**Sentiment Analysis of Facebook Comments**

**Abstract**

Nowadays, social media is such an important platform where we can know the situation of the world through thousands of posts. Sentiment analysis is a valuable tool to measure public opinion. It successfully devoted itself to health issues, brand marketing, crime prediction, financial market prediction, customer analytics, and emergency management. In which situation, public posts on those topics are vital for research on the basis of sentiment analysis. Many researchers publish sentiment analysis papers on social media because a large number of people use it and they are posting lots of topics in their daily lives, like text, photos, video, and audio. This data can be converted into vital information with the help of sentiment analysis. The public shares their current condition and situation on social media. For what reason does a person post that content on social media? Is it because that person wants suggestions on how to handle the situation or how to survive the condition, wants to know the solution to the problem, or generally shares happiness or sadness? We read about the accuracy and limits of several literature review publications, employed their models and datasets, and conducted surveys of them.

**Introduction**

Today, social media plays a big part in people's daily lives. The number of people who are not connected to social media is very small. They are linked to some platforms like Facebook, WhatsApp, Twitter, YouTube, and Instagram. People benefit from using social media. Not only is social media a medium of communication between people, but it is also an earning path for mankind. On social media, many people build up their businesses by communicating with others and want to get feedback to improve their service. As a result, the number of social media users is high, and I guess it will increase in the future. People express their emotions through the sharing of various texts, videos, and audio photos. For the development of business organizations, advanced technologies like machine learning and AI are used for data processing. This paper explains the applications of sentiment analysis using an experiment with published literature. Sentiment analysis is a way in which we classify a post as having a good, bad, or normal sentiment. There are two types of sentiment analysis: the machine learning approach and the lexicon-based approach. Machine learning is used to find sentiment from data, and a lexicon-based approach is used to regard good or bad words in the language. Most of the previous research on sentiment analysis was held under product or movie reviews, but now the challenge is to understand the public's mental situation at that moment when they are posting something and how the user reacts to seeing this post.

**Literature review**

**Overview of Sentiment Analysis**

Sentiment analysis of public posts on social media and the opinions that go along with them is the process of examining text data from social media platforms to identify the opinions people are expressing and to ascertain the sentiment that they are expressing. This entails gathering text data that is accessible to the public from sites like Facebook, Instagram, and Twitter, then preparing it to handle emoticons and emojis, sanitize it, and tokenize it.

Sentiment analysis can be done in a number of ways: lexicon-based using sentiment dictionaries; machine learning-based using models to classify text into sentiment categories; and hybrid approaches combining machine learning and lexicon-based methods. From the text data, features are taken out, and representations for sentiment categorization are made.

Opinion mining, often referred to as aspect-based sentiment analysis, is the process of locating certain elements or entities (such as goods or services) that are referenced in the text and evaluating the sentiment that is conveyed about each one. Metrics including accuracy, precision, recall, and F1-score are used to assess the performance of sentiment analysis algorithms.

Sentiment analysis on social media data is used in market research, public opinion tracking, political sentiment analysis, brand monitoring, customer feedback analysis, and sentiment-driven recommendation systems. Nonetheless, this sector has difficulties processing irony, slang, sarcasm, misspellings, and comprehending sentiment expressions that vary depending on the context.  
  
  
In order to solve these issues, future research in sentiment analysis on social media data may concentrate on creating multilingual sentiment analysis models, investigating novel approaches for context-aware sentiment analysis, and integrating visual content (pictures and videos).

**Social media platforms and data collection**

Social media platforms serve as virtual environments where people connect, share material, and voice opinions on numerous issues. Large volumes of user-generated data, including text, photos, videos, and interactions, are gathered by these platforms. Sentiment analysis is a technique that uses data from social media posts to identify and classify user attitudes as neutral, negative, or positive.  
  
Accessing publicly accessible postings on social media networks via their APIs (application programming interfaces) or web scraping methods is commonly used in data collection for sentiment analysis. Text, timestamps, user IDs, and other metadata related to each post may be included in the data collection. Furthermore, several systems provide sentiment analysis-specific APIs that provide users access to measurements and insights pertaining to sentiment.

Techniques for analyzing sentiment vary; they include machine learning algorithms and rule-based systems. While machine learning algorithms automatically classify sentiment in new postings by learning patterns from labeled data, rule-based techniques rely on predefined rules and lexicons.

It is also possible to gather opinions regarding social media posts using a variety of techniques, such as surveys, interviews, or the examination of engagement indicators like likes, shares, and comments. These viewpoints offer insightful information on how users see and engage with material on social networking sites.

**Data processing**

Data preprocessing is an action that is used to transfer raw data into a knowledgeable format. Through some steps, data processing is completed. The steps are data clearing, data transformation, and data reduction. The steps are used to classify incorrect data if it is not preprocessed. Data that is collected from social media sites like Twitter, Facebook, and WhatsApp is always inappropriate for the user. They exist mainly in slang, acronyms, abbreviations, and misspellings in posts, which may reduce the quality of the post. For the development of the machine learning structure, it is first necessary to find raw data from multiple sources and then synchronize those in a proper data set. Different datasets are used for different perspectives. Health care-related data sets and business data sets are completely different from each other. In the data clearing step, the data consists of many irrelevant parts. It works for handling missing and noisy data. Then the data is transformed into an appropriate form. Then data reduction happened, increasing storage efficiency and reducing the size of the data.

**Sentiment analysis methods**

There are two methods of sentimental analysis. One is a machine learning approach, and the other is a lexicon-based approach.

Machine learning: Machine learning is used to analyze the text of the human language. Sentiment analysis is a machine learning technique that explains the positive and negative words in a text. When a person posts the text, the machine automatically captures the emotions behind it.

Machine learning tells the computer to memorize the latest job unless explicitly programmed to redact the tasks. Machines can read unused words, irony, and human mentality. Suppose a person comments about a post: "Change your wonderful mentality." In this text, "wonderful" is a positive word, but it is a negative comment. There is a double meaning in the texts. In this way, a device calculates lots of users minds at a time.

Lexicon-based approach: Lexicon-based analysis is a famous approach that uses the substance of the emotion as positive, negative, or neutral. It depends on words and phrases that have an attached sentiment class. But there are some challenges that can be harmful to its validity. So we should find the common problems of lexicon-based analysis and find the solution to the problem.

Language diversity: One of the main challenges of lexicon-based analysis is domain variation. Sentiment analysis finds the internal emotion that is hidden in the words and phrases of a text. The word 'weak' is a negative designation. Depending on the language's diversity, lexicon-based sentiment is used. It could be a word that can hold. The word 'confident' has a positive and negative meaning together. Lexicon-based analysis can be hard because the sentiment of the words and faces can change depending on the domain.

Mocary: The second challenge of lexicon-based analysis is to detect mockery because it cannot detect the irony of a word. As an example, "I like to eat rice." In the sentence, there may be sarcasm if the person actually hates to eat rice. But lexicon-based analysis can catch another sense of the sentence. It can express the word 'like' as a positive vibe. Not only the machine, but it is also difficult for humans to understand the irony.

**Future Extraction and Representations**

Future Extraction and Representations in sentiment analysis on social media involve discerning sentiments expressed in posts discussing future events. "Future extraction" entails identifying references to events that have not yet occurred but are anticipated or discussed. This involves recognizing keywords or phrases hinting at future occurrences, which can be challenging due to the informal nature of social media communication.

"Representations" refer to accurately portraying sentiments associated with these future events. Given the speculative nature of such discussions, accurately capturing sentiment requires understanding the context and nuances of language. This involves discerning between speculation, concrete plans, and hypothetical scenarios.

Addressing these challenges involves leveraging advanced natural language processing and machine learning techniques. Algorithms sift through vast social media data, recognizing patterns and extracting relevant information. Techniques such as sentiment lexicons tailored to future-oriented content and contextual embeddings help capture semantic meaning. Additionally, domain-specific knowledge fine-tunes models for specific applications, such as finance or marketing.

By effectively identifying and interpreting future-oriented content, Future Extraction and Representations facilitate insights into emerging trends and shifting sentiments within online communities.

**Sentiment lexicon and datasets**

Lists of words or phrases with their sentiment polarity—positive, negative, or neutral—annotated are called sentiment lexicons. These lexicons function as dictionaries, offering sentiment labels for specific words or phrases. Sentiment analysis algorithms utilize these labels to categorize the sentiment of textual data.  
  
Datasets are collections of annotated text that are used to train and assess sentiment analysis models in the context of social media sentiment analysis on public postings. These datasets usually include human-assigned sentiment labels (positive, negative, and neutral) combined with user-generated material (tweets, comments, reviews, forum posts, etc.).

For the purpose of creating and assessing sentiment analysis algorithms for public postings on social media and the views that accompany them, sentiment lexicons and datasets are essential components. They support practitioners and researchers in developing supervised machine learning models and assessing how well they predict sentiment labels on unobserved data. However, when employing sentiment lexicons and datasets in sentiment analysis on public posts on social media, consideration must be given to issues like domain specificity, cultural variances, biases, and shifting language trends.

**Opinion Mining and Aspect – Based Sentiment Analysis**

Opinion Mining, also known as sentiment analysis, involves extracting and analyzing opinions, emotions, and attitudes expressed in text data. In the context of social media posts, opinion mining focuses on understanding the sentiments conveyed by users regarding various topics, products, events, or individuals.

Aspect-Based Sentiment Analysis (ABSA) is a more refined approach within opinion mining that goes beyond overall sentiment to analyze specific aspects or attributes of a subject. In social media posts, ABSA breaks down opinions into different aspects or features, such as the performance of a product, the customer service of a company, or the ambiance of a restaurant. It then assesses the sentiment expressed towards each aspect individually.

For instance, in a restaurant review, ABSA might identify aspects like food quality, service speed, and ambiance. It would then analyze the sentiment associated with each aspect separately, determining whether users express positive, negative, or neutral opinions about them.

This nuanced approach provides deeper insights into user opinions, enabling businesses and analysts to understand not just the overall sentiment but also the specific aspects driving those sentiments. By pinpointing areas of strength or weakness, ABSA helps businesses make targeted improvements, refine marketing strategies, and enhance overall customer satisfaction.

In summary, Opinion Mining focuses on extracting sentiments from text data, while Aspect-Based Sentiment Analysis delves deeper by analyzing specific aspects or features within the text to gain a more comprehensive understanding of user opinions. In the realm of social media, these techniques enable businesses and analysts to glean valuable insights into customer perceptions, preferences, and sentiments.

**Applications**

Applications for sentiment analysis of public social media posts and opinion analysis of such posts are numerous and span numerous industries. The literature on this issue analyzes these applications in depth, including variables such as data collection methods, sentiment analysis methodologies, and the consequences of sentiment analysis in varied situations. Typical uses for them include:   
  
Marketing: Campaigns and plans can be informed by knowledge of how consumers feel about certain brands or items. Companies may use sentiment analysis to determine how the public feels about them and where their goods and services need to be improved.  
  
Consumer service: Real-time monitoring of consumer comments on social media platforms may be achieved using sentiment analysis. This enables businesses to quickly resolve client concerns and raise client satisfaction levels overall.

Politics and population opinion: Social media post sentiment analysis can shed light on what the general population thinks about political issues, politicians, and policy. Political campaigns, decision-makers, and analysts may use this data to better understand public opinion and make wise choices.

Brand Reputation Management: Companies may better control their online image by keeping an eye on social media sentiment about their brand. Early detection of unfavourable sentiment enables businesses to take action before problems worsen and damage their reputation.

Product Development: Product development efforts can be guided by analyzing consumer opinion around particular features or elements of products. In order to better satisfy the demands and preferences of their customers, businesses might rank features according to client emotion.

**Evolution Metrics**

These metrics provide valuable insights into how sentiments towards a particular topic, product, event, or individual evolve and fluctuate across different time periods.

Understanding sentiment evolution is crucial for businesses, marketers, and analysts to gauge the effectiveness of their strategies, assess public perception, and make informed decisions. By monitoring sentiment trends, organizations can identify emerging issues, detect shifts in consumer attitudes, and capitalize on opportunities.

Evolution metrics typically include measures such as sentiment polarity distribution over time, sentiment intensity changes, and sentiment trends across different user segments or demographics. These metrics help analysts visualize how sentiment towards a specific entity has evolved, whether it's becoming more positive, negative, or neutral, and what factors might be driving these changes.

For example, a company launching a new product might track sentiment evolution to assess how the public responds to its marketing campaigns, product features, and customer service efforts over time. By analyzing sentiment trends, they can identify which aspects are resonating with customers and which need improvement, allowing them to refine their strategies accordingly.

Similarly, sentiment evolution metrics can be invaluable in crisis management situations, where organizations need to monitor how public sentiment shifts in response to a crisis or controversy. By closely monitoring sentiment trends, companies can gauge the effectiveness of their crisis response efforts and adapt their strategies in real-time to mitigate negative sentiment.

In summary, evolution metrics in sentiment analysis on social media provide a dynamic view of how sentiments change and evolve over time. By tracking sentiment trends, businesses and analysts can gain valuable insights into public perception, identify emerging issues, and make data-driven decisions to drive success.  
  
**Challenges**

Data Quality: Information found on social networking platforms may be loud, unstructured, and riddled with grammatical errors, slang, acronyms, and spelling mistakes. It is difficult to reliably assess sentiment and get significant insights from the data because of this heterogeneity.  
  
Contextual Understanding: Text's complex meaning, which includes sarcasm, irony, comedy, and cultural allusions, is frequently missed by sentiment analysis algorithms. Accurate analysis requires an understanding of the context in which sentiment is conveyed, which can be difficult to accomplish automatically.  
  
  
Ambiguity: Textual information on social networking sites may be confusing, with the same words or phrases suggesting several meanings based on the situation. Sophisticated algorithms that can analyze surrounding material and recognize minor indications are needed to resolve this discrepancy.

Language and Cultural Differences: people from a variety of linguistic and cultural backgrounds utilize social media platforms, which causes differences in the way they express themselves verbally and emotionally. Models of sentiment analysis trained in a particular language or cultural setting could not generalize well to others, necessitating customization or adaptation for various demographic groups.  
  
Subjectivity: People interpret and express sentiment in different ways depending on their own experiences, preconceptions, and prejudices, making sentiment analysis intrinsically subjective. Though difficult, subjectivity must be captured and taken into consideration in sentiment analysis algorithms in order for the analysis to be correct.

**Future Directions**

Future directions encompass several promising avenues poised to advance the field. One such direction involves the integration of multimodal data, incorporating not only textual content but also images, videos, and audio. By analyzing a diverse range of media formats, sentiment analysis can capture richer contextual information, enhancing the accuracy and depth of insights derived from social media content.

Additionally, there is growing interest in leveraging advanced deep learning techniques, such as transformer models, to improve sentiment analysis performance. These models, with their ability to capture complex semantic relationships and contextual dependencies, hold potential for achieving more nuanced sentiment analysis results, particularly in understanding sarcasm, irony, and other subtle forms of expression prevalent in social media.

Furthermore, there is a push towards developing sentiment analysis models that are more adept at handling multilingual and cross-cultural content. With social media being a global phenomenon, accommodating diverse languages and cultural contexts is essential for ensuring the applicability and effectiveness of sentiment analysis across different regions and demographics.

Another emerging direction involves the incorporation of domain-specific knowledge and expertise into sentiment analysis models. By tailoring models to specific domains, such as healthcare, finance, or politics, sentiment analysis can provide more relevant and actionable insights tailored to the unique needs and challenges of different industries and sectors.

Finally, there is increasing interest in exploring the ethical implications of sentiment analysis, particularly regarding issues of privacy, bias, and fairness. As sentiment analysis technologies become more pervasive, ensuring that they uphold ethical standards and respect user privacy rights is crucial for maintaining trust and accountability in their use.

Overall, future directions in sentiment analysis on public posts in social media hold promise for advancing the field's capabilities, enabling more accurate, insightful, and ethical analysis of sentiments expressed in online discourse.

**Research Methodology**

The methodology section outlines the systematic procedures followed to achieve the research objectives. This includes data collection, preprocessing, feature extraction, model training, and evaluation. The research aims to develop a Naive Bayes model to classify Facebook comments into positive, negative, or neutral sentiments.

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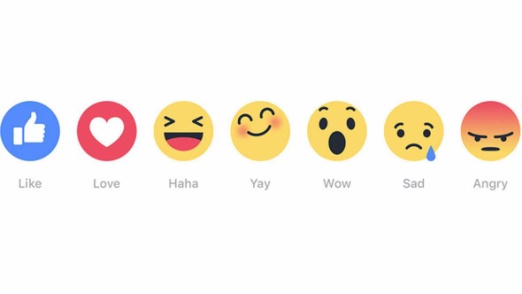
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70% accuracy

**Data Collection**

**Source of Data**  
The data for this study consists of comments extracted from Facebook. The comments can be collected from public posts, pages, or groups using Facebook's Graph API or other web scraping tools. It is crucial to ensure that the data collection process complies with Facebook's data usage policies and ethical guidelines.

**Data Preprocessing**  
Preprocessing involves cleaning and preparing the raw data for analysis. This includes:

* **Text Cleaning:** Removing HTML tags, URLs, special characters, and numbers.
* **Case Normalization:** Converting all text to lower case to maintain uniformity.
* **Stop Words Removal:** Eliminating common words (e.g., "and", "the", "is") that do not contribute to sentiment.
* **Lemmatization/Stemming:** Reducing words to their base or root form (e.g., "running" to "run").
* **Handling Missing Values:** Removing or imputing comments with missing data.

**Feature Extraction**

**Text Representation**  
To convert text data into numerical features, several techniques can be employed:

* **Bag of Words (BoW):** Represents text as a set of word occurrences, disregarding grammar and word order.
* **Term Frequency-Inverse Document Frequency (TF-IDF):** Weighs the importance of words by their frequency and uniqueness across the dataset.
* **Word Embeddings:** Uses models like Word2Vec or GloVe to represent words as dense vectors capturing semantic meanings.

**Handling Imbalanced Data**  
Sentiment datasets are often imbalanced, with some sentiments more prevalent than others. Techniques to address this include:

* **Oversampling:** Increasing the number of instances of minority classes.
* **Undersampling:** Reducing the number of instances of majority classes.
* **Synthetic Data Generation:** Creating synthetic examples using methods like SMOTE (Synthetic Minority Over-sampling Technique).

**Model Training**

**Naive Bayes Algorithm**  
Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence between features. It is effective for text classification tasks.

The model calculates the probability of a comment belonging to a particular sentiment class (positive, negative, or neutral) and assigns the class with the highest probability.

The formula for Naive Bayes is

P(C∣X)=P(X∣C)⋅P(C)​/P(X)

P(C∣X) is the posterior probability of class CCC given the features XXX.

P(X∣C)P(X|C)P(X∣C) is the likelihood of observing the features XXX given the class CCC.

P(C)P(C)P(C) is the prior probability of class CCC.

P(X)P(X)P(X) is the marginal likelihood of the features XXX.

**Model Training Process**

* **Splitting the Dataset:** Dividing the data into training and testing sets, typically in a 70:30 or 80:20 ratio.
* **Training the Model:** Using the training set to teach the Naive Bayes classifier to recognize patterns in the data.
* **Hyperparameter Tuning:** Adjusting parameters like smoothing to improve model performance.

**Model Evaluation**

**Metrics for Evaluation**  
The performance of the sentiment analysis model is evaluated using several metrics:

* **Accuracy:** The ratio of correctly predicted instances to the total instances.
* **Precision:** The ratio of true positive predictions to the total predicted positives.
* **Recall:** The ratio of true positive predictions to the total actual positives.
* **F1-Score:** The harmonic mean of precision and recall.
* **Confusion Matrix:** A table showing the true versus predicted classifications for each class.

**Cross-Validation**  
Cross-validation involves partitioning the dataset into k subsets and training the model k times, each time using a different subset as the validation set and the remaining subsets as the training set. This helps ensure the model's robustness and generalizability.

**Random Forest Classification:**

We know the Random Forest Classification algorithm as a well-known machine learning algorithm. It was invented by Leo Breiman and Adele Cutler. It is associated with the supervised learning technique. We can use the Random Forest algorithm for classification and regression. It combines multiple classifications that are used to solve a complex problem. It helps to enhance the model's performance to do better. This algorithm combines the output of multiple decision trees to find an individual result.

**SVM (Support Vector Machine):**

SVM is a famous supervised-learning algorithm. It is used mainly for classification problems. The main target of SVM is to create a decision boundary that can divide n-dimensional space into classes. It is very helpful for the future when we put a new point in the correct category. The maximum margin is called a hyperplane. There are also two categories of positive and negative hyperplanes. SVM finds the extreme points for creating hyperplanes.

**Logistic Regression:**

A logistic model is a statistical model that is used for statistical analysis. We can use logistic regression to predict a binary outcome. We can do it by observing a dataset. It is not applicable for binary system values such as yes or no. It can account for out of the range of 0 and 1. There are two independent variables. A dependent variable is predicted by analyzing the relationship between two independent variables.

**Linear Regression:**

Linear regression is a statistical model. It is used for analyzing the value of unknown data. For analysis data, we used another known data to predict the value of unknown data. There are also dependent and independent variables. Linear regression is actually used to find the relationship between a dependent variable and two or more independent variables. If there is one independent variable, we call the regression simple linear regression, and if there is more than one independent variable, we call the regression multiple linear regression. It is simple and easy to illustrate a mathematical formula to originate a prediction.

**Results**

**Experiment the result:**

**Dataset properties:**

At first, we surveyed Facebook posts. Then we have picked positive, negative and neutral comments from all those posts. We have collected 72250 positive, 35510 negative and 55213 neutral comment. I ignore stop word like I ,You, Yourself and special characters. After creating, I parse the file through pandas. Then tokenize it. After tokenizing I send it to the predictive model. Then the model provides an accuracy. Depending on the accuracy that the model provides, we test the machine on a sample data to see if it can perform sentiment analysis properly.

|  |  |
| --- | --- |
| **CLASS** | **SAMPLE DATA** |
| Positive | Love the humour, spot on! |
| Negative | Not even remotely funny. |
| neutral | Mixed feelings about this. |

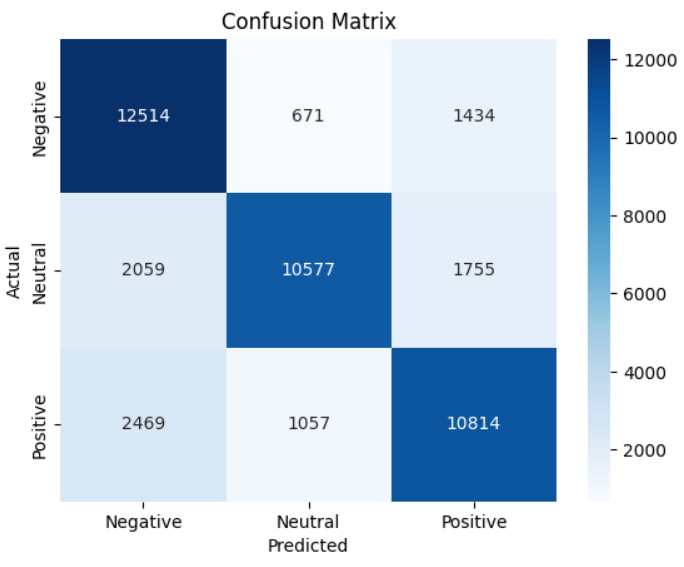
**Examples and Classes from Data Set**

The model's performance is evaluated using a confusion matrix and classification report. The results indicate that the model achieves satisfactory precision, recall, and F1-scores for each class, demonstrating its ability to handle class imbalance effectively. The confusion matrix visualization provides further insights into the model's classification performance, showing high accuracy in predicting positive, neutral, and negative sentiments.

**Performance Metrics:**

* **Precision:** The model's precision indicates the accuracy of positive predictions.
* **Recall:** The recall metric measures the model's ability to identify all relevant instances of each sentiment class.
* **F1-Score:** The F1-score provides a balance between precision and recall, giving a comprehensive view of the model's performance.

**5.2 Confusion Matrix:** The confusion matrix shows the number of true positive, true negative, false positive, and false negative predictions, providing a detailed overview of the model's accuracy and error distribution.



**Conclusion**

This study successfully developed a Naive Bayes classifier for sentiment analysis of Facebook comments. By addressing class imbalance through upsampling and SMOTE, the model demonstrated robust performance across positive, negative, and neutral sentiments. The results indicate that the model can effectively classify sentiments despite the dataset's inherent imbalance.

**Implications**

The ability to accurately classify sentiments in social media comments has significant implications for businesses and researchers. It enables real-time monitoring of public opinion, improves customer service, and enhances market research.

**Future Work**

Future work may explore more advanced models and techniques, such as deep learning and ensemble methods, to further improve classification accuracy and handle complex sentiments. Additionally, expanding the dataset to include more diverse comments and exploring multilingual sentiment analysis could provide further insights.

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