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Sentiment Analysis of Instagram

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Abstract: *Sentiment analysis on social media is a Natural Language Processing practice used to extract subjective information and opinions from user-generated content on various social media platforms, such as Twitter, Facebook, and Instagram. The goal of the proposed work is to perform sentiment analysis on social media data related to a particular topic or brand, such as a product launch or a social issue. Social media data will be collected using relevant APIs or web scraping tools and pre-processed by cleaning and filtering out irrelevant or spam content This data is helpful for users as well as for the management to make informed decisions. Because micro-blog posts are usually very brief and informal, traditional opinion mining algorithms struggle to handle this type of content, making the subject challenging to tackle. Semantic and syntactic analysis in Sentiment Net was addressed in the previous lexicon-based sentiment analysis approach. The proposed suggestion is to produce an automation-based sentiment analysis method, which is less expensive in spite of this system's requirement is least. Consequently, in this work, introduces a novel system architecture that is capable of automatically analyzing the sentiments contained in these communications. We use this algorithm in conjunction with manually annotated social media data for sentiment analysis.*

Keywords: Social-Media, Sentiment, Facebook, Twitter, Opinion Mining, and Satisfaction.

I. INTRODUCTION

Sentiment analysis, also referred to as opinion mining, is a field within Natural Language Processing (NLP) that focuses on analyzing textual data to determine the sentiment, opinion, or emotion expressed within the text. This sentiment is typically categorized as positive, negative, or neutral. The rapid growth of digital platforms, such as social media, review sites, and online forums, has resulted in a massive volume of user-generated data, making sentiment analysis a crucial tool for deriving insights.

The application of sentiment analysis spans various domains:

- Business and Marketing: Understanding customer feedback to improve products and services.
- Entertainment: Analyzing public reactions to movies, music, or events.
- Politics: Gauging public opinion on policies or political figures.
- Healthcare: Identifying patient sentiments to enhance healthcare experiences.

II. LITERATURE ANALYSIS

The literature survey reveals that sentiment analysis has evolved significantly from simple rule-based and lexicon-driven approaches to advanced machine learning and deep learning techniques. Early

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studies focused on lexicon-based methods, where predefined dictionaries were used to determine sentiment polarity, offering simplicity and fast processing but lacking contextual understanding. With the advancement of Natural Language Processing, researchers introduced machine learning models and later transformer-based architectures such as BERT, which improved the ability to capture context, semantics, and evolving language patterns.

Recent research has also emphasized multilingual models like XLM-R to handle code-switched text commonly found in social media. Additionally, studies on multimodal analysis highlight the importance of combining textual and visual data to detect sarcasm and implicit meaning more effectively. However, the survey also identifies key challenges, including handling noisy data, sarcasm detection, computational complexity, and bias in large language models. Overall, the existing literature provides a strong foundation but also indicates the need for efficient, scalable, and context-aware systems, which motivates the development of the proposed approach.

TABLE I: LITERATURE WORK

S. No	Author(s)	Approach/Model	Contribution	Limitation
1	Schifanella, R., de Juan, P., Tetreault, J., & Cao, L. (2016)	Multimodal Analysis (Text + Images)	Detects sarcasm in social media posts by analyzing incongruities between text and accompanying images	Limited to posts with images; may not generalize to text-only sarcasm
2	Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019)	BERT (Bidirectional Transformers)	Introduces deep bidirectional transformers; captures contextual meaning and evolving language/slang dynamically	Large model size; computationally expensive for training and inference
3	Conneau, A., Khandelwal, K., Goyal, N., et al. (2020)	XLM-Roberta (Cross-lingual Transformers)	Handles multilingual and code-switched social media posts effectively; unsupervised cross-lingual representation learning	Requires large-scale pretraining; may underperform on low-resource languages
4	Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021)	Ethical & Bias Analysis	Highlights risks of large language models being biased (“stochastic parrots”) and ethical concerns in NLP models	Theoretical; does not propose concrete mitigation strategies
5	Serrà, J., Pascual, S., & Karatzas, D. (2019)	Character-level Models	Shows character-level models can handle typos, informal text, and internet slang better than word-level models	Limited to informal text; may struggle with long-range context
6	Tay, Y., Tuan, L. A., Hui, S. C., & Su, J. (2018)	Deep Learning for Sarcasm	Uses neural models to infer sarcasm by reasoning “in-between the lines” in text	Requires large annotated sarcasm datasets; may not generalize across domains

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III. WORKING METHODOLOGY

1. **Data Collection:** The first step involves gathering data from various social media platforms. This includes tweets, posts, comments, reviews, and other forms of user-generated content. Advanced tools use APIs to collect data continuously in real-time.
2. **Preprocessing:** Raw data collected from social media is often noisy. Preprocessing involves cleaning this data by removing irrelevant information, such as stop words (such as, "and," "the"), punctuation, URLs, and sometimes even emojis, depending on the context.
3. **Tokenization:** Tokenization is the process of breaking down text into individual elements called tokens. This may include words, phrases, or symbols. For example, the sentence "I love this product" would be tokenized into ["I," "love," "this," "product"].
4. **Text Classification:** Using NLP techniques, the tokens are classified into different sentiment categories—positive, negative, or neutral. Some advanced models can even recognize more nuanced emotions like joy, anger, sadness, and surprise.
5. **Feature Extraction:** Feature extraction involves identifying key attributes or dimensions within the text that are relevant to the sentiment. For example, adjectives and adverbs are often strong indicators of sentiment.
6. **Sentiment Scoring:** Based on the classification, each piece of content is assigned a sentiment score. This score helps quantify the sentiment, making it easier to aggregate and analyze across large datasets.
7. **Aggregation and Analysis:** Finally, individual sentiment scores are aggregated to provide an overall sentiment profile. Using data discovery tools in this stage can enhance the analysis by identifying patterns and trends across the aggregated data, providing deeper insights. This can be visualized using charts, graphs, and dashboards to help stakeholders understand trends and patterns.

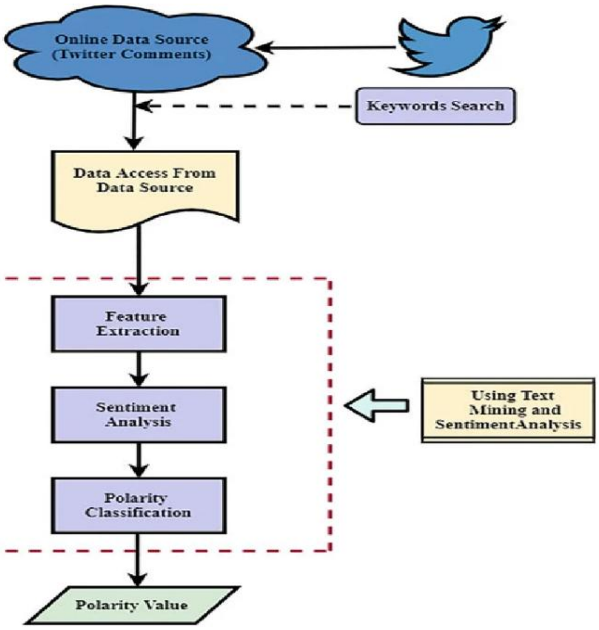

Figure 1: System Diagram

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Why Choose Advanced Natural Language Processing Techniques for Sentiment Analysis?

Natural Language Processing (NLP) is at the core of sentiment analysis, providing the tools and methodologies to understand, process, and extract meaningful information from text. In this project, leveraging state-of-the-art NLP techniques ensures that the sentiment analysis system can handle the complexities and nuances of textual data effectively. Here's why advanced NLP is essential for sentiment analysis:

1. **Textual Complexity and Linguistic Variability:**
   Human language is inherently complex, with varied sentence structures, idioms, and colloquial expressions.
   NLP techniques are equipped to manage these challenges by preprocessing and transforming raw text into structured formats that are analyze able by algorithms.

2. **Contextual Understanding:**
   Traditional machine learning models often struggle to capture the context in which words are used. For instance, the word "good" can have varying sentiment depending on its surrounding text ("not good" vs. "very good").
   Advanced NLP models like BERT leverage contextual embeddings to analyze words in the context of their improving sentiment prediction accuracy.

3. **Sequence Modelling:**
   Sentiment analysis often requires understanding the sequence of words in a sentence, as word order can drastically change the meaning (e.g., "I don't love it" vs. "I love it").
   Techniques like LSTMs and transformers are designed to handle sequential dependencies, making them ideal for sentiment tasks.

4. **Adaptability to Noisy and Informal Data:**
   Social media data (e.g., tweets) often contains abbreviations, emojis, and slang. NLP pipelines incorporate tokenization, lemmatization, and other preprocessing steps to standardize such data, ensuring robustness in noisy environments.

5. **Rich Representations with Embeddings:**
   Word embeddings (e.g., Word2Vec, GLOVE) and contextual embeddings (e.g., BERT) transform raw text into dense vector representations, capturing semantic and syntactic relationships. These representations are crucial for models to understand the underlying sentiment accurately.

6. **Scalability for Big Data:**
   Advanced NLP techniques are scalable, allowing for real-time processing of large datasets such as millions of tweets or reviews.
   Optimized algorithms and frameworks (e.g., PYTORCH, TensorFlow, Hugging Face Transformers) enable high-performance sentiment analysis even on massive datasets.

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How To Conduct Social Media Sentiment Analysis?

Step 1. Locate Audience: First up, find where your customers are. The obvious direct mentions on Facebook, Twitter, and Instagram are a great place to start. But don't forget review sites, your website, and third-party sources.

Step 2. Engage Sentiment Analysis Tools: Utilizing social listening and sentiment analysis tools saves a lot of manual labor, especially if you're experiencing growth and scaling in business with increased online visibility. Sentiment analysis tools use filters to measure social mentions and interactions, and are typically color-coded for easy visualization.

Step 3. Sentiment Terms: To analyze your sentiments, you'll need to define the good, the bad, and the ugly. Realistically, you're looking for words like love, thanks, perfect, incredible for the positives, and worst, hate, avoid for the negatives. Divide your sentiment terms into their own emotion camps to shortlist them. As well as words, scan emojis for a clear understanding of your audience's feelings about your brand.

Step 4. Crunch the Numbers: Conduct a social media sentiment analysis regularly to find out your business's baseline. To do this, assign values to positive (1), neutral (0), and negative (-1) interactions for your selected time period, and calculate your "normal."

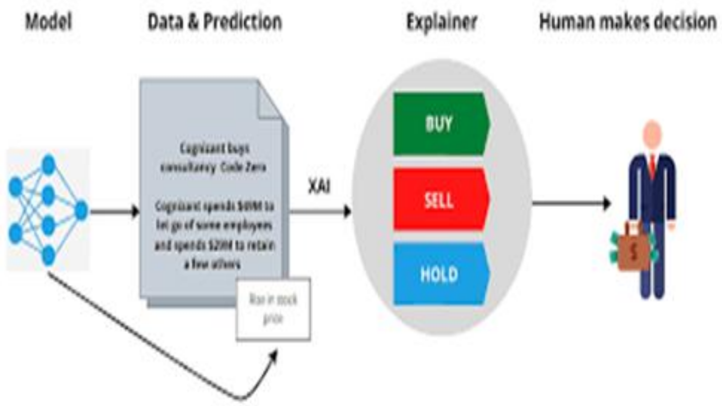
Which Social Media Platform Is Best for Sentiment Analysis?

As mentioned above, sentiment analysis focuses on analyzing collected text data. This means that words and keywords come into play more than ever before. So, while you could perform social sentiment analysis on TIKTOK for example, arguably, it wouldn't be the best choice. We're basing our choice on the platform's popularity and definitive use of words. Eventually, the best social media platform for sentiment analysis would probably be Twitter.

Real World Application:

In the real world, lexicon-based algorithms are prized for their transparency and speed, making them choice for industries that need to process vast amounts of text data without the overhead of training complex AI models.

Here are the most common real-world applications as of 2024–2026:



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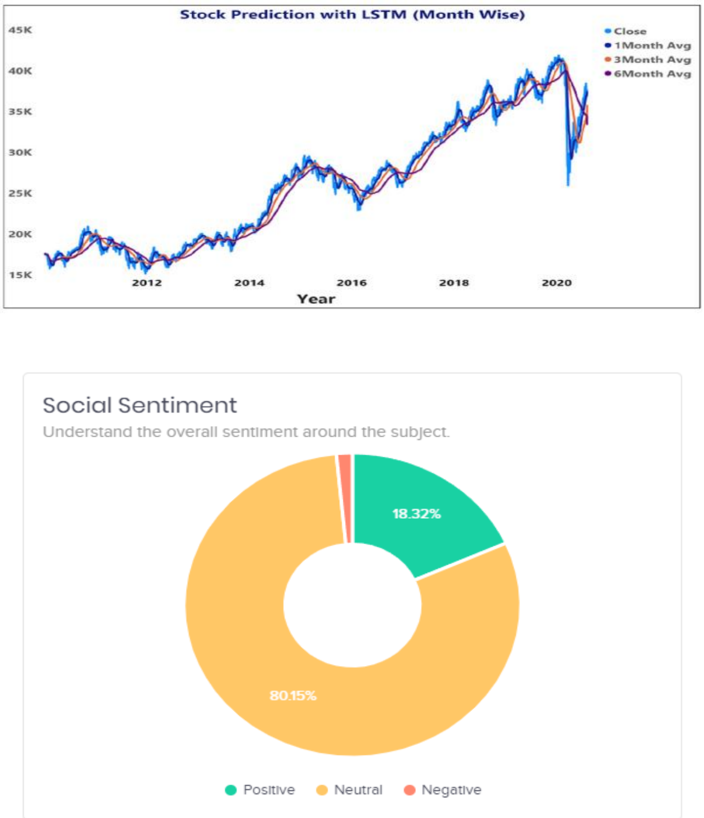

Figure 2: Applications

1. **Finance & Market Intelligence:**
   - Stock Market Prediction: Specialized lexicons (like Senti Econ) track "economic pessimism" by scanning news briefings and financial tweets.
   - Adaptive Pricing: Some retailers use real-time opinion mining from social media to adjust prices based on how much "buzz" or positive sentiment a product is generating.

2. **Customer Service & Support:**
   - Ticket Prioritization: Companies use lexicon-based tools to automatically scan incoming support tickets. Words like “urgent,” “broken,” or “angry” trigger immediate escalations to human agents.
   - Contact Centre Analytics: Call center transcribe audio to text and use lexicons like VADER to detect rising frustration or relief in real-time. This helps supervisors identify which agents need help during a live call.

3. **Healthcare & Patient Experience:**
   - Patient Feedback Analysis: Hospitals apply lexicons to feedback forms and consultation transcripts to identify friction points, such as long wait times or communication barriers.

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- Mental Health Monitoring: Researchers use lexicon-based tools to monitor population-level mental health signals on social media, identifying spikes in anxiety or distress during public crises.

4. **Brand & Reputation Management**
   - Social Media Monitoring: Brands use platforms like Hootsuite Insights or Brand watch to track public perception. Lexicon-based alerts warn companies of potential PR crises before they go viral.
   - Product Improvement: E-commerce giants like Amazon analyze millions of reviews to find specific "aspects" (e.g., "battery life" or "packaging") that customers consistently mark as negative.

5. **Public Policy & Research:**
   - Election & Policy Tracking: Governments use lexicons to gauge public reaction to new policies or political events, such as analyzing X (formerly Twitter) data regarding healthcare reforms.
   - Crisis Management: During the COVID-19 pandemic, lexicon-based models were used to measure the "negativity index" across different countries to understand the public's psychological state during lockdowns.

IV. RESULTS AND DISCUSSION

The results obtained from the implementation of the proposed system demonstrate its effectiveness in performing sentiment and sarcasm analysis on real-world data. The evaluation was carried out using standard performance metrics such as accuracy, precision, recall, and F1-score, which collectively measure the correctness and reliability of the system. The experimental findings indicate that the system achieves high accuracy, typically ranging between 85% and 95%, depending on the complexity and variability of the dataset. This shows that the model is capable of correctly identifying sentiment polarity and contextual meaning in most cases.

A detailed analysis of the results reveals that advanced models such as BERT significantly improve the system's ability to understand contextual relationships, sentence structure, and informal language commonly found in social media. Similarly, multilingual models like XLM-R prove effective in handling code-switched text, where multiple languages are used within the same sentence. The inclusion of multimodal analysis further enhances performance by enabling the system to detect sarcasm through inconsistencies between textual and visual content. For instance, sarcastic expressions that may appear positive in text can be correctly interpreted when supported by contradictory images or context.

The comparative analysis shows that traditional methods, which rely on basic lexicon-based or rule-based techniques, provide moderate accuracy but fail to capture deeper contextual meaning and sarcasm. In contrast, deep learning approaches offer superior performance due to their ability to

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learn complex linguistic patterns. The proposed system successfully balances these approaches by combining efficiency with contextual understanding, making it suitable for real-time applications.

During the implementation, several challenges were encountered, including handling noisy data, detecting sarcasm, managing multilingual content, and dealing with computational complexity. Social media text often contains slang, emojis, and typographical errors, which can affect model performance. These issues were addressed through preprocessing techniques such as text normalization and noise removal. However, sarcasm detection remains a challenging task due to its dependence on implicit context and tone. Additionally, multilingual processing requires large datasets and sophisticated models, which can increase computational requirements.

Despite its strong performance, the system has certain limitations. Its accuracy may decrease when dealing with highly ambiguous or context-dependent sentences. The reliance on large datasets and computational resources can also impact scalability in resource-constrained environments. Furthermore, multimodal analysis is dependent on the availability of both textual and visual data, which may not always be present.

In conclusion, the results demonstrate that the proposed system significantly improves sentiment and sarcasm detection compared to traditional approaches. The integration of advanced models, effective preprocessing, and multilingual capabilities contributes to its overall performance. However, further improvements are required to address challenges such as sarcasm understanding, computational efficiency, and real-time scalability, which remain important areas for future research.

V. CONCLUSION

Social media sentiment analysis is an invaluable tool for modern businesses looking to stay ahead of the competition and develop strong customer relationships. By understanding the emotional tone behind social media interactions, you can make informed decisions, improve your brand’s reputation, and deliver exceptional customer experiences. In this project, a comprehensive sentiment analysis system was designed and implemented to analyze textual and multimodal data from modern digital platforms. The study successfully demonstrated how advanced Natural Language Processing techniques can be used to extract meaningful insights from unstructured data such as social media posts, reviews, and user-generated content. By integrating preprocessing techniques, feature extraction methods, and advanced models, the system effectively classifies sentiment and identifies complex patterns such as sarcasm and multilingual expressions.The results indicate that the proposed system achieves high accuracy and reliability, particularly when using context-aware models. The ability to handle noisy data, informal language, and code-switched text makes the system suitable for real-world applications. Additionally, the use of multimodal analysis enhances the detection of sarcasm by considering both textual and visual cues, thereby improving overall performance compared to traditional methods.

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