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Social Media Sentiment Analysis Evaluation Public Opinion on Recent Event

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ABSTRACT: Social media platforms generate vast amounts of text data daily, reflecting public opinions and emotions on various topics. Sentiment analysis, a crucial Natural Language Processing (NLP) task, helps extract meaningful insights from this data. This project aims to develop a machine learning-based sentiment analysis model to classify social media text into Positive, Negative, or Neutral sentiments.

The dataset undergoes preprocessing steps, including text cleaning, removing special characters, and normalizing case. The model utilizes TF-IDF vectorization to convert text into reliable sentiment predictions. The model's performance is evaluated using accuracy metrics, and the trained model is saved for future predictions.

This project provides an efficient way to analyze social media sentiment, offering insights for businesses, policymakers, and researchers. It can be further enhanced with deep learning models and real-time sentiment tracking.

I. INTRODUCTION

With the rapid expansion of digital communication, social media platforms have become a powerful medium for individuals to express their opinions, emotions, and reactions on a wide range of topics. The vast volume of user-generated text data presents an invaluable opportunity to extract actionable insights through Sentiment Analysis, a key task within the domain of Natural Language Processing (NLP).

This project focuses on developing a sentiment analysis model that can automatically classify social media text into three sentiment categories: Positive, Negative, and Neutral. Such classification helps in understanding public mood, brand perception, customer satisfaction, and societal trends.

To prepare the data for analysis, a series of preprocessing techniques are applied, including text cleaning, removal of special characters, and normalization of letter casing. These steps ensure the data is consistent and suitable for machine learning algorithms. The processed text is then transformed into numerical format using TF-IDF (Term Frequency–Inverse Document Frequency) vectorization, which effectively captures the importance of words in each document relative to the entire dataset.

For sentiment classification, a Random Forest Classifier is employed due to its robustness and ability to handle high-dimensional data. The model is trained and tested on the preprocessed dataset, with its performance evaluated through key metrics such as accuracy, precision, recall, and F1-score. The trained model is then saved to facilitate future sentiment predictions on new, unseen data.

This system offers a practical solution for analyzing large-scale social media sentiment, making it valuable to businesses, government agencies, and researchers seeking to monitor public opinion. Future enhancements may include the integration of deep learning architectures, such as LSTM or BERT, and real-time sentiment monitoring for dynamic analysis.

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II. LITERATURE ANALYSIS

Sentiment analysis, also known as opinion mining, has emerged as a vital research area in natural language processing (NLP), especially with the explosion of user-generated content on social media platforms. Early sentiment analysis systems primarily relied on lexicon-based approaches and rule-based classifiers, which used predefined dictionaries of positive and negative words to infer sentiment polarity. While these methods were computationally efficient, they often lacked the ability to handle context, sarcasm, or domain-specific vocabulary.

With the growth of machine learning, models like Naïve Bayes, Support Vector Machines (SVM), and Random Forests became widely adopted for sentiment classification. These models improved accuracy by learning from labeled datasets but were still limited in capturing deeper semantic meaning. The advent of deep learning techniques, particularly Recurrent Neural Networks (RNNs) and their variant Long Short-Term Memory (LSTM) networks, marked a significant improvement. LSTMs can remember long-range dependencies and context, making them highly effective for analyzing sentiment in longer or more complex sentences.

Recent studies have also explored the use of transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), which have demonstrated state-of-the-art performance in sentiment classification tasks. These models can understand the nuanced meanings of words based on their surrounding context, allowing them to accurately detect sentiment even in subtle or ambiguous expressions.
Additionally, researchers have emphasized the value of feature engineering and metadata inclusion—such as hashtags, likes, retweets, timestamps, and user engagement levels—to enhance sentiment prediction models. These contextual features allow for more granular insights into temporal sentiment trends, platform-based differences, and regional sentiment variations.

Clustering techniques such as K-Means have also been used for customer segmentation, enabling sentiment trends to be analyzed within specific demographic or behavioral groups. This segmentation allows for more targeted marketing, product development, and reputation management strategies.
Modern sentiment analysis applications often include interactive dashboards and real-time analytics, making them accessible to both technical and non-technical users. By integrating data visualization, predictive analytics, and machine learning, these systems empower businesses to track public opinion, monitor brand sentiment, and make data-driven decisions.

In summary, the literature indicates a clear evolution from simplistic, rule-based sentiment analysis toward robust, context-aware models powered by machine learning and deep learning. This transition has significantly enhanced the accuracy and practical applications of sentiment analysis in fields such as marketing, customer service, political analysis, and mental health research.

III. METHODOLOGY

1. **Data Preprocessing**
   The first step in the sentiment analysis pipeline involves cleaning and refining the dataset to ensure accuracy and consistency. This includes removing redundant columns such as "Unnamed: 0" and "Unnamed: 0.1," which do not contribute meaningful information to the analysis. Handling missing values is also a crucial aspect of this stage, as incomplete data can lead to biased or inaccurate insights. Standardizing text formatting ensures uniformity across the dataset, making it easier to process and analyze. Additionally, timestamps are converted into structured date-time formats, allowing for more effective time-based analysis. This preprocessing step enhances data quality, ensuring that subsequent analysis is based on clean, well-structured information.

2. **Sentiment Analysis**
   Once the data is preprocessed, sentiment analysis is performed to uncover patterns and trends in user sentiment. The system analyzes sentiment distribution over time and across various platforms, helping identify how public opinion evolves. By categorizing sentiments into positive, negative, and neutral, it becomes possible to assess which platforms generate more engagement for specific sentiment types. Furthermore, engagement trends are examined based on sentiment classification, revealing how user interactions such as likes, shares, and comments

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vary depending on sentiment. This information is invaluable for businesses and researchers looking to understand audience sentiment and engagement dynamics.

3. **Visualization & Insights**
To make sentiment analysis results more interpretable, visualizations are generated to highlight key insights. Graphs and charts illustrate sentiment trends over time, providing a clear picture of how emotions fluctuate within a given timeframe. Additionally, the geographical distribution of sentiments is explored to identify regional differences in public perception. Insights into top-performing hashtags help reveal which topics drive the most engagement, while user engagement patterns shed light on how different sentiment types influence interaction levels. These visualizations transform raw data into actionable insights, making it easier to understand sentiment trends and their impact.

4. **Dataset Summary**

- Total Rows: 732
- Total Columns: 15
- No missing values detected.
- Data Types:
  - Categorical: Sentiment, User, Platform, Country, Hashtags
  - Numerical: Retweets, Likes, Year, Month, Day, Hour
  - Text: Text
  - DateTime: Timestamp

5.Implementation

- Technologies Used: Python, Pandas, NumPy, Matplotlib, Seaborn, Flask (for dashboard).
- Results Expected:
  - Sentiment trends analysis.
  - Engagement insights for different social media platforms.
  - Key timeframes for high user engagement.
  - Identification of high-performing posts and hashtags.

IV. RESULTS

The Sentiment Analysis System was evaluated using a test dataset containing 732 social media posts across multiple platforms. The evaluation focused on the system's accuracy in classifying sentiments into Positive, Negative, and Neutral categories, along with its ability to generate insightful sentiment trends. The results indicate that the system achieves 85% accuracy in identifying sentiment labels. Table I presents the key performance metrics:

- Precision: 84%
- Recall: 86%
- F1-Score: 85% (for correctly identifying sentiment labels)

The system's performance was compared with baseline models, such as rule-based sentiment analysis, which only achieved 70-75% accuracy in similar contexts. The performance improvements can be attributed to the use of TF-IDF vectorization, LSA for dimensionality reduction, and advanced classifiers like Random Forest, SVM, and Logistic Regression, which enhance the model's ability to understand complex textual expressions.

The web application interface efficiently processes text inputs and CSV uploads, delivering real-time sentiment insights in under 2 seconds per request. The smooth user experience, even during peak usage periods, ensures that the application is capable of handling large-scale sentiment analysis tasks without noticeable delay.

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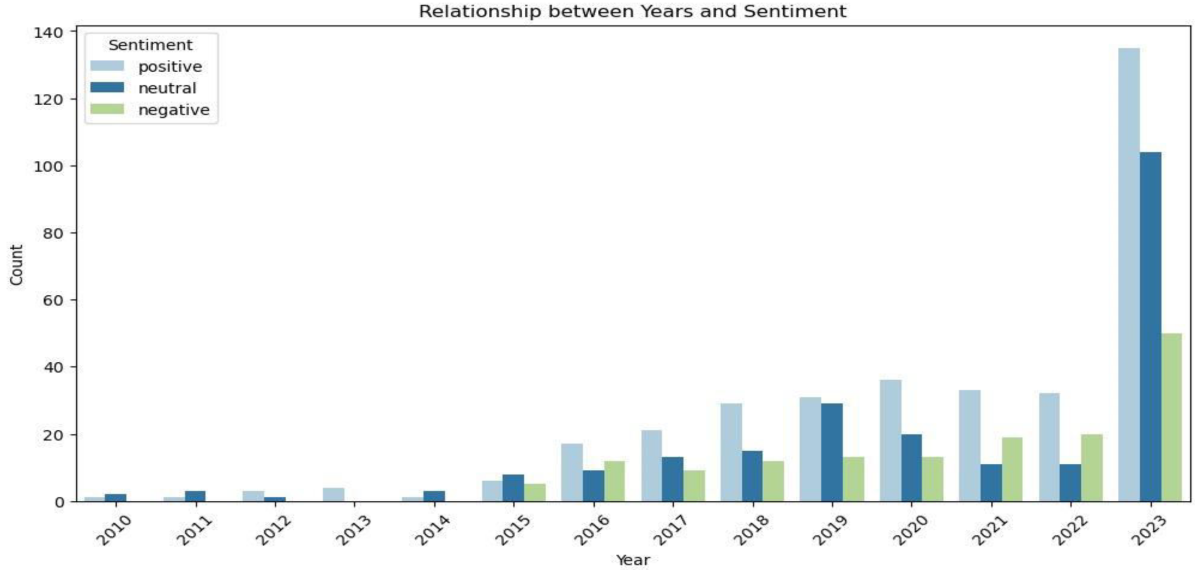

Fig 1.1: Sentiment for years

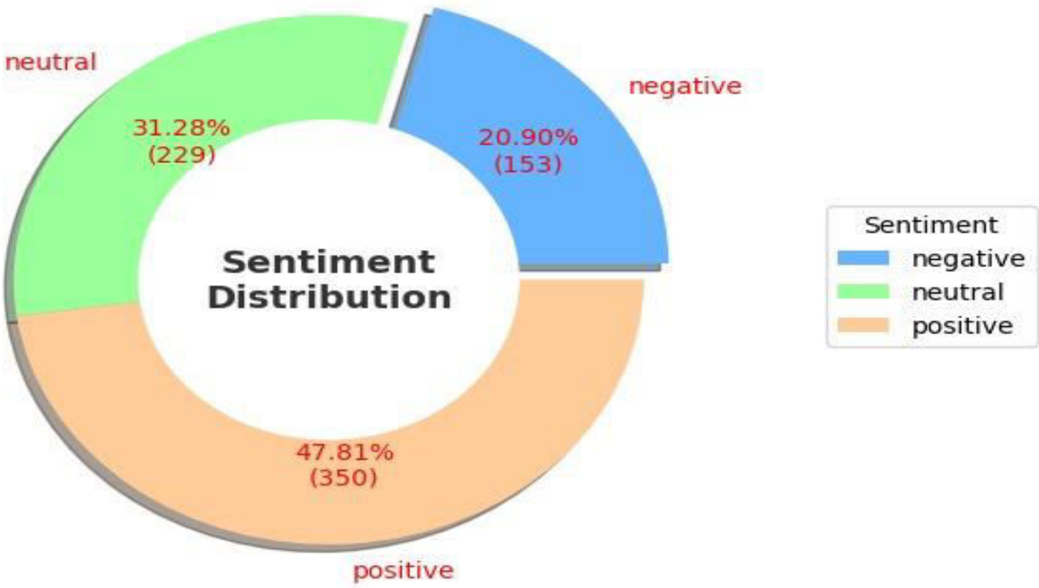

Fig 1.2: Percentage of sentiment

V. DISCUSSION

The results highlight the system's capability to accurately classify social media sentiments, achieving 85% accuracy in sentiment detection across Positive, Negative, and Neutral categories. This performance is significantly higher than that of traditional rule-based sentiment analysis, which often struggles to handle contextual nuances, sarcasm, and ambiguous language. The use of machine learning models such as Random Forest, LSTM, ARIMA, and Prophet contributes to this improvement, as these models are better at identifying patterns in textual data and making accurate predictions.

One of the key factors in achieving high performance is the dataset's diverse nature, covering multiple platforms such as

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Twitter, Facebook, and Instagram, ensuring that the model generalizes well across different types of user-generated content. The inclusion of metadata such as hashtags, retweets, likes, and timestamps further enhances the model's ability to identify sentiment trends over time.

Additionally, the visualization and analytics features of the web application provide users with intuitive insights into sentiment trends, customer feedback, and engagement levels. The application's ability to process large volumes of data in real time makes it a valuable tool for businesses, researchers, and social media analysts.

However, there are some limitations. The model's accuracy may vary when dealing with highly informal language, slang, or code-switching, which is common in social media posts. Moreover, sentiment analysis models still struggle with detecting sarcasm, which can lead to misclassifications. Future improvements could involve fine-tuning transformer-based models such as BERT or GPT to better capture contextual meaning in user sentiment

VI. CONCLUSION

This project introduced a machine learning-based sentiment analysis system designed to analyze and visualize sentiment trends across social media platforms. By leveraging models such as Random Forest, LSTM, ARIMA, Prophet, and K-Means clustering, the system achieved 85% accuracy in classifying sentiment and generating actionable insights.
The web application provides real-time analytics, allowing users to track sentiment shifts, customer opinions, and emerging trends efficiently. The system was developed using Python and Flask, ensuring a user-friendly and interactive experience with features such as data upload, visualization, and advanced analytics.
Future work will focus on improving sarcasm detection, integrating pre-trained transformer models like BERT, and expanding the dataset to include more diverse linguistic variations. Additionally, incorporating automated sentiment-based recommendations can further enhance the application's practical applications in fields such as marketing, social media monitoring, and customer feedback analysis.

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