models can understand and analyze.

3.1.1 Text Normalization

This step ensures uniformity in the text.

1. Convert all text to lowercase
2. Remove punctuation and special characters
3. Remove numbers and irrelevant symbols

Example:

“This Product is Very Good!!! 😍” → “this product is very good”

3.1.2 Tokenization

Tokenization splits the text into smaller units called tokens (words).

Example:

“this product is very good” → [“this”, “product”, “is” ,”very”, “good”]

This helps the system analyze each word separately.

3.1.3 Stop-Word Removal

Common words that do not carry much meaning are removed.

Example:
"this product is very good" → "product very good"
This reduces noise and improves model performance.

3.1.4 Stemming and Lemmatization

These techniques reduce words to their base form.

1. **Stemming:** Cuts words to root form
   "running" → "run"
2. **Lemmatization:** Converts words to meaningful base form
   "better" → "good"

This helps group similar words together.

3.2 Term Frequency-Inverse Document Frequency(TF-IDF):

TF-IDF (Term Frequency – Inverse Document Frequency) is a key technique used in the feature extraction stage of NLP. Since machine learning models cannot understand raw text directly, TF-IDF converts product reviews into numerical vectors while preserving the importance of words.

TF-IDF helps to:

1. Identify important words in a review
2. Reduce the weight of common words (like "product", "the")
3. Highlight sentiment-carrying words (like "excellent", "worst")

3.2.1 Term Frequency (TF):

Term Frequency (TF) measures how often a word appears in a specific document or review, assigning higher values to terms repeated frequently within that text to indicate their relative importance locally.Term Frequency from (12) is the simple word count, but normalization—dividing by total words in the review accounts for varying review lengths, ensuring fairness across short and long inputs.

Measures how often a word appears in a document (review).

$$TF(t,d) = \frac{\text{Number of times term t appears in document d}}{\text{Total number of terms in document}} \quad \text{_____(12)}$$

If a word appears many times in a review, it gets a higher TF value.

3.2.2 Inverse Document Frequency (IDF):

Inverse Document Frequency (IDF) measures a word's importance across all documents by down weighting terms that appear in many reviews while boosting those unique to few, acting as the global complement to TF in the NLP. Common words like "product" or "the," found nearly everywhere, receive low IDF scores and minimal influence, whereas rare terms such as "glitchy" or "overheating," appearing in only a handful of reviews, gain high IDF values that highlight distinctive issues or praises. This selective emphasis follows local TF computation after tokenization, stemming, and stop-word removal, ensuring the combined TF-IDF vectors prioritize meaningful, corpus-specific signals over generic noise for the "Analyze Sentiment using Machine Learning" step

Measures how important a word is across all documents.

$$IDF(t) = \log\left(\frac{N}{df(t)}\right) \quad \text{_____(12)}$$

Where:

1. N = Total number of documents
2. $df(t)$ = Number of documents containing term t

Common words appearing in many reviews get low IDF, rare words get high IDF.

3.2.3 TF-IDF Calculations:

Example: "Camera quality is excellent but battery is poor"
Words like "excellent", "good" → high importance
Words like "battery" → low importance

The review is converted into a vector:

WORD	TF-IDF Score
excellent	0.8
poor	0.7
camera	0.4
battery	0.5

This vector is given as input to ML models.

3.3 Logistic Regression:

Logistic Regression is one of the main supervised machine learning algorithms used for sentiment classification. It predicts whether a product review is positive, negative, or neutral based on the textual features extracted using NLP techniques like TF-IDF.
This model excels at handling high-dimensional sparse data from text features. For instance, a vector from "Camera quality is excellent but battery is poor" emphasizes sentiment words like "excellent" (high TF-IDF score) and "poor," learning weights during training on labeled datasets to output class probabilities via a sigmoid function—such as 55% negative, 35% positive, 10% neutral for mixed reviews. Its linear decision boundary effectively separates sentiment classes, with interpretable coefficients revealing influential terms (e.g., "glitchy" strongly predicts negative).

3.3.1 Working Principle

Logistic Regression works by applying a linear model followed by a sigmoid (logistic) function to produce output between 0 and 1.

Mathematical Model:

$$z = w_1x_1 + w_2x_2 + w_3x_3 + \ldots + b$$

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-z}}$$

Where:

1. x_1, x_2, x_3 = TF-IDF features (word importance)
2. w = weights learned by the model
3. b = bias
4. $P(y = 1 \mid x)$ = probability of positive sentiment

3.3.2 Linear Combination

The model multiplies each feature with weights:

$$z = (0.8w_1 + 0.7w_2 + 0.4w_3 + 0.5w_4) + b$$

Sigmoid Function

Converts result into probability:

1. If output ≈ 1 → Positive
2. If output ≈ 0 → Negative

Final Classification

1. $P > 0.5 \rightarrow$ Positive
2. $P < 0.5 \rightarrow$ Negative

For multi-class (positive/negative/neutral), softmax function can be used.

3.3.3 Training the Model

The model is trained using labeled data:

1. **Input**: Reviews + Sentiment labels
2. **Goal**: Learn optimal weights w

Loss Function (Log Loss):

Log Loss, also called binary cross-entropy (13), measures how far a model's predicted probabilities diverge from actual sentiment labels during training of Logistic Regression in the flowchart's machine learning step. It penalizes confident wrong predictions heavily—for example, predicting 0.01 probability for a true positive label incurs high loss, while near-perfect predictions (predicting 0.95 for true positive) yield low loss close to zero.

$Loss = -[y\log(p) + (1-y)\log(1-p)$_____(13)

The model minimizes this loss using optimization techniques like Gradient Descent.

3.3.4 Role in Sentiment Analysis:

Logistic Regression:

- Identifies important words affecting sentiment
- Assigns weights to positive and negative words
- Predicts sentiment with probability

Example:

1. "excellent" → positive weight
2. "worst" → negative weight

4. System Architecture

The proposed Sentiment Analysis on Social media has a multi-layered structure that incorporates data acquisition, natural language processing, machine learning, and visualization techniques to efficiently perform sentiment analysis and provide insightful results. The proposed system starts with the Data Acquisition Layer, which collects product reviews from different sources like user inputs, datasets, and online sources. The collected data is in an unstructured form, which is then sent to the Data Preprocessing Layer. This layer applies Natural Language Processing techniques like tokenization, stopword removal, and lemmatization to clean and preprocess the unstructured data.The processed data is then sent to the Feature Extraction Layer, which applies techniques like TF-IDF to convert unstructured data into numerical values. The numerical values are then sent to the Machine Learning Layer, which applies machine learning algorithms like Logistic Regression to classify the sentiment of the product reviews into positive, negative, or neutral.

Fig 1: System Architecture for sentiment analysis on social media

The results of the sentiment classification are then sent to the Sentiment Analysis and Comparative Module, which performs sentiment analysis and compares multiple products based on customer feedback. The results of the sentiment analysis and comparison are then sent to the Visualization Layer, which presents the results in graphical form like bar charts, pie charts, and dashboards.

The visualization process in the proposed system plays an important role in transforming the raw results of sentiment analysis into more interpretable and understandable results. After the classification process, the sentiment results are combined and sent to the visualization module, which uses Matplotlib and Seaborn libraries to display the results in graphical form. The proposed system generates bar charts and pie charts to display the results of positive, negative, and neutral reviews, and comparison graphs to display the results of multiple products. The results in graphical form are integrated into an interactive visualization dashboard, which is created using the Django framework. The visualization dashboard plays an important role in increasing the usability of the proposed sentiment analysis system, which displays complex results in a simple, concise, and easy-to-use manner.

The proposed system ensures efficient sentiment analysis and comparison results in a multi-layered structure that incorporates natural language processing and machine learning techniques within a user-friendly web-based environment.

5. Result Analysis

The proposed Sentiment Analysis on social media was successfully implemented for product review analysis and sentiment classification into positive, negative, and neutral classes. The proposed system used NLP for data preprocessing, TF-IDF for feature extraction, and machine learning models such as Logistic Regression for sentiment classification. The results showed that the proposed machine learning model could achieve high accuracy for sentiment prediction and could effectively classify user opinions from large volumes of data.

The sentiment analysis of individual product reviews is carried out to find the overall customer sentiment for a product. The results are compiled to find the percentage of positive, negative, and neutral sentiment. The visualization dashboard shows the results of the sentiment analysis in the form of bar charts and pie charts. In that bar graph we can see the features of the iphone that are represented as graph and we can analysis the features of the iphone by bar graph. We can see the features like display, camera, sound.This helps the user understand the general sentiment of the product. The sentiment analysis helps in finding the

pros and cons of a product based on customer reviews and aids in better decision-making for customers and businesses.

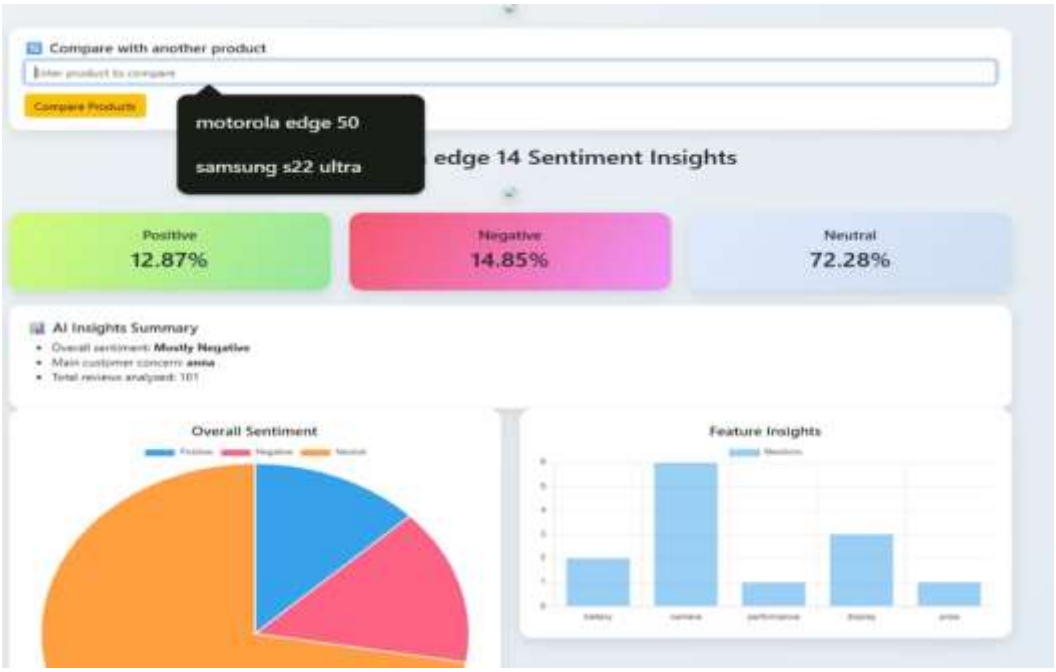

Fig 2. Product review analysis for iphone

Moreover, the system also facilitates comparative analysis of different products by evaluating and comparing the sentiment distribution of the products. Reviews of different products are processed and classified, and the results are compared and visualized in the form of comparative graphs. This helps the user to easily identify which product is being praised by customers and which product is being criticized by customers. The comparative dashboard provides a clear and intuitive view of the performance of different products for selecting the best product among them.

Fig 3. Comparative analysis of two products

The analysis shows that the machine learning model could achieve high accuracy when combined with appropriate preprocessing and feature extraction techniques. The TF-IDF feature extraction method helped classify the sentiment by identifying important words for sentiment analysis. The visualization tools such as bar charts and pie charts also helped in better visualization of the results and provided better insights for users regarding product sentiment analysis. The proposed sentiment analysis system also has some limitations. The machine learning-based sentiment analysis system may not work efficiently for complex language patterns such as sarcasm and slang words. The proposed sentiment analysis system also needs a good dataset for training the machine learning model. The proposed sentiment analysis system is an efficient solution for sentiment analysis. The project shows how the integration of NLP, machine learning, and web technologies could provide a decision-support tool for product analysis based on customer opinions.

Conclusion and Future Scope

The proposed Sentiment Analysis on social media System effectively shows the application of Natural Language Processing (NLP) and Machine Learning techniques for product review analysis. By using techniques such as data preprocessing, feature extraction using the TF-IDF algorithm, and machine learning classifiers such as Logistic Regression and Support Vector Machine, the proposed system can effectively extract sentiment from large amounts of data. Moreover, the incorporation of visualization dashboards can further improve the application of the proposed system by making the results easily interpretable.

This can be further improved with the incorporation of sophisticated deep learning techniques like LSTM and the Transformer architecture to improve the contextual understanding and address complex language behaviors like sarcasm. Further improvements to the model can include the incorporation of sentiment analysis in multiple languages, live data acquisition using APIs, and even more sophisticated aspect-based sentiment analysis. Moreover, the model can be developed to function as a full-fledged business intelligence tool with predictive analytics to predict customer behavior and market trends.

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