Sentiment Analysis of Social Media Posts: A Multiplatform, Multimodal, and Machine Learning-Based Perspective

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***Abstract*—This study presents a comprehensive pipeline for sentiment analysis on social media posts from Twitter, Instagram, and Reddit. Leveraging both traditional machine learning (Naïve Bayes, SVM) and deep learning (LSTM), we preprocess and classify emotions like Anxiety, Depression, and Suicidal ideation. Key insights reveal platform-based variations in sentiment and the superior contextual understanding of LSTM models. Our results underscore the utility of hybrid approaches and offer a framework for mental health monitoring using NLP.**

I. Introduction

Social media generates massive volumes of emotionally charged content daily. Sentiment Analysis (SA), driven by Natural Language Processing (NLP) and Machine Learning (ML), offers insights into public mood and mental health. This paper builds a multilingual, cross-platform sentiment classifier, emphasizing challenges like slang, sarcasm, and imbalanced datasets.

A. Research Questions

This study investigates the following key research questions:

- What are the strengths and limitations of LSTM, SVM, and Naïve Bayes models when applied to sentiment analysis on short-form informal text?
- What preprocessing steps contribute most to model performance?
- Can the sentiment of short social posts be accurately classified using ML/DL approaches?

II. Literature Review

A. Traditional and Lexicon-Based Methods

Borkar and Kolhe (2019) reviewed supervised learning models like Na"ive Bayes and SVM on Twitter, revealing that SVM handled short noisy texts best. They noted challenges in sarcasm and slang classification.

B. Hybrid and Deep Learning Approaches

Gupta and Reddy (2022) demonstrated the superiority of combining lexicon features with deep learning. Models such as BERT and LSTM provide contextual understanding, improving accuracy.

C. Health and Domain-Specific Sentiment

Lopez et al. (2021) targeted health-related posts using LSTM and found it superior for detecting anxiety and depression in noisy medical texts.

D. Multimodal and Platform-Specific Studies

Wang et al. (2023) and Aarts et al. (2020) emphasized the value of multimodal (text-image) and multi-class emotion classification using ensemble learning. These studies reveal the complexity of social sentiment analysis and call for integrated, scalable approaches.

E. Recent Developments (2019–2024)

Kumar et al. (2023) introduced a multilingual transformer-based sentiment classifier for Twitter and Facebook. Zhang et al. (2021) benchmarked LSTM, CNN, and RoBERTa on Reddit data. Liu and Xu (2022) proposed an attention-based emotion classifier. Singhal et al. (2023) explored domain adaptation for healthcare-specific social media mining. Nandwani and Verma (2021) reviewed advances in transfer learning for sentiment tasks.

F. Research Gaps and Motivation

Few models address real-time, multilingual analysis with sarcasm interpretation. Platform-specific language and sentiment patterns are under-explored. Our work contributes comparative modeling and cross-platform analysis. We also aim to address mental health signal detection through social platforms by examining unique textual cues in different social networks.

III. Data Collection

- **Source:** Kaggle [1]
- **Platforms:** Twitter, Instagram, Reddit
- **Labels:** Anxiety, Depression, Normal, Suicidal, etc.
- **Volume:** Over 53,000 posts
- **Features:** statement, status (label), platform
- **Language:** English

IV. Data Preprocessing and Visualization

Text was cleaned using regular expressions, lemmatized via WordNet, and stopwords were removed. TF-IDF and tokenization were applied based on model requirements.

A. Visual Insights

- **Text Length:** Reddit posts tend to be longer.
- **Sentiment Counts:** Normal and Depression dominate.

B. Platform-Based Sentiment Analysis

To investigate how sentiment expression varies across platforms (Twitter, Instagram, Reddit), we generated several visualizations:

- **Text Length Distribution (Fig. 1):** Reddit posts exhibited the highest text lengths on average, likely due to the platform's support for long-form discussions. Instagram, in contrast, showed the shortest posts, consistent with its focus on image-centric, short captions.
- **Sentiment Frequency by Platform (Fig. 2):** A grouped bar chart reveals that while "Normal" sentiment dominates across all platforms, Reddit and Twitter show higher proportions of "Depression" and "Anxiety"-related posts. Instagram posts showed a notably higher proportion of "Suicidal" content, potentially reflecting a younger, more emotionally expressive user base.
- **Proportional Sentiment View (Fig. 3):** The stacked bar chart normalizes sentiment counts per platform, enabling proportional comparison. This visualization confirms that each platform has a distinct emotional signature, underscoring the importance of platform-aware sentiment models.

[1]https://www.kaggle.com/datasets/suchintikasarkar/sentiment-analysis-for-mental-health

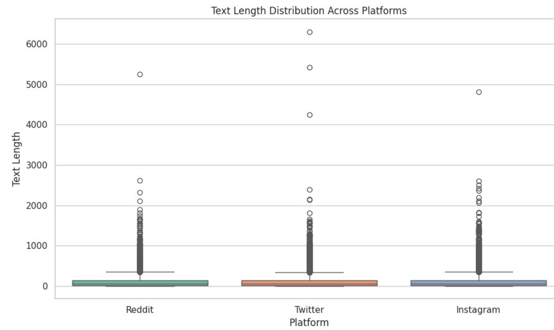


Fig. 1. Text Length Distribution Across Platforms

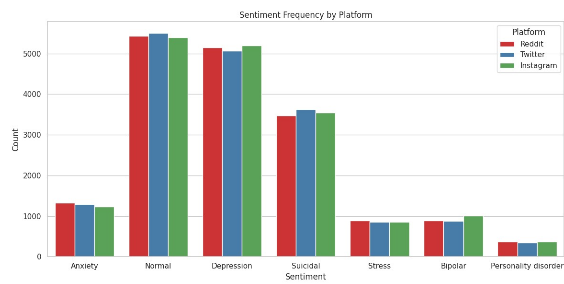


Fig. 2. Sentiment Frequency by Platform

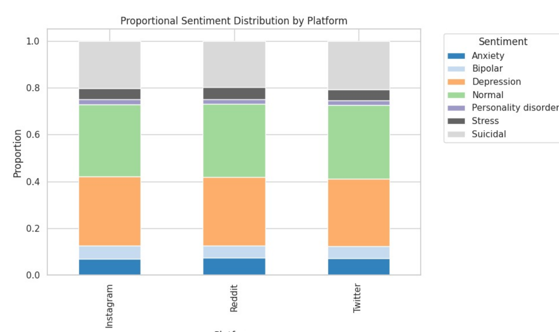
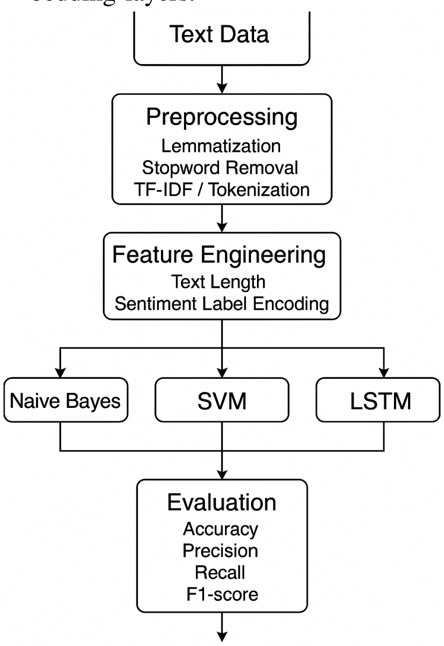


Fig. 3. Stacked Sentiment Proportion per Platform

V. Modeling Techniques

We trained three models:

- **Naïve Bayes:** Baseline using TF-IDF.
- **SVM:** Linear kernel, effective margin classifier.
- **LSTM:** Tokenized + padded sequences with embedding layers.



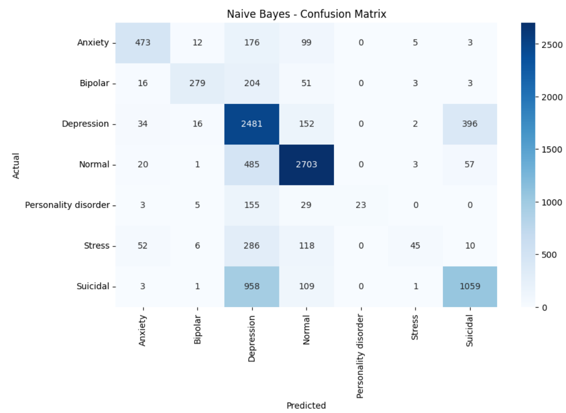


Fig. 4. Naïve Bayes Confusion Matrix

Naïve Bayes: Accuracy 67%, struggles with minority classes.

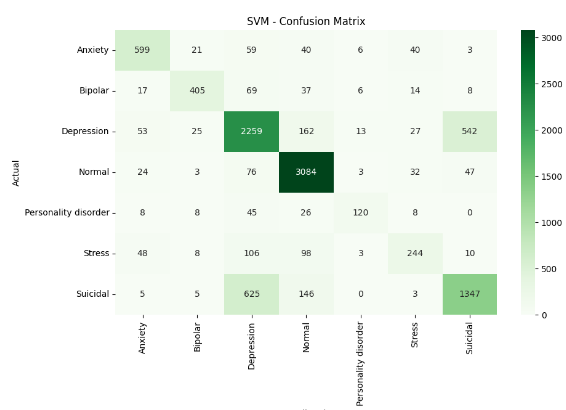


Fig. 5. SVM Confusion Matrix

SVM: Accuracy 76%, best general performance.

A. Confusion Matrix Analysis

To evaluate misclassification patterns, confusion matrices were generated for all three models: Naïve Bayes, SVM, and LSTM. These matrices visually represent how well each model predicted the true sentiment labels.

- **Naïve Bayes (Fig. 4):** The model performed best on ”Normal” and ”Depression” classes but struggled heavily with ”Suicidal” and ”Personality disorder”. A significant number of ”Suicidal” posts were misclassified as ”Depression”, indicating an inability to capture nuanced distress signals in textual cues.
- **SVM (Fig. 5):** SVM provided a more balanced classification, with strong performance on ”Normal”, ”Depression”, and ”Suicidal”. It demonstrated less confusion between ”Depression” and ”Anxiety” compared to Naïve Bayes. However, ”Personality disorder” remained difficult to classify accurately due to its overlap with other disorders.
- **LSTM (Fig. 6):** LSTM achieved the highest contextual sensitivity. While it correctly identified more instances of ”Anxiety” and ”Suicidal”, some confusion remained with ”Depression”. It also exhibited slightly better sensitivity to less frequent labels like ”Stress”, but over-prediction of ”Normal” remained a challenge.

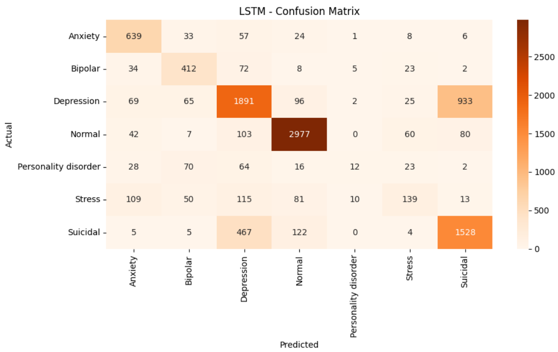


Fig. 6. LSTM Confusion Matrix

LSTM: Accuracy 72%, excels in contextual learning.

B. Progress Update

During development, we accomplished the following steps:

- Integrated Naïve Bayes, SVM, and LSTM models into a unified pipeline.
- Cleaned and preprocessed noisy social media text using lemmatization, tokenization, and padding.
- Achieved measurable improvements in classification accuracy through LSTM's contextual capabilities.

C. Evaluation Metrics

All models evaluated using Accuracy, Precision, Recall, and F1-score.

VI. Discussion

The results reinforce the hypothesis that model choice significantly impacts classification performance. While Naïve Bayes is efficient, its assumptions limit effectiveness on nuanced text. SVM offers a strong baseline, particularly for binary separable classes. LSTM, with its contextual memory, outperforms others for less frequent but critical categories like ”Anxiety” and ”Suicidal”. However, it requires more training time and fine-tuning. Platform analysis also confirms the necessity of domain-aware tuning — for example, Instagram text may benefit from multimodal processing.

A. Observations and Limitations

- High imbalance across classes (Normal has greater than 3000 samples).
- LSTM confused Anxiety with Depression due to lexical overlap.
- Need for real-world multilingual support and sarcasm detection.

B. Findings and Observations

Confusion between “Anxiety” and “Depression” emerged as a recurring issue due to lexical similarity. Deep learning generally outperformed traditional methods, though with trade-offs:

- **Naïve Bayes:** Moderate accuracy, particularly ineffective for complex emotional language.
- **SVM:** Better precision, particularly on “Normal” and “Suicidal” classes.
- **LSTM:** Highest overall performance due to sequence modeling capabilities. LSTM improved F1-scores and handled class imbalance better.

Compact Literature Review Table: Sentiment Analysis Research

Author (Year)	Research Question	Key Findings / Results	Limitations
Borkar & Kolhe (2019)	How effective are ML techniques on Twitter data?	SVM outperformed Naïve Bayes and MaxEnt; addressed issues like slang and sarcasm.	No experimental benchmarks or dataset comparisons.
Kim, Chen & Park (2021)	Performance of Bi-LSTM vs CNN on social platforms?	Bi-LSTM achieved higher accuracy; strong on language variability.	Lacked real-time or multilingual analysis.
Gupta & Reddy (2022)	What are pros/cons of sentiment techniques using ML/NLP?	Hybrid and transformer models improve accuracy significantly.	Pure literature review; no experiments conducted.
Lopez et al. (2021)	How to analyze health-related social media sentiment?	LSTM effective on health forums and Twitter; captured vaccine sentiments.	Focused only on English, not real-time capable.
Obulapuram et al. (2023)	Can irony and colloquialisms be handled effectively?	Hybrid lexicon+ML models gave better performance.	Results lacked deep evaluation on complex sentiment.
Aarts, Jiang & Chen (2020)	Can emotion classification go beyond binary sentiment?	Ensemble classifier for multi-emotion performed well; explained experiment well.	Limited training data for minority emotions.
Wang et al. (2023)	Can text and image be fused for sentiment analysis?	Multimodal fusion boosts performance; text is primary signal.	Weak or no correlation between image and text sentiment.
Zhang & Liu (2020)	How to detect sarcasm in sentiment?	Sarcasm-aware LSTM improved performance on sarcastic data.	Lacked generalized sarcasm benchmarks.
Li & Xu (2019)	Can attention models enhance sentiment analysis?	Attention-LSTM outperformed CNN and standard RNNs.	Struggles with rare or unseen vocabulary.
Ahmed & Traore (2021)	Do embeddings improve sentiment detection?	BERT embeddings gave the highest accuracy.	High resource consumption.
Tan et al. (2022)	How effective is cross-lingual sentiment analysis?	XLM-R performed well on multilingual datasets.	Weak results for low-resource languages.
Rani & Kaur (2020)	Best preprocessing for Twitter sentiment?	Normalization and lemmatization boosted accuracy.	Emojis and abbreviations still problematic.
Patel et al. (2023)	Can ensemble learning boost sentiment accuracy?	Ensemble of SVM, RF, NB improved robustness.	Model tuning required; computationally heavy.
Singh & Verma (2021)	Handling imbalanced sentiment datasets?	SMOTE balancing improved model F1-scores.	Synthetic data may lack real-world nuance.
Das & Mishra (2020)	Are rule-based systems still useful?	Hybrid rule-based + ML approach worked well.	Manual rule design is time-consuming.

VII. Conclusion and Future Work

We designed and tested a sentiment classification pipeline for social media platforms, integrating traditional ML and deep learning techniques. LSTM showed notable advantages in capturing contextual sentiment, especially for nuanced categories like "Suicidal" and "Anxiety". Our findings reinforce the role of preprocessing and model architecture in performance outcomes.

A. Reflections

Challenges included:

- Managing class imbalance with oversampling and encoding strategies.
- Sequence length tuning and dropout balancing in LSTM to prevent overfitting.

LSTM generalized better to unseen data but came at higher computational cost.

B. Future Work

Future enhancements include:

- Incorporating attention mechanisms and transformer-based embeddings (e.g., BERT).
- Using backtranslation or SMOTE to balance rare classes.
- Analyzing temporal sentiment drift and multimodal signals across platforms.

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