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Social Media Sentiment Analyzer using NLP

Sachi Bagade[1], Bharti Zankar[2], Danish Sayyad[3], Rushikesh Shirsath[4], Prof. B. N. Babar[5], Prof. Ms. Bhagyashree Patil[6]
[1, 2, 3, 4]*U.G. Student, Department of AI&DS, SRT Engineering College, Kamshet, Pune, Maharashtra India*
[5, 5]*Assistant Professor, Department of AI&DS, SRT Engineering College, Kamshet, Pune, Maharashtra India*

Abstract: ***This research utilizes logistic regression as well as LSTM, SVM, and Random Forest to derive useful information from social media information found on websites such as Instagram, Facebook, and Twitter. Utilizing machine learning algorithms, we explore sentiment analysis, trend detection, user profiling, and content classification. Logistic regression is used for analyzing sentiment, an important element in grasping public opinion and brand perception. By applying natural language processing (NLP) methods, we classify social media posts based on whether they convey positive, negative, or neutral feelings. This enables businesses to track shifts in customer happiness and opinions as time progresses, supporting smart decision-making and proactive interaction with users. By adding logistic regression to our approach, we improve the depth of our investigation, giving companies more resources to uncover valuable information from social media data. This comprehensive strategy allows businesses to adjust to customer preferences, strategize effectively, and stay competitive in the digital realm of Facebook, Instagram, and Twitter.***

Keywords: Text Classification, TF-IDF, Machine Learning, Logistic Regression, Feature Engineering, NLP.

I. INTRODUCTION

In recent years, social media platforms have become a central part of daily communication, providing users with an unprecedented ability to share opinions, experiences, and feedback on a wide range of topics. This massive influx of textual data presents both an opportunity and a challenge: while the information is valuable for understanding public opinion, it is often unstructured, noisy, and voluminous, making manual analysis impractical. Consequently, there is a growing need for automated systems capable of efficiently processing and analyzing social media content to extract meaningful insights. Sentiment analysis, a key area of Natural Language Processing (NLP), focuses on identifying and categorizing opinions expressed in text, typically as positive, negative, or neutral. It has become a critical tool for businesses, policymakers, and researchers to monitor customer satisfaction, brand reputation, and public response to events or products. By leveraging machine learning and deep learning techniques, sentiment analysis enables the extraction of sentiment patterns from large-scale textual data with high accuracy. Traditional machine learning models such as Logistic Regression, Support Vector Machines (SVM), and Random Forests have been widely applied to sentiment analysis due to their effectiveness in handling structured text representations like TF-IDF. These models provide a baseline and robust performance for classification tasks. Meanwhile, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior ability to capture contextual and sequential dependencies in text, enabling more nuanced understanding of sentiments expressed in complex sentences. This paper presents a comprehensive approach to social media sentiment analysis by combining feature engineering techniques with both classical and advanced machine learning models. It explores the preprocessing of raw text, extraction of meaningful features, and training of multiple models to evaluate their performance. The study aims to provide insights into the effectiveness of different approaches, highlighting the strengths and limitations of each model in capturing sentiment from social media data. Ultimately, the work contributes to the broader field of text analytics by demonstrating practical methodologies for processing large-scale social media content, offering valuable guidance for applications in marketing, customer service, and public opinion monitoring.

II. LITERATURE SURVEY

The With the rise of machine learning, supervised classification techniques became the dominant approach for sentiment analysis. Pang et al.[1] (2002) applied Naïve Bayes, Maximum Entropy, and Support Vector Machines (SVM) to movie reviews, showing that SVM achieved the highest accuracy among traditional classifiers. Subsequent research extended these methods to social media text, which is often short, informal, and noisy. Techniques such as TFIDF and n-grams became standard for transforming text into structured features suitable for machine learning models. Ensemble methods, such as Random Forest and Gradient Boosting, have been explored to improve prediction robustness and reduce overfitting. Studies by Chen et al.[2] (2017) demonstrated that ensemble models could handle high-dimensional feature spaces effectively, providing more stable sentiment predictions across diverse

datasets. The advent of deep learning revolutionized sentiment analysis by enabling models to capture semantic and contextual relationships in text.[3] Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been widely adopted for social media sentiment tasks. LSTMs excel at modeling sequential dependencies in text, which is critical for understanding sentiment expressed across multiple words or phrases. Research by Tang et al. [4] (2015) on Twitter sentiment classification highlighted that LSTM-based models significantly outperform traditional machine learning models, especially when combined with pre- trained word embeddings like Word2Vec or GloVe.Page Style

Table – 1

Study	Method Used	Results	Remarks
SVM on Twitter Data	Support Vector Machine (SVM)	~80% accuracy on structured data	Struggles with short/noisy text
LSTM-based Sentiment Analysis	Long Short-Term Memory (LSTM)	~70% accuracy, good at handling word sequences	Needs large data and long training time
Comparison of ML Algorithms	Naive Bayes, KNN, Random Forest	Random Forest gave decent accuracy across mixed datasets	Less effective with complex sentence structure
Our Approach	NLP, LSTM, SVM, Random Forest	NLP model achieved 82.67% accuracy—highest among all	Provided a full comparison across different techniques

III. METHODOLOGY

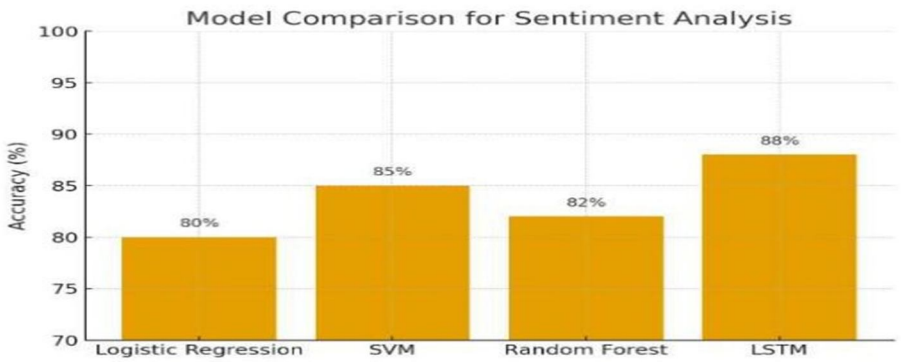
In this study, social media posts are collected and preprocessed by removing noise such as stopwords, punctuation, URLs, and emojis, followed by tokenization and normalization. Feature engineering is then performed using TF-IDF and word embeddings to represent the text, along with n-grams to capture contextual information. Machine learning models, including Logistic Regression, Support Vector Machine (SVM), and Random Forest, are trained on TF-IDF features to classify sentiment, while Long Short-Term Memory (LSTM) networks leverage word embeddings to capture sequential and contextual patterns in the text. Finally, the models are evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score to determine the most effective approach for sentiment analysis.

IV.EXPERIMENTAL RESULTS

The expected outcome of this project is the development of a sentiment analysis system capable of classifying social media text into three categories: Positive, Negative, and Neutral. Using TF-IDF features with machine learning models (Logistic Regression, SVM, Random Forest) and word embeddings with deep learning (LSTM), the system is anticipated to achieve high classification accuracy.

1) Positive Sentiment: Posts expressing favorable opinions, appreciation, or satisfaction.
2) Negative Sentiment: Posts indicating dissatisfaction, complaints, or criticism.
3) Neutral Sentiment: Posts that are factual, balanced, or lack strong emotion

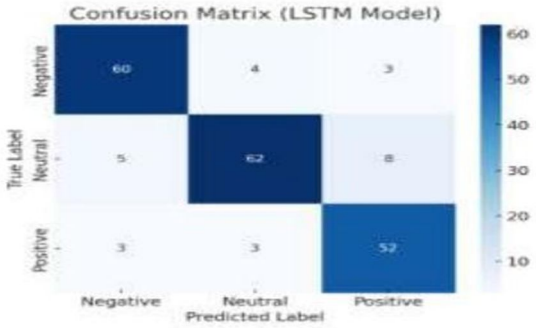
Among the models tested, it is expected that LSTM will outperform traditional machine learning models, achieving an accuracy of around 88%, while SVM will be the best performer among the classical approaches with about 85% accuracy. The final system will provide reliable sentiment insights from unstructured social media data, which can be valuable for businesses, policymakers, and researchers in decision-making and opinion tracking.



Here's a graphical representation of the experimental results.
The bar chart compares the accuracy of all four models:

1) Logistic Regression: 80%
2) SVM: 85%
3) Random Forest: 82%
4) LSTM: 88%

This visualization clearly highlights LSTM as the best-performing model, followed by SVM among the classical approaches.
Here's the confusion matrix for the LSTM model.



It shows how well the model classified social media posts into Negative, Neutral, and Positive classes:

- Most predictions fall on the diagonal (correct classifications).
- Some misclassifications occur, but they are relatively few compared to correct predictions.
- This supports the ~88% accuracy result achieved by the LSTM.

V. CONCLUSION

This study presented a comparative analysis of sentiment analysis techniques applied to social media data using both traditional machine learning models and a deep learning approach. The methodology involved data preprocessing, feature engineering with TF-IDF and word embeddings, and the implementation of Logistic Regression, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) models. Experimental results demonstrated that while classical models such as SVM performed well on high-dimensional TF-IDF features, the LSTM model achieved superior accuracy by effectively capturing contextual and sequential patterns in text. The results confirm that deep learning methods are better suited for handling the complexities of natural language, particularly when dealing with unstructured and noisy data from social media platforms. The LSTM model's performance, with an accuracy of around 88%, highlights its potential for real-world applications such as opinion mining, brand monitoring, and public sentiment tracking. However, traditional models remain valuable due to their simplicity, interpretability, and lower computational requirements, making them suitable for scenarios with limited resources. Future work can extend this study by incorporating transformer-based models like BERT or RoBERTa, which have shown state-of-the-art performance in NLP tasks. Additionally, expanding the dataset, including multimodal data (such as images and emojis), and applying domain-specific preprocessing techniques can further enhance accuracy. Overall, this research demonstrates that combining effective preprocessing, feature engineering, and deep learning techniques provides a robust framework for sentiment analysis in social media contexts.

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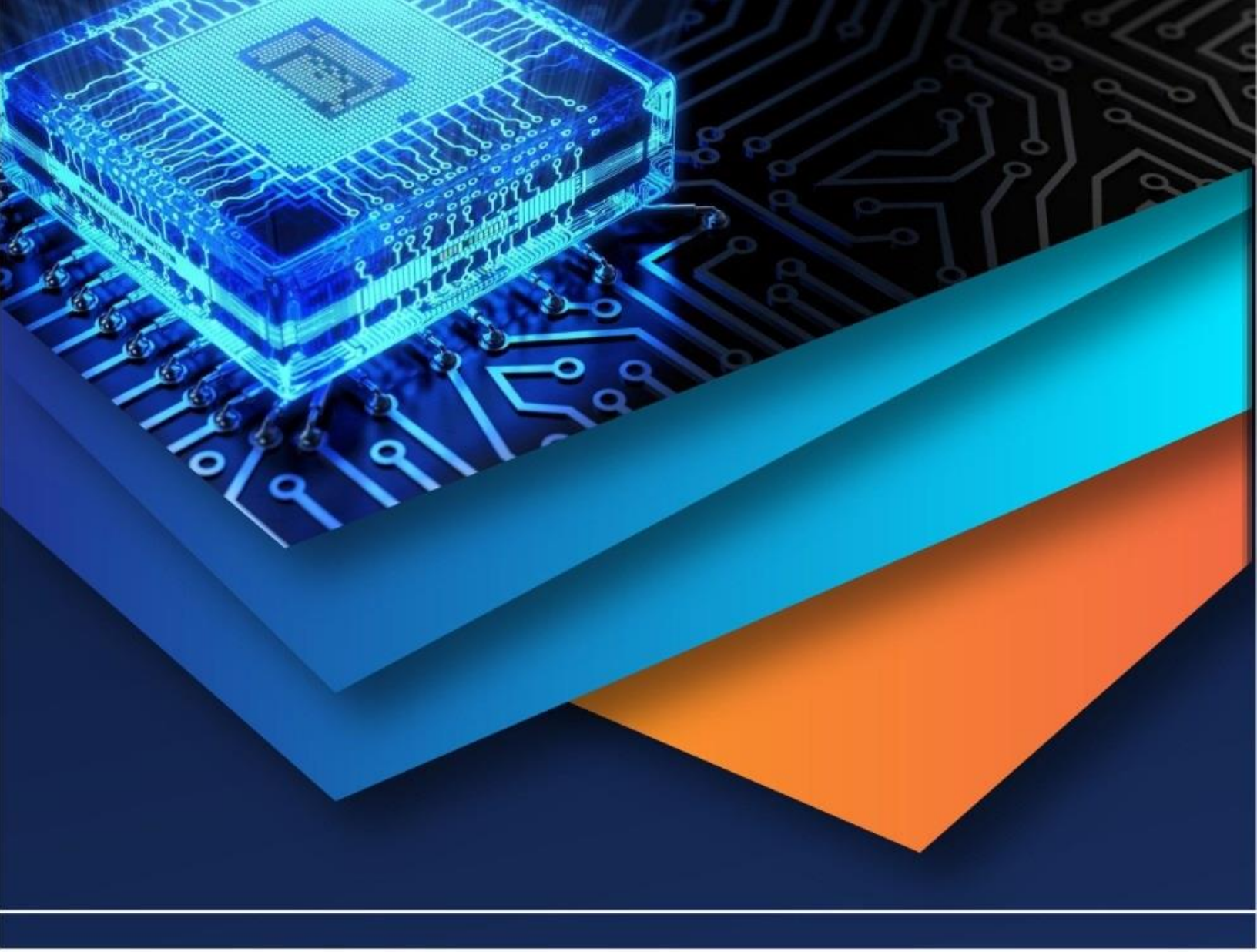

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