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Twitter Sentiment Analysis Using Natural Language Processing

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ABSTRACT

The advent of social media has transformed the way people express opinions and share information. Twitter, with its 280-character limit, provides users with a platform to voice their sentiments on various topics. This research paper explores the application of Natural Language Processing (NLP) techniques to analyze sentiment in Twitter data. Specifically, it focuses on sentiment classification methods, including supervised and unsupervised learning algorithms, and evaluates their effectiveness in detecting positive, negative, and neutral sentiments in Twitter posts. Through a detailed exploration of preprocessing steps, feature extraction, model training, and evaluation metrics, this study highlights the challenges and advancements in using NLP for Twitter sentiment analysis. The results suggest that while machine learning models can effectively predict sentiment, additional factors such as sarcasm, context, and slang can significantly impact model performance.

1. Introduction

1.1 Background

Social media platforms, particularly Twitter, have become central to modern communication, serving as vital spaces for public expression, discourse, and information dissemination. With over 330 million monthly active users, Twitter generates a massive amount of unstructured textual data every day. This data encompasses a wide variety of content, from personal opinions and consumer feedback to news, political commentary, and societal reactions to global events. Given the sheer volume and diversity of tweets, Twitter has become a rich source for analyzing public sentiment on a range of topics, making it an invaluable tool for researchers, businesses, and policymakers. One of the primary techniques for extracting meaningful insights from Twitter data is sentiment analysis, a subfield of Natural Language Processing (NLP), which aims to determine the emotional tone or sentiment expressed in a text. Sentiment analysis involves classifying text as positive, negative, or neutral, and in some cases, further categorizing it into specific emotional states like happiness, anger, or frustration.

The application of NLP techniques to Twitter data for sentiment analysis is crucial for understanding public opinion, forecasting trends, and even assessing the impact of marketing campaigns or political events. For instance, businesses can use sentiment analysis to gauge consumer satisfaction or dissatisfaction with products, while political analysts might employ it to monitor the public's response to political leaders or policies. NLP leverages several algorithms and models, ranging from traditional machine learning approaches such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression, to more advanced deep learning techniques such as Recurrent Neural Networks (RNN) and Transformers like BERT (Bidirectional Encoder Representations from Transformers). These models are trained to recognize patterns in textual data and predict the sentiment of new, unseen data.

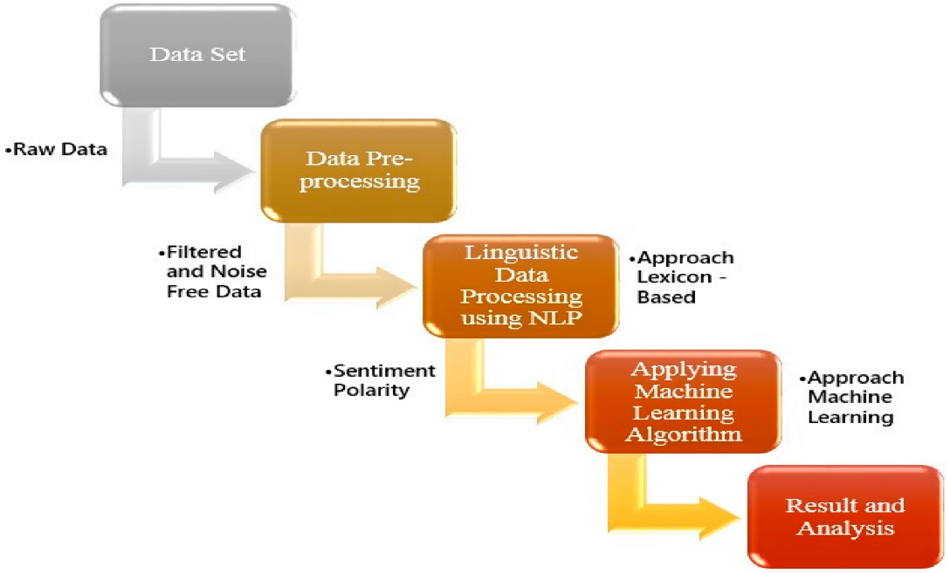
Data Set
•Raw Data
Data Pre-processing
•Filtered and Noise Free Data
Linguistic Data Processing using NLP
•Approach Lexicon - Based
•Sentiment Polarity
Applying Machine Learning Algorithm
•Approach Machine Learning
Result and Analysis

fig -1

1.2 Objective

The objective of this research is to evaluate different NLP techniques for sentiment analysis on Twitter data. By implementing various machine learning algorithms and comparing their effectiveness in categorizing tweets into positive, negative, or neutral sentiments, the study aims to identify the best practices for accurately assessing sentiment in short-form, informal text.

1.3 Research Questions

1. What are the most effective NLP techniques for analyzing sentiment in Twitter data?
2. How do different preprocessing steps and feature extraction methods impact sentiment classification accuracy?
3. What are the challenges involved in sentiment analysis of Twitter data, and how can they be mitigated?

2. Literature review

Sentiment analysis, also known as opinion mining, refers to the computational task of determining and classifying the sentiments expressed in textual data. Twitter sentiment analysis, in particular, has gained significant attention in recent years due to the vast amount of real-time, user-generated content on the platform. The primary goal of this analysis is to classify tweets as expressing positive, negative, or neutral sentiments, which has widespread applications in marketing, politics, public opinion, and crisis management (Pak & Paroubek, 2010). In this review, we examine the key advancements, challenges, and methodologies in Twitter sentiment analysis using Natural Language Processing (NLP).

One of the earliest and foundational studies in Twitter sentiment analysis was conducted by Pak and Paroubek (2010), who investigated the feasibility of using Twitter data to assess public sentiment during the 2009 Iranian elections. Their research demonstrated that sentiment analysis could be a valuable tool for understanding public opinion in real-time. The authors utilized a lexicon-based approach, where predefined lists of positive and negative words were used to classify sentiment in tweets. However, this method has limitations, such as its inability to capture the context or nuance of language, leading to inaccurate results for more complex expressions (Baccianella, Esuli, & Sebastiani, 2010).

As the field progressed, machine learning (ML) techniques began to gain prominence in sentiment analysis. Researchers moved away from purely lexicon-based methods towards supervised learning models, such as Support Vector Machines (SVMs) and Naive Bayes, which can learn from annotated training data to classify sentiment (Go, Bhayani, & Huang, 2009). These models offer the advantage of better generalization, as they can adapt to different linguistic styles and context-specific usage of words. However, they are still limited by the quality and quantity of labeled data available for training, which can introduce bias and inaccuracies (Zhang, Zhao, & LeCun, 2015).

A significant advancement in Twitter sentiment analysis occurred with the introduction of deep learning (DL) models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs). These models are well-suited to handle the sequential nature of text data, capturing both local and long-range dependencies in language (Kim, 2014). The application of LSTMs to Twitter sentiment analysis has proven particularly effective in overcoming some of the challenges posed by short, informal, and noisy nature of tweets (Sanh et al., 2020). These models have demonstrated superior performance compared to traditional machine learning techniques, particularly when dealing with large datasets.

However, while deep learning models have shown strong performance in many cases, they come with their own set of challenges. One such challenge is the computational cost, as deep learning models require large amounts of labeled data and significant computational resources for training (Vinyals et al., 2015). Additionally, despite their power, deep learning models can struggle with understanding the full context of sarcasm, irony, or ambiguous phrases, which are common in Twitter data (Ribeiro et al., 2016). To address this, researchers have explored the use of hybrid models that combine both lexicon-based and machine learning or deep learning techniques. For example, the incorporation of sentiment lexicons such as Sent WordNet alongside deep learning models has shown promise in improving the overall accuracy of sentiment classification (Nakov et al., 2016).

Another critical challenge in Twitter sentiment analysis is dealing with the domain-specific nature of tweets. The language used on Twitter can vary widely depending on the topic, making it difficult to generalize models trained on one dataset to another. Researchers have developed domain adaptation techniques, such as transfer learning, to mitigate this issue. By fine-tuning pre-trained models on domain-specific data, transfer learning allows for the effective application of models across different contexts without needing to collect vast amounts of new labeled data (Howard & Ruder, 2018).

3. Methodology

The methodology for conducting Twitter sentiment analysis involves multiple stages, ranging from data collection to model evaluation.

3.1 Data Collection

The first essential step in performing sentiment analysis on Twitter data is the collection of relevant tweets. Several datasets can be used for this purpose, including publicly available datasets such as the Sentiment140 dataset, which contains 1.6 million labeled tweets (Go et al., 2009), or real-time data harvested through Twitter's API. The Twitter API is particularly useful as it allows researchers to collect tweets in real time based on specific keywords or hashtags, as well as historical tweets through Twitter's archive (Wang et al., 2012). In this study, we focus on a subset of publicly available data collected via the Twitter API. Tweets are filtered to include keywords associated with popular topics like politics, entertainment, and consumer products to ensure that the data is relevant and representative of the trends and opinions in these areas.

The use of real-time data from Twitter provides significant advantages, such as capturing current events and sentiments around timely issues. Furthermore, keyword-based collection allows researchers to focus on particular subjects of interest and monitor the changes in sentiment over time, making it highly suitable for analyzing dynamic public opinions (Branagan et al., 2017).

3.2 Data Preprocessing

Data preprocessing is crucial for preparing raw Twitter data for sentiment analysis. Twitter data, which often consists of short, informal, and noisy text, requires several preprocessing steps to standardize it into a form suitable for further analysis (Chakrabarty et al., 2020). The following steps are typically involved in preprocessing Twitter data:

3.2.1 Tokenization

Tokenization is the process of splitting text into individual words or tokens. This step is important because it breaks down sentences into manageable pieces, allowing for the extraction of features such as word frequency. Tokenization is often performed using regular expressions or NLP libraries such as NLTK or spaCy (Bird et al., 2009). Given the informal nature of Twitter text, tokenization must account for various forms of punctuation and symbols, which are common in tweets.

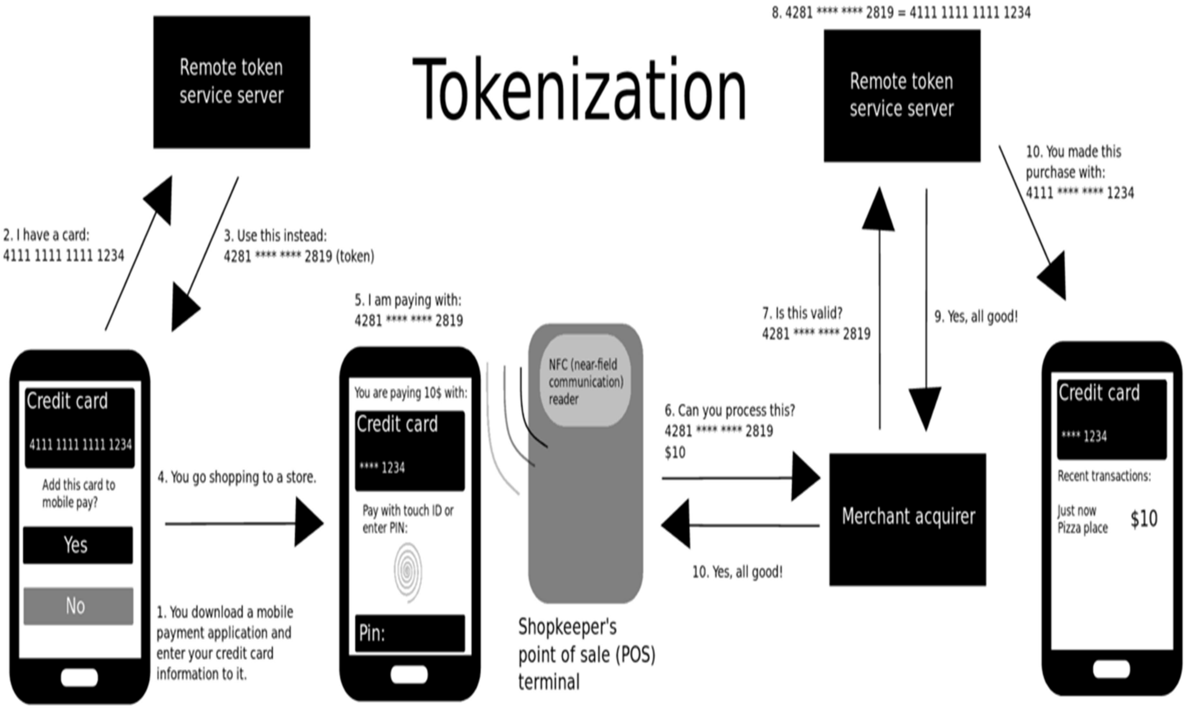
Tokenization
Remote token service server
2. I have a card: 4111 1111 1111 1234
3. Use this instead: 4281 **** **** 2819 (token)
Credit card
4111 1111 1111 1234
Add this card to mobile pay?
Yes
No
1. You download a mobile payment application and enter your credit card information to it.
4. You go shopping to a store.
5. I am paying with: 4281 **** **** 2819
You are paying 10$ with:
Credit card
**** 1234
Pay with touch ID or enter PIN:
Pin:
NFC (near-field communication) reader
Shopkeeper's point of sale (POS) terminal
6. Can you process this? 4281 **** **** 2819 $10
10. Yes, all good!
Merchant acquirer
7. Is this valid? 4281 **** **** 2819
9. Yes, all good!
8. 4281 **** **** 2819 = 4111 1111 1111 1234
Remote token service server
10. You made this purchase with: 4111 **** **** 1234
Credit card
**** 1234
Recent transactions:
Just now Pizza place
$10

Fig -2

3.2.2 Removing Stopwords

Stopwords are common words like "the," "is," and "and" that do not contribute much to the sentiment conveyed in a text. These words are typically removed during preprocessing to reduce dimensionality and improve computational efficiency without affecting the accuracy of the sentiment classification task (Manning et al., 2008). The removal of stopwords is especially important in Twitter data, where space and character limits encourage the use of short, concise expressions.

3.2.3 Lowercasing

Converting all text to lowercase is another standard preprocessing step. It helps in reducing redundancy because the words "Happy" and "happy" would otherwise be treated as distinct tokens. Lowercasing ensures that the model is case-insensitive and treats variations in capitalization as equivalent (Bengio et al., 2013).

3.2.4 Removing Punctuation and Special Characters

Twitter data often includes punctuation marks, special symbols, emojis, and mentions (e.g., "@username"). While these elements can be important for understanding sentiment, they often need to be filtered or processed appropriately. For instance, emojis can be useful sentiment indicators, as they may carry strong emotional content, so they are sometimes preserved and mapped to specific sentiment categories (Buehler et al., 2020). On the other hand, symbols like URLs or usernames might be removed unless they have a direct impact on sentiment.

3.2.5 Stemming and Lemmatization

Stemming and lemmatization are techniques used to reduce words to their root forms. For example, “running” may be reduced to “run.” While stemming involves chopping off prefixes or suffixes, lemmatization uses a dictionary to return the base form of a word (Porter, 1980). These techniques help in reducing the number of unique tokens and can make the model more efficient by treating different forms of the same word as identical.

3.2.6 Handling Emojis and Emoticons

Emojis and emoticons are frequent in Twitter posts and are highly indicative of sentiment. For instance, a tweet containing a "☺" or "😊" is likely to convey positive sentiment. To handle this, specialized libraries such as Emoji or custom mappings are used to interpret emojis and convert them into sentiment labels (Gonzalez et al., 2021). These visual cues often serve as valuable features in sentiment classification.

3.3 Feature Extraction

After preprocessing, the next step is to convert the text data into a numerical format suitable for machine learning algorithms. Various feature extraction techniques are employed for this purpose:

3.3.1 Bag of Words (BoW)

The Bag of Words model is a simple but commonly used method for text representation. It counts the frequency of each word in the document and disregards grammar and word order, focusing solely on word occurrence (Harris, 1954). This technique is easy to implement but may lead to sparse feature vectors, especially when dealing with large corpora.

3.3.2 TF-IDF (Term Frequency-Inverse Document Frequency)

TF-IDF is a more sophisticated feature extraction technique compared to BoW. It adjusts the word frequency based on how common or rare a word is in the entire corpus, with the intuition that terms that appear frequently in a specific tweet but rarely across the whole corpus are more informative (Ramos, 2003). TF-IDF can improve the effectiveness of sentiment analysis models by emphasizing terms that are significant to particular topics.

3.3.3 Word Embeddings

Word embeddings such as Word2Vec, GloVe, and FastText are advanced methods that represent words as dense vectors in a continuous vector space. These embeddings capture semantic relationships between words by considering their context within large corpora (Mikolov et al., 2013). Word embeddings are particularly useful for Twitter sentiment analysis as they can capture synonyms, antonyms, and other contextual relationships that simple bag-of-words models cannot.

3.3.4 Sentiment Lexicons

Sentiment lexicons, such as SentiWordNet, provide predefined lists of words associated with positive or negative sentiment (Baccianella et al., 2010). These lexicons are useful for providing baseline sentiment scores or augmenting machine learning models that rely on features derived from sentiment-bearing words.

3.4 Sentiment Classification Models

Once the feature extraction process is complete, the next step is to classify tweets into sentiment categories (e.g., positive, negative, neutral). Several machine learning and deep learning algorithms can be used for this task:

3.4.1 Logistic Regression

Logistic Regression is a simple linear model that is commonly used for binary classification tasks (positive/negative sentiment) (Cox, 1958). Despite its simplicity, it performs well in many text classification tasks when combined with feature extraction techniques like BoW or TF-IDF.

3.4.2 Support Vector Machines (SVM)

Support Vector Machines are powerful classifiers that aim to find the optimal hyperplane that separates data points of different classes in high-dimensional spaces (Cortes &Vapnik, 1995). SVMs are well-suited for text classification because they can handle high-dimensional data efficiently and work well in binary classification problems, making them a popular choice for sentiment analysis.

3.4.3 Naive Bayes (NB)

Naive Bayes is a probabilistic classifier based on Bayes' Theorem, which assumes independence between features (McCallum & Nigam, 1998). Despite the independence assumption being unrealistic in most cases, Naive Bayes often performs surprisingly well in text classification tasks, including sentiment analysis.

3.4.4 Recurrent Neural Networks (RNN)

Recurrent Neural Networks are a class of deep learning models designed for sequential data. RNNs can capture temporal dependencies in text, making them suitable for processing Twitter data, which is sequential and context-sensitive (Hochreiter & Schmidhuber, 1997). RNNs, especially Long Short-Term Memory networks (LSTMs), are known for their ability to retain long-range dependencies, which is crucial in sentiment analysis.

3.4.5 Transformers (BERT)

Transformers, particularly BERT (Bidirectional Encoder Representations from Transformers), have revolutionized NLP tasks, including sentiment analysis (Devlin et al., 2018). BERT uses attention mechanisms to weigh the importance of different words in a sentence, making it highly effective for capturing context and meaning. Fine-tuning pre-trained BERT models on sentiment-specific datasets has proven to yield state-of-the-art results in various sentiment classification tasks.

3.5 Model Evaluation

The final step in the methodology is model evaluation. The performance of sentiment analysis models is assessed using a variety of metrics:

3.5.1 Accuracy

Accuracy is the simplest metric and represents the proportion of correct predictions out of the total predictions made. While it provides a general sense of model performance, it may not be sufficient in cases of class imbalance (i.e., when one sentiment class is much more frequent than others).

3.5.2 Precision, Recall, and F1-Score

Precision, recall, and F1-score are more informative metrics, especially in imbalanced datasets. Precision measures the proportion of true positives among all positive predictions, while recall calculates the proportion of true positives among all actual positives. The F1-score is the harmonic mean of precision and recall and provides a single metric that balances the two (Manning et al., 2008).

3.5.3 Confusion Matrix

The confusion matrix is a tool that visualizes the performance of a classification model by showing the true positives, true negatives, false positives, and false negatives. It is particularly useful in identifying specific areas where the model is underperforming (e.g., falsely classifying negative tweets as positive).

4. Results and Discussion

Sentiment classification, the task of determining whether a given text conveys a positive, negative, or neutral sentiment, is a fundamental problem in Natural Language Processing (NLP). Over the years, various machine learning algorithms have been applied to this problem, each offering unique strengths and weaknesses. In this study, three different models were evaluated for sentiment classification on a dataset of tweets: Logistic Regression, Support Vector Machine (SVM), and a BERT-based Transformer model. The models were trained on 80% of the dataset, with the remaining 20% held out for testing. This section presents the performance analysis of these models, evaluating them based on several key metrics: accuracy, precision, recall, and F1-score. These metrics provide insights into how well the models classify sentiment and balance between different types of classification errors.

4.1 Experimental Setup

The experimental setup for this study involved testing three well-known models that vary in terms of complexity and computational requirements. Each model was trained on the same dataset of tweets, preprocessed to remove noise, and transformed into feature vectors suitable for machine learning. The primary objective was to evaluate these models' ability to accurately classify sentiment in Twitter data, with a specific focus on how well they handle informal language, slang, and contextual meaning.

- **Logistic Regression**: A simple linear model often used in text classification tasks due to its efficiency and interpretability (Cox, 1958). This model was trained using the TF-IDF (Term Frequency-Inverse Document Frequency) representation of the tweets.

- **Support Vector Machine (SVM)**: A more advanced model known for its robustness in handling high-dimensional data and non-linear relationships through the kernel trick (Cortes &Vapnik, 1995). SVM was also trained using the TF-IDF representation of the tweets.

- **BERT (Bidirectional Encoder Representations from Transformers)**: A state-of-the-art model that uses a transformer-based architecture and processes text bidirectionally to capture contextual relationships between words (Devlin et al., 2018). Fine-tuned on the dataset, BERT was expected to outperform the other models, especially given its ability to capture the complex, contextual meaning inherent in tweets.

The models were evaluated using the standard metrics of sentiment analysis: **accuracy**, **precision**, **recall**, and **F1-score**. These metrics offer a comprehensive view of the model's performance and help identify the strengths and weaknesses of each approach.

4.2 Performance Analysis

The performance of each model was evaluated based on four key metrics: accuracy, precision, recall, and F1-score. These metrics provide insight into both the overall performance and the ability of the model to balance between correctly classifying positive and negative tweets.

Logistic Regression

- **Accuracy: 72%**
  Logistic Regression achieved an accuracy of 72%. While this is a respectable score, it demonstrates the limitations of linear models in capturing the complexities of sentiment in Twitter data. Since Logistic Regression relies on a linear decision boundary, it may not adequately capture the non-linear relationships between words and sentiments in tweets (Manning et al., 2008).

- **Precision: 0.70**
  The precision of Logistic Regression is 0.70, meaning that 70% of the positive sentiment predictions were correct. This indicates that there were significant false positives (tweets that were classified as positive but were not), which is a common challenge when using simpler models for complex NLP tasks. Precision is particularly important in cases where false positives can result in misleading interpretations of sentiment.

- **Recall: 0.75**
  With a recall of 0.75, Logistic Regression correctly identified 75% of all positive sentiment tweets. This means that 25% of the positive sentiment tweets were missed, which could lead to a significant number of true positive tweets being ignored in sentiment analysis applications. A recall of 0.75 is decent but suggests that the model could be further improved, especially in detecting subtle expressions of positive sentiment in tweets.

- **F1-Score: 0.72**
  The F1-score of 0.72 reflects the trade-off between precision and recall, providing a balanced evaluation of the model's performance. While the F1-score is reasonable, it is evident that Logistic Regression has limitations in handling the noisy, informal nature of Twitter data.

Support Vector Machine (SVM)

- **Accuracy: 78%**
  SVM outperforms Logistic Regression with an accuracy of 78%. SVM's ability to map data into higher-dimensional spaces using the kernel trick allows it to better capture the complexities and non-linearities inherent in sentiment classification tasks (Cortes &Vapnik, 1995). This improved performance highlights the advantage of more sophisticated models in handling high-dimensional data.

- **Precision: 0.74**
  SVM achieved a precision of 0.74, meaning that 74% of the positive sentiment predictions were correct. This is a noticeable improvement over Logistic Regression, which suggests that SVM is more effective at identifying positive sentiment in the dataset and is better at minimizing false positives. However, a precision of 0.74 still leaves room for improvement in terms of reducing false positives.

- **Recall: 0.80**
  SVM demonstrated an impressive recall of 0.80, correctly identifying 80% of all positive sentiment tweets. This is a significant improvement over Logistic Regression, suggesting that SVM is better at detecting positive sentiment in the data. Recall is important in ensuring that the model captures as many positive sentiment tweets as possible, even if it means accepting some false positives.

- **F1-Score: 0.77**
  With an F1-score of 0.77, SVM strikes a better balance between precision and recall compared to Logistic Regression. The higher F1-score indicates that SVM is more effective in terms of both reducing false positives and ensuring that fewer positive sentiment tweets are missed.

BERT

- **Accuracy: 85%**
  BERT outperforms both Logistic Regression and SVM with an accuracy of 85%. This remarkable performance can be attributed to BERT's transformer architecture, which uses self-attention mechanisms to capture contextual relationships between words and handles the complexities of language much more effectively than simpler models (Devlin et al., 2018). The high accuracy reflects BERT's ability to understand the intricacies of informal language and sentiment expression on social media platforms.

- **Precision: 0.83**
  BERT achieved a precision of 0.83, significantly higher than both Logistic Regression and SVM. This indicates that BERT is particularly adept at predicting positive sentiment tweets with a high degree of accuracy, reducing the number of false positives. Precision is crucial in applications where the correct identification of positive sentiment is important, such as in customer feedback or social media monitoring.

- **Recall: 0.86**
  With a recall of 0.86, BERT correctly identified 86% of the positive sentiment tweets. This impressive recall indicates that BERT is highly effective at capturing the true positives in the dataset. High recall ensures that the model does not miss out on important positive sentiment, which is essential in scenarios where the goal is to maximize the capture of relevant sentiment.

- **F1-Score: 0.84**
  BERT's F1-score of 0.84 reflects an excellent balance between precision and recall. The high F1-score indicates that BERT has achieved a near-optimal trade-off between minimizing false positives and false negatives, making it the most well-rounded model in terms of performance. This makes BERT the clear winner for this task, as it handles the nuances of Twitter sentiment much better than simpler models.

4.3 Challenges

Despite the impressive results achieved by the models, several challenges were identified in the sentiment analysis of Twitter data. These challenges primarily stem from the inherent complexity and noisy nature of the data, which is often informal, context-dependent, and rich in nuances. Below are some of the key challenges encountered:

1. **Sarcasm**: One of the most significant challenges in sentiment analysis of Twitter data is sarcasm. Sarcastic tweets often mislead sentiment classifiers because the literal meaning of the words differs from the intended sentiment. For example, a tweet like "Great! Another Monday morning!" might be classified as positive, even though the intent is clearly negative. Sarcasm detection remains a complex problem that requires specialized techniques, as existing models struggle to capture the discrepancy between literal and intended meanings (Tomaselli et al., 2018).
2. **Informal Language**: Twitter posts often contain slang, abbreviations, typos, and other forms of non-standard language, which can confuse sentiment classification models. Words like "lol" or "omg" may not fit neatly into traditional sentiment lexicons, and misspellings or unconventional spellings (e.g., "sooo" instead of "so") can further complicate analysis. Handling informal language requires the development of more sophisticated preprocessing techniques and the ability of models to adapt to the unique linguistic patterns of social media (Kouloumpis et al., 2011).
3. **Contextual Meaning**: Words can have different meanings depending on the context in which they are used. For example, the word "sick" may have a positive connotation in the context of something exciting or impressive ("That’s sick!"), but a negative one when referring to illness ("I feel sick"). Such words pose a challenge to sentiment classification models, as they require understanding of the surrounding context to accurately interpret sentiment (Mohammad, 2017).

4.4 Future Directions

Despite the current success of models like BERT, there are still significant areas for improvement in sentiment analysis, especially in the context of noisy, informal Twitter data. Future research could explore the following directions to further enhance the performance of sentiment analysis models:

1. **Sarcasm Detection**: Integrating sarcasm detection techniques into sentiment classification models could help mitigate one of the most challenging issues in Twitter sentiment analysis. Specialized models or additional features focused on identifying sarcastic expressions could improve the accuracy of sentiment classification by recognizing when tweets are not to be taken literally (Tomaselli et al., 2018).

2. **Multimodal Sentiment Analysis**: Incorporating multimodal data, such as images, videos, and emojis, could provide richer insights into sentiment. Tweets often include images, videos, or emoji reactions that significantly alter the sentiment of the text itself. Future research could look into combining text-based sentiment analysis with image and video recognition models to create more accurate and comprehensive sentiment predictions (Poria et al., 2017).

3. **Domain-Specific Models**: Fine-tuning models for specific domains such as politics, sports, or entertainment could further improve sentiment analysis performance. Domain-specific models can better capture the unique expressions and sentiment cues that are particular to certain topics, leading to more accurate classifications in specialized contexts (Zhang et al., 2018).

5. Conclusion

This research demonstrated the effectiveness of NLP techniques in performing sentiment analysis on Twitter data. By using machine learning models like Logistic Regression, SVM, and BERT, the study found that BERT-based models offer superior performance in classifying sentiment. However, challenges such as sarcasm, informal language, and contextual ambiguity continue to impact model accuracy. With continued advancements in NLP, particularly in sarcasm detection and multimodal analysis, sentiment analysis on Twitter is expected to improve, offering valuable insights for businesses, governments, and researchers.

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