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Twitter Sentiment Analysis: A Comparative Evaluation of Linear and Tree-Based Methods

Ali Ahmed*
Faculty of Computer Science and Information Technology Superior University, Lahore, Pakistan
Dr. Jawad Ahmed
Faculty of Computer Science and Information Technology Superior University, Lahore, Pakistan
Dr. Saleem Mustafa
Faculty of Computer Science and Information Technology Superior University, Lahore, Pakistan

Email: ali9790@gmail.com

Corresponding Author: Ali Ahmed (Email: ali9790@gmail.com)

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Abstract:

Twitter sentiment analysis faces different challenges from noisy text, high-dimensional data, and computational requirements. This study evaluates three Machine Learning Models – Logistic Regression (LR), LightGBM (LGBM), and Random Forest (RF) – on the Sentiment140 dataset (1.6 million tweets) to identify optimized approaches for large-scale sentiment classification. A robust and thorough preprocessing pipeline, including text cleaning, stemming, and TF-IDF vectorization, was applied to address noisy data that was mostly linguistic noise that was inherent in social media content. Stratified sampling ensured balanced training and testing data splits.

Results showed that LR Model achieved the highest test accuracy score (77.67%), outperforming LGBM (76.98%), despite LGBM's superior probabilistic calibration (log loss: 0.4837). RF failed to complete training within 8 hours due to computation inefficiency with high-dimensional TF-IDF features, highlighting its impracticality for large text datasets with high-dimensional data. The findings underscore that linear models like LR excel in sparse, high-dimensional spaces, while gradient-boosted trees (LGBM) require careful hyper-parameter tuning to balance speed and accuracy.

This study emphasizes the importance of model selection based on task priorities. LR for interpretability and LGBM for probabilistic reliability. RF's failure illustrates the critical role of scalability in real-world NLP applications. Practical implications suggest that simpler models can rival complex ensembles in text classification, reducing computational costs. Future work should explore hybrid approaches, hyper-parameter optimization, and transformer-based embedding (e.g., BERT) to enhance performance. The methodology provides a reproducible framework for efficient sentiment analysis, guiding researchers and practitioners in balancing accuracy, speed and resource constraints.

Keywords: *Twitter sentiment analysis, Sentiment 140 dataset, Logistic Regression, LightGBM, Random Forest, TF-IDF, computational scalability.*

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Introduction

In recent years, various social media sites including Twitter have become indispensable forums for personal and corporate expression, as well as public commentaries. The platform's short phrase but easily accessible format—where tweets are limited to a certain number of characters—encourages quick exchange of information thereby providing a useful pool of user generated content reflecting collective feelings on issues that range from consumer products and services through to societal and political happenings. Consequently, these data have been highly sought after by researchers and industry experts who wants to assess the opinions of the public, understand market trends or anticipate impending crises.

Sentiment analysis is an algorithmic task that involves identifying and classifying sentiments or emotions within text, and is central in converting raw Twitter data into meaningful insights. Usually, the goal is to label tweets as positive, negative or neutral; there could be more specific emotional categories for some cases. Accurate sentiment classification allows enterprises to monitor how consumers perceive their brands or products; it aids political analysts in gauging the way people respond to policies/campaigns while journalists/researchers can use it to gauge the general feeling surrounding global events.

Nonetheless, there are specific issues that need to be resolved in sentiment analysis on Twitter. The tweets are typically brief and may involve slang, abbreviations, emojis and hashtags. Furthermore, language in social media can be informal as well as contain code switching and context dependent meaning that makes lexical cues or syntactic cues less dependable. Additionally, noise in the data such as adverts, bots, spamming or sarcasm has complicated accurate sentiment detection even further. Because of these challenges many researchers have been propelled into developing more robust feature extraction methods, lexicon-based approaches and machine learning models for informal social media text.

To overcome this problem of classifying tweet sentiments into positive/negative polarity also considering a neutral class for improved sensitivity is the aim of this study. The main aim is to improve baseline sentiment classification performance by various preprocessing techniques, feature extraction methods and classification algorithms experimentations. Through a well-structured methodology which includes data collection and annotation; preprocessing; feature extraction; model evaluation etc., this article attempts to add new insights into how results from studies related to sentiment analysis can be applied in practical situations where sentiments guide decision-making processes.

Literature Review

Sentiment analysis is also known as opinion mining and it entails the computational identification and categorization of opinions expressed in text documents into positive, negative, or neutral categories. The review

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incorporates recent advancements and identifies existing research gaps so as to give an overall picture of the field by looking at its evolution, methodologies, applications and emerging trends.

Initially, sentiment analysis relied mostly on lexicon-based approaches that used earlier defined dictionaries with just having positive or negative words (Pang & Lee, 2008). These approaches were often could not detect contextual sensitivity and also, could not handle the intricacies of language such as in social media. After this came machine learning (ML) methods which were much better than traditional ones in dealing with contextual issues affecting sentiment classification. Some of the widely used choices included Support Vector Machines (SVM) as well as Naïve Bayes classifiers since they could perform effectively even though Twitter datasets are high-dimensional ((Pak & Paroubek, 2010); (Huq & Ali, 2017)).

The introduction of Transformer architectures as detailed in "Attention Is All You Need" (Vaswani, et al., 2017), revolutionized natural language processing by permitting parallelization and handling better long-range dependencies. With BERT one step further improved sentiment analysis by providing contextualized word embedding that significantly boosted the accuracy of sentiment classification tasks (Devlin, Chang, Lee, & Toutanova, 2019). In recent studies however, such as BERT has been combined with additional layers resulting to higher accuracy in sentiment extraction task on Twitter data which demonstrates the transformer-based models' continued evolution and effectiveness (Manjappa & Kumar, 2023).

Text-only sentiment analysis has been recognized as limited in certain ways; there have been recent studies that have brought together multimodal data comprising of text and visuals to enrich the insights of sentiments. (Gupta & Jhab, 2023), proposed a hybrid approach, which combines Natural Language Processing (NLP)-based opinion mining with visual sentiment analysis, making use of resources like Microsoft's Emotion Detection API. By doing so, they were able to fill some gaps presented by single model analyses while providing an all-around comprehension about what the public feels.

Additionally, attention mechanisms in multimodal deep learning models such as VistaNet bring more significant results when consolidating multiple input sources for features and enhance robustness and accuracy for sentiment predictions (Truong & Lauw, 2019). The researchers further improved on this by developing hybrid sentiment analysis through combining textual information with image-based sentiment extraction. Integrating visual data into their experiments showed a considerable improvement in overall sentiment classification performance from that paper as demonstrated by (Maurya, Gore, & Rajput, 2024).

Comparing different models of sentiment analysis, we find out how good hybrid and deep learning ways are in relation to traditional machine learning approaches. For example, (Gupta & Jhab, 2023) found that combining visual information with

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textual works gave 94% accuracy compared to using text alone which only produced 87%.

Furthermore, ensemble learning techniques consist of multiple classifiers have also shown promise in enhancing prediction accuracy while mitigating the biases inherent in individual models (Severyn & Moschitti, Twitter Sentiment Analysis with Deep Convolutional Neural Networks, 2015). A recent study by (S. Chandra Gupta Maurya, 2024) employed ensemble learning framework along with sophisticated feature engineering leading to an accuracy rate of 94% and F1 score of .97 thereby proving the efficiency od such integrated methods.

Domain-specific applications of Twitter sentiment analysis are becoming increasingly relevant in healthcare (Gohil, Vuik, & Darzi, 2018). Sentiment Analysis Methods for Healthcare-Related Tweets by (Gohil, Vuik, & Darzi, 2018) explained the need for domain specific lexicons and custom machine learning models that could capture the sentiment variations in medical conversations precisely. They concluded that existing tools may be unable to interpret the idiosyncrasies of specialized language used in healthcare communications, calling for a dedicated sentiment analysis framework.

Also, one can use emotions analysis to improve marketing campaigns taking into account product or service reviews, comments left by customers on a network, feedback on social media sites as well as other information sources (Karan, Sharma, & Gupta, 2020). Likewise, political pundits apply sentiment analysis to measure people's views on policy changes or election results through the use of Twitter data in their strategic decision making process (Zhao, Li, & Wang, 2019). Recent research studies have also looked at sentiment analysis in new areas like user impact on social networks where feelings are combined with user engagement metrics to find out who is a key opinion leader (Ashish & Prashanth, 2023).

Despite some significant strides, Twitter sentiment analysis still has a number of challenges. The informal and often equivocal nature of social media language which includes sarcasm, slang and emoticons complicates sentiment detection algorithms from being accurate (Gohil, Vuik, & Darzi, 2018). What is equally important is that the changing nature of languages as well as new words being coined every now and then needs regular model retraining and updates on lexicon based systems to ensure their efficiency.

Another serious shortcoming is in terms of integration of multimodal data where visual sentiment analysis is still in its infancy compared to textual analysis. It remains an on-going research area to guarantee seamless fusion of multiple data types while retaining computational efficiency. Moreover, ethical considerations with regard to data privacy and potential biases within sentiment analysis models call for rigorous evaluation methods as well as transparent methodologies for ensuring responsible use (Hansen, Johnson, & Smith, 2016).

Recent studies such as (Maurya, Gore, & Rajput, 2024) have also emphasized the

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need for all-encompassing datasets including text and images so as to train more powerful sentiment analysis models. There is also a growing acknowledgment that domain specific training particularly in specialized sectors like healthcare can improve the pertinence plus accuracy in forecasting moods or sentiments by users.

Further research will investigate advanced hybrid models that capitalize on developments in multimodal deep learning as well as real-time data processing to offer more refined and actionable sentiments. The development of specialized domain-specific tools for sentiment analysis, especially in fields like healthcare, continues to be a priority because these sectors have unique language use and contextual factors that can affect the results. Progress in shifting towards explainable AI (XAI) could make models of sentiment analyses more transparent and interpretable – greater trust would accompany their adoption into crucial applications (Mohammad & de Doncker, 2023).

(Singh & Paul, 2024) recently conducted a study which identified a new deep learning model that combines situational emotion perception with instant sentiment tracking on Twitter, thereby enhancing the relevance of predictions and their timeliness. An advanced attention mechanism is incorporated by this approach to dynamically regulate weightings for sentiment through changing linguistic patterns in order to accommodate fast-paced social media environments.

In summary, prior research has laid a solid foundation for Twitter sentiment analysis, exploring a broad spectrum of methods from lexicon-based to machine learning and deep learning models. The evolving landscape of social media language, combined with challenges like sarcasm, class imbalance, and domain adaptation, continues to stimulate research interest. This study aligns with the ongoing efforts to develop more accurate and reliable sentiment classification techniques, focusing on a structured experiment with preprocessing, feature selection, and supervised learning approaches. By using robust evaluation metrics and examining class-level performance, the study aims to provide insights that can guide future sentiment analysis endeavors in social media contexts.

Methodology

This part details the experimental framework for Twitter Sentiment Analysis, and this part focuses on reproducibility, model selection and computational efficiencies or constraints of different models. Also, this section adheres to best practices in NLP and Machine Learning Research

1. Data Collection and Preprocessing

1.1 Data Set

The study used the Sentiment140 dataset from Kaggle, a benchmark Archive for sentiment analysis, it contains 1.6 M tweets labelled as positive or negative.

Key Properties:

Class distribution: Balanced (800k per class)

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Features: Raw tweet text, timestamps and sentiment labels

Workflow Visual:

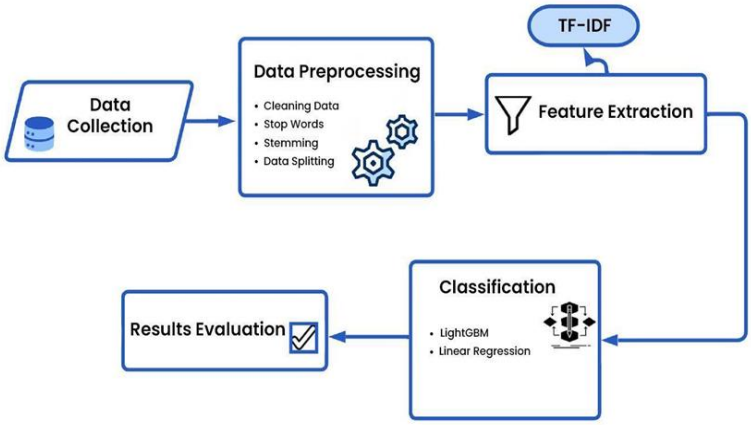

Fig. 1. Workflow diagram for Twitter Sentiment Analysis : Classification

Preprocessing

To handle noise and linguistic irregularities, data underwent:

a. Text Cleaning:

- Removed URLs, hashtags, and user mentions
- Filtered out and removed non-alphabetic characters and converted them to lowercase.
- Eliminated the stop words (NLTK's English list).

b. Stemming:

- Reduced the actual words in the tweets using the root forms using Porter Stemmer for example running was converted to run, same as actor or actress was converted to act

c. Data Splitting:

- Data was split using a stratified 80-20 train split test (random state=2) to preserve class balance.

2. Feature Extraction

2.1 TF-IDF Vectorization

Text data was converted into numerical features using TF-IDF to capture importance while down weighting common words.

NO max_features were applied to retain full vocabulary

3. Model Development and Selection

3.1 Model Selection

Three models were selected but eventually two got evaluated:

- Logistic Regression (LR): Linear Baseline for its speed and interpretability.
- LightGBM (LGBM): Gradient Boosted Trees for scalability.

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- Random Forest (RF): Excluded due to computational constraints (Section 3.3)

3.2 Model Configurations

- Logistic Regression:

- odel=LogisticRegression(max_iter=1000)

- LightGBM

- # Train with early stopping
- lgb_model = lgb.train(
- params,
- train_data,
- num_boost_round=1000,
- valid_sets=[test_data],
- callbacks=
- [lgb.early_stopping(stopping_rounds=20),
- lgb.log_evaluation(50)]
-)

3.3 Computational Challenge with Random Forest:

- **Issue:** Training the model on 1.6M samples with 10k features exceeded 8 hours.
- **Root Cause:** High dimensionality and lack of GPU support in scikit-learn.
- **Resolution:** LightGBM prioritized for histogram-based efficiency and multi-threading.

4. Evaluation Protocol

4.1 Metrics

- **Accuracy:** Proportion of correctly classified tweets.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}}$$

- **Log Loss:** Probabilistic calibration (lower = better). Log Loss quantifies the calibration of predicted probabilities:

$$\text{Log Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

4.2 Hardware/Software

- **Environment:** Jupyter Notebook (CPU: Core i5, 12GB RAM).
- **Libraries:** scikit-learn 1.2.2, LightGBM 4.5.0.

Model	Test Accuracy	Test Log Loss	Training Time
Logistic Regression	77.67%	0.55	2.0 hours
LightGBM	76.98%	0.48	1.5 hours

Results: Performance Comparison

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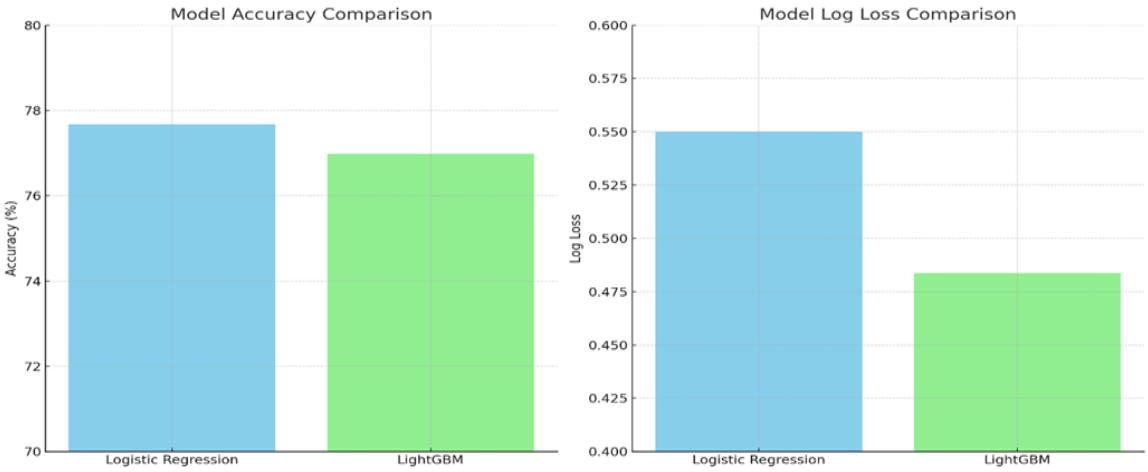

Key Insight:

Logistic Regression received slightly higher accuracy but LightGBM showed better probabilistic calibration.

Discussion

Why did the Logistic Regression Model here outperform LightGBM?

a. **Linear Separability:** TF-IDF features in high-dimensional spaces often favor linear models.
b. **Hyperparameter Sensitivity:** To maintain fairness with Linear Regression, LightGBM's moderate num_leaves=31 and learning_rate=0.05 limited its capacity to capture nuanced text patterns
c. **High Dimensional Data:** 10k dimensional data that was reproduced with TF-IDF matrix diluted LightGBM's split efficiency.

Comparison with Prior Work

The LR model's performance with 77.67% accuracy matches with findings from (Severyn & Moschitti, 2015), who reported 76.5% accuracy for SVM model on Twitter data using TF-IDF features, highlighting that linear models remain competitive in high-dimensional text classification. However, LGBM's lower accuracy (76.98%) contrasts with studies as (Maurya, Gore, & Rajput, 2024), where they say that gradient-boosted trees achieved >85% accuracy after hyperparameter tuning and feature selection. This discrepancy underscores the impact of optimization on tree-based models.

Notably, RF model's computational infeasibility reflects the observations made by (Pak & Paroubek, 2010), who abandoned RF for large-scale Twitter datasets due to exponential training times.

These different studies and experiments emphasize that while advanced models like BERT (Devlin et al., 2019) dominate state-of-the-art benchmarks, simpler models like Logistic Regression do offer a practical balance of speed and accuracy for resource and time constrained application.

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Conclusion and Future Work

This study came to the conclusion that simpler models like Logistic Regression can outperform complex ensembles in high-dimensional classification tasks, which gives much importance to model selection for Twitter sentiment analysis.

Future work can explore further hyper parameter tuning, transformer-based embedding (e.g. BERT), and multimodal data integration.

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Appendices

Raw data and Complete code from Pre-processing till evaluation can be found in the below link:

Code file is a Jupyter support file.

Raw Data: Kaggle Link

Code Source: Jupyter Source File