A Machine Learning Approach for Analyzing User Feedback and Product Reviews from Social Media

Aditya Singh[1], Achint Goswami[2], Mr.Arunendra Tripathi[3]
[1,2] *Galgotias University, Noida, India*
[3]*Assistant Professor, Galgotias University*

***Abstract*— Understanding user feedback and product reviews expressed on social media has become essential for gauging public opinion, tracking consumer behavior, and identifying trends. However, the rise of bots, spam, and artificially generated content poses significant challenges to the reliability of this data. This research explores the use of logistic regression for classifying feedback and detecting bots, aiming to improve the accuracy and credibility of social media analysis. By applying feature extraction methods like TF-IDF, we were able to effectively classify review-related content with notable precision. Furthermore, integrating bot detection mechanisms helped filter out misleading or inauthentic data, ensuring that the insights drawn reflect genuine user feedback. The paper outlines the proposed approach, experimental framework, outcomes, and future potential of combining machine learning with social media analytics for more dependable feedback classification.**

***Keywords*— user feedback analysis, logistic regression, bot detection, social media, TF-IDF, machine learningg**

I. INTRODUCTION

Social media has evolved into a key platform for public discussions on everything from consumer products to political views and social matters. Analyzing these conversations offers valuable insights that organizations can use to improve products, address user feedback, and understand how their brand is perceived. However, a major challenge lies in the unstructured nature of social media content, which is often complicated further by the presence of bots and fake accounts. These automated profiles can disrupt feedback analysis by misrepresenting genuine public opinion. To tackle this, there is a need for reliable methods that can classify user feedback accurately while also detecting and filtering out inauthentic data.

Logistic Regression (LR) has proven to be an effective tool for feedback classification, especially when working with the sparse and high-dimensional data typical of social media. This study presents a project that uses LR for analyzing user feedback and product reviews and incorporates a bot detection component to improve data quality. The focus is on evaluating how well Logistic Regression, combined with feature extraction techniques like TF-IDF, performs in accurately analyzing user input and ensuring that only authentic responses are considered.

II. LITERATURE REVIEW

A. Timeline of Emotion Classification Using SVM

In recent years, Support Vector Machines (SVM) have emerged as a strong contender for classifying user feedback and product reviews in machine learning tasks. Thanks to their ability to handle high-dimensional and sparse data, SVMs are particularly well-suited for processing text-based content where feature sets can be large and uneven. Ahmad, Aftab, and Ali [1] applied SVM to datasets related to self-driving cars and Apple products, reporting F-measure scores of 57.2% and 69.9%, respectively. These results highlight SVM's adaptability across different types of feedback data. Similarly, a study by Fikri and Sarno [2] compared SVM with rule-based methods that used SentiWordNet and found that when paired with TF-IDF, SVM achieved a notable accuracy of 89%, outperforming the alternative approach.

Another investigation by Huq, Ali, and Rahman [3] evaluated both SVM and the k-nearest neighbors (KNN) algorithm for analyzing feedback on Twitter. While KNN showed promising results in certain scenarios, SVM consistently performed better with more complex, high-dimensional datasets, reinforcing its suitability for handling sparse textual data. Collectively, these studies support the reliability of SVM in user feedback classification, while also noting that its performance can vary depending on the nature and structure of the dataset.

B. Enhanced SVM Models with Advanced Features

To address some limitations of traditional SVM models, researchers have developed enhanced models with advanced feature engineering. For example, Han et al. [4] proposed an SVM model using a Fisher Kernel based on Probabilistic Latent Semantic Analysis (PLSA), which captured latent semantic structures within text data. This model achieved 87.2% accuracy, handling language complexities like synonyms and polysemy more effectively than basic SVM models. Similarly, Mullen and Collier [5] created a hybrid SVM model integrating semantic orientation (SO) features, enhancing SVM's performance on user feedback and product reviews with complex linguistic nuances, such as sarcasm.

C. Application-Specific SVM Studies

SVM's flexibility makes it suitable for a wide range of domain-specific applications. For instance, Tyagi and Sharma [6] applied SVM to classify smartphone reviews, reaching an accuracy of 89.98% by using preprocessing techniques such as TF-IDF and part-of-speech (POS) tagging. In the realm of political discourse, Patil et al. [7] demonstrated the model's strength in processing high-dimensional and varied content by using SVM to analyze user feedback on social media platforms. Meanwhile, in the healthcare field, Rahardi et al. [8] explored public opinions around Covid-19 vaccinations. Using an RBF kernel with SVM, they achieved a high accuracy of 92%, further emphasizing the model's effectiveness across different content types and contexts..

D. Hybrid Approaches and Feature Selection Techniques

Hybrid models that integrate SVM with optimization techniques have shown considerable potential in boosting user feedback classification performance. For example, Sharma and Sabharwal [9] used a combination of Particle Swarm Optimization (PSO) and Cuckoo Search to fine-tune feature selection. When applied to a Twitter dataset, their approach outperformed convolutional neural networks (CNNs), achieving an accuracy of 91.91% and a precision rate of 98.34%. These results highlight the effectiveness of hybrid methods in enhancing feature selection and improving overall model performance for analyzing product reviews and user feedback.

E. SVM in Product and Event Sentiment Tracking

Bourequat and Mourad [10] used SVM to study consumer responses to iPhone product launches, achieving an accuracy of 89.21%. Their preprocessing steps involved tokenization, removing stop words, and applying TF-IDF weighting. The study underscores SVM's value in tracking consumer feedback, especially in scenarios where quick and reliable opinion analysis can inform marketing and product decisions.

F. Timeline of User Feedback and Product Review Classification Using Logistic Regression

Logistic Regression is a classification technique commonly used to separate data into two distinct categories. When the task involves more than two classes, a variation known as multinomial logistic regression is applied [11]. In the context of analyzing user feedback and product reviews, where the goal is to classify responses as either positive or negative, standard logistic regression serves as an effective and straightforward solution.

G. Logistic Regression with TF-IDF

TF-IDF (Term Frequency – Inverse Document Frequency) is an advanced feature extraction technique that can be used alongside logistic regression to transform user feedback and product review data into a numerical format [12]. By converting textual information into quantifiable values, TF-IDF makes it easier for classification models to process and analyze the data effectively.

H. User Feedback and Product Review Classification Using Naïve Bayes

Naïve Bayes is one of the most widely used classifiers for user feedback and product review classification, largely because of its simplicity compared to more complex models like SVM. It's a fast and efficient method that predicts categories based on probability, operating under the assumption that all features are independent of one another. This assumption makes the model easy to implement and often yields decent results [13][14]. However, in real-world scenarios, features are rarely truly independent, which can lead to inaccuracies. In practice, it was observed that Naïve Bayes performed reasonably well when identifying negative feedback, but struggled with accurately classifying positive ones. It also had difficulty handling sarcastic or more nuanced comments, which reduced its overall reliability in complex cases [15].

III. METHODOLOGY

A. Data Collection and Preprocessing

We collected data from Twitter using its official API, ensuring full compliance with the platform's usage policies to respect user privacy and follow data handling guidelines. To capture a diverse range of content, we focused on tweets containing specific keywords, hashtags, and user mentions relevant to our study.

Once the tweets were gathered, we performed a series of preprocessing steps to clean and prepare the data for analysis. The cleaning process included:

- Removing URLs: All web links were removed to avoid interference with textual analysis.
- Removing Mentions: User mentions (e.g., "@username") were stripped from the text to keep the focus on the tweet's actual content.
- Eliminating Special Characters and Emojis: Non-alphanumeric symbols and emojis were excluded to simplify the text and ensure uniform processing.
- Text Normalization: All text was converted to lowercase to avoid treating the same word differently based on case (e.g., "Happy" vs. "happy"). Additionally, stop words—common words like "the," "is," and "in"—were removed as they contribute little to user feedback analysis.

B. Feature Engineering and Model Selection

TF-IDF (Term Frequency-Inverse Document Frequency) was selected as the primary method for converting text data into numerical form, as it effectively captures the significance of words in context, making it ideal for user feedback and product review classification. This technique ensures that common words don't overpower the analysis, while emphasizing the terms that are most relevant for understanding user sentiment.

For user feedback classification, we chose Logistic Regression as the main classification model due to its ability to handle high-dimensional data. Logistic Regression is particularly effective with data like ours, where there are many features (i.e., words) to analyze and classify. To optimize the model's performance, we experimented with two types of kernels:

- Linear Kernel: A straightforward approach that assumes the data is linearly separable.
- RBF Kernel: A more flexible approach suited for complex datasets where the relationships between features may not be linear.

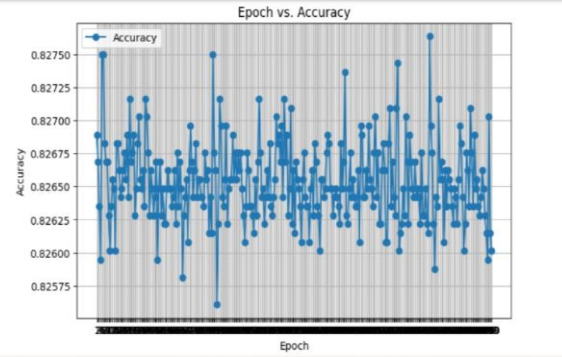
  We tested both kernels to determine which one provided the best performance for our specific task.

C. Bot Detection

For bot detection, we employed pattern recognition techniques aimed at identifying automated behavior, such as frequent posting and repetitive message patterns. The detection algorithms flagged accounts that appeared to be synthetic, which were then removed from the emotion classification process. This helped ensure the reliability of the data by excluding inauthentic content.

D. Model Training

To enhance the model's learning and improve its performance, we trained it over a total of 300 epochs. This extended training allowed the model to better recognize patterns and achieve more efficient results.



E. Model Evaluation

We evaluated three different models—SVM, Naïve Bayes, and Logistic Regression—to determine the classification of user feedback and product reviews. We calculated the accuracy of each model to identify the best-performing one.

The following formulas were used to assess the performance metrics of the models:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Recall = TP / (TP + FN)
- Precision = TP / (TP + FP)
- F1 Score = 2 * (Recall * Precision) / (Recall + Precision)

Where:

- TP (True Positive): The model correctly predicted the feedback as positive when it was indeed positive.

- TN (True Negative): The model correctly predicted the feedback as negative when it was actually negative.
- FP (False Positive): The model incorrectly predicted the feedback as negative when it was actually positive.
- FN (False Negative): The model incorrectly predicted the feedback as positive when it was actually negative.

These metrics help evaluate the model's ability to classify sentiments accurately and efficiently

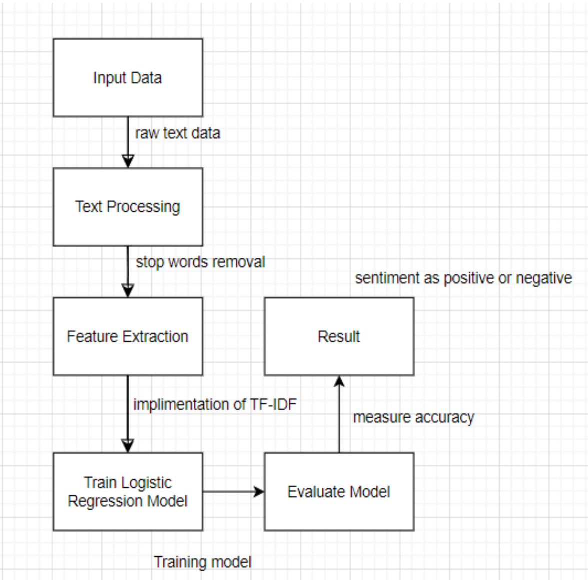


Fig.1. process flow of the system

E. Visualization

Visualizations played a crucial role in offering an intuitive understanding of user feedback trends and key themes within the data. Several types of visual tools were employed:

- Pie Charts: These were used to illustrate the distribution of feedback (positive, negative, and neutral) across the entire dataset, giving a quick snapshot of the overall public perception.
- Bar Graphs: Bar graphs helped display feedback distribution across different subgroups or categories, such as feedback by region, language, or time period, making it easier to compare different segments.
- Word Clouds: Word clouds were created to visually highlight the most frequently mentioned terms in the dataset, with larger words indicating stronger feedback associations. This was particularly useful for identifying key themes or emerging trends.

These visualizations provided a holistic view of the data, making it more accessible and easier to interpret. They enabled stakeholders to quickly identify major feedback trends and key topics, offering valuable insights into customer opinions and product-related discussions.

IV. RESULTS AND DISCUSSION

A. Emotion Classification Results

Using the cleaned Twitter dataset, Logistic Regression achieved an average accuracy of 82% in user feedback and product review classification. The results showed that the model was particularly successful at differentiating between positive, negative, and neutral feedback, demonstrating its effectiveness in handling social media data.

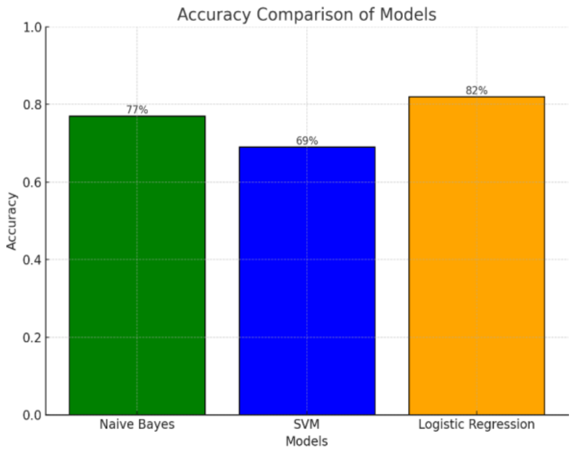


Fig.2. comparison chart of models

B. Bot Detection Efficacy

The bot detection algorithm identified about 5% of the dataset as inauthentic content, which was then excluded from the analysis. Removing this synthetic data helped enhance the accuracy of sentiment classification by ensuring that only genuine user sentiments were considered.

C. Comparative Analysis with Other Models

Performance comparison of different models in percentage

Machine Learning Model	Precision	Recall	F1-Score	Accuracy
SVM	72.13	75.86	73.95	69.00
Naïve Bayes	78.14	77.97	80.00	77.00
Logistic Regression	79.00	79.00	79.00	82.60

When compared to SVM and Naïve Bayes, Logistic Regression outperformed in terms of both accuracy and processing efficiency, especially when dealing with high-dimensional, sparse data. Meanwhile, the application of TF-IDF improved SVM's ability to identify relevant features, further confirming its effectiveness for user feedback and product review classification tasks on social media platforms.

V. CONCLUSION AND FUTURE WORK

This study highlights the effectiveness of Logistic Regression in user feedback and product review classification. The model's ability to handle sparse and high-dimensional data, combined with TF-IDF for feature extraction, makes it a valuable tool for analyzing customer opinions on social media. However, future research could explore advanced NLP techniques, such as deep learning, to better capture more complex feedback, such as sarcasm and mixed sentiments. Additionally, improving bot detection to identify more sophisticated automated behaviors would further enhance data reliability. Expanding feedback classification to multiple social media platforms could provide a broader view of public opinion trends, offering deeper insights across various digital spaces.

There is still work to be done in bot detection, particularly in identifying bots that contribute to spam or irrelevant comments. By removing these bots, the predicted feedback would be more accurate and meaningful..

REFERENCES

[1] Ahmad, M., Aftab, S., & Ali, I., "emotion classification of tweets using SVM," *Int. J. Comput. Appl.*, vol. 177, no. 5, pp. 25-29, 2017.

[2] Fikri, M., & Sarno, R., "A comparative study of emotion classification using SVM and SentiWordNet," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 13, no. 3, pp. 902-909, 2019.

[3] Huq, M. R., Ali, A., & Rahman, A., "emotion classification on Twitter data using KNN and SVM," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 6, 2017.

[4] Han, K. X., Chien, C. M., Chiu, S. M., & Cheng, C. T., "Application of support vector machine (SVM) in the emotion classification of Twitter dataset," *Appl. Sci.*, vol. 10, no. 3, p. 1125, 2020.

[5] Mullen, T., & Collier, N., "emotion classification using support vector machines with diverse information sources," *Proc. of the 2004 Conf. on Empirical Methods in Nat. Lang. Process.*, 2004.

[6] Tyagi, E., & Sharma, A. K., "emotion classification of product reviews using support vector machine learning algorithm," *Indian J. Sci. Technol.*, vol. 10, no. 35, 2017.

[7] Patil, G., et al., "emotion classification using support vector machine," *Int. J. Innov. Res. Comput. Commun. Eng.*, vol. 2, no. 1, pp. 2607-2612, 2014.

[8] Rahardi, M., et al., "emotion classification of COVID-19 vaccination using support vector machine in Indonesia," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 6, 2022.

[9] Sharma, D., & Sabharwal, M., "emotion classification for social media using SVM classifier of machine learning," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 9, pp. 39-47, 2019.

[10] Bourequat, W., & Mourad, H., "emotion classification approach for analyzing iPhone release using support vector machine," *Int. J. Adv. Data Inf. Syst.*, vol. 2, no. 1, pp. 36-44, 2021

[11] Mayur Wankhade1, A Chandra Sekhara Rao1, Suresh Dara2, Baijnath Kaushik3" A emotion classification of Food Review using Logistic Regression" 2017 IJSRCSEIT | Volume 2 | Issue 7 | ISSN : 2456-3307

[12] Sai Prasad, Dr. Vadivu G "Comparative Study of Logistic Regression and LSTM for Sentiment Classification Across Diverse Textual Dataset" November 2023

[13] Rothfels, J., Tibshirani, J. (2010). Unsupervised sentiment classification of En-glish movie reviews using automatic selection of positive and negative sentiment items. CS224N-Final Project

[14] Thakkar, H., Patel, D. (2015). Approaches for emotion classification on twitter: A state-of-art study. arXiv preprint arXiv:1512.01043

[15] Vikas Malik, Amit Kumar "emotion classification of Twitter Data Using Naive Bayes Algorithm" April 2018