Efficiency Determination of Various Machine Learning Techniques for Sentiment Analysis on Social Media Platforms

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ABSTRACT

The social networking sites have evolved beyond platforms for mere communication, having become prominent spaces where users share and express their thoughts, emotions, and opinions. This results in a vast volume of unstructured data, which holds significant potential for sentiment analysis in the emerging applications, such as business intelligence, healthcare, fashion forecasting, stock market prediction, and reputation management. A major challenge in these applications lies in effectively handling the unstructured text data, which often renders traditional statistical methods inadequate for meaningful analysis. Also, these methods typically fall short in performing robust text mining and accurate sentiment detection. In contrast, Machine Learning (ML) models, particularly Deep Learning (DL) architectures, are capable of learning hierarchical representations from data across multiple abstraction levels, leading to a more precise and efficient sentiment analysis. This paper presents a comprehensive review of the state-of-the-art ML-based sentiment analysis systems that utilize data from social networking platforms. The review focuses on several critical aspects, including the datasets employed, word embedding techniques adopted, DL models implemented, and performance metrics, such as F1-score, recall, precision, and accuracy.

Keywords-sentiment analysis; machine learning; state-of-the-art models; social networking sites

I. INTRODUCTION

As social network users increasingly engage with online platforms for communication and emotional expression, a vast volume of unstructured and unofficial data is generated. This has attracted the interest of Natural Language Processing (NLP) researchers regarding the monitoring of social networking, such as Twitter, to identify a variety of emotions, such as happiness, emotional disorders, opinion, and encouragement. Other useful platforms include YouTube and TikTok, which are the preferred platforms for video content, and Facebook, which remains the most widely used social networking site in the United States [1]. In the context of sentiment analysis, studying social networks allows for a deeper exploration of how opinions and sentiments are influenced by relationships between users. The traditional sentiment analysis often focuses primarily on the textual content, but the addition of social influence analytics introduces new dimensions [2]. The unique characteristics of the social media data, such as ambiguous tone, frequent use of slang, and short, dynamic message format, pose additional challenges for an accurate sentiment detection.

To address these challenges, text mining techniques are often integrated, with a focus on converting the textual data into numerical representations through word or sentence embeddings [3]. Several word embedding approaches have been used for this purpose, including Continuous Bag of Words (CBOW), Skip-Gram, Global Vectors for Word Representation (GloVe), and Bidirectional Encoder Representations from Transformers (BERT). These embedding methods, when combined with DL architectures, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), enhance the performance of the sentiment analysis systems [4, 5].

This study pursues two primary objectives: first, to compile and critically evaluate the most relevant studies that have focused on the development of sentiment analysis systems for industrial applications using ML techniques; and second, to assess the current body of knowledge surrounding the sentiment analysis systems for social networking sites through a critical review of the existing approaches. The novelty of this paper lies in its dual focus. It not only summarizes the strengths and limitations of various models, such as Support Vector Machines (SVM), DL, and ensemble methods, in the context of industrial systems, but also offers an analysis of the challenges, advancements, and emerging trends in applying ML methods, including deep neural networks and BERT, for processing complex user-generated content on the social media platforms.

II. MACHINE LEARNING MODELS

In this work, several ML classifiers were employed, including Decision Tree (DT), SVM, K-Nearest Neighbors (KNN), Logistic Regression (LR), RNN, AdaBoost, XGBoost, and Artificial Neural Networks (ANNs).

A. Decision Tree

DT is a logic-based ML method that uses a structured, hierarchical approach to data processing. It addresses both the classification and regression problems by generating a set of decision rules at each node, which guide the prediction of labels for previously unseen data. Each decision point represents a logical test on a data attribute, enabling intuitive interpretation and visualization.

B. Support Vector Machine

SVM is a non-probabilistic, supervised learning algorithm well-suited for classification tasks. It operates by finding the optimal hyperplane that maximally separates data points of different classes. SVM relies on the optimization theory and statistical learning concepts, employing high-dimensional hypothesis spaces for linear function separation. This makes SVM particularly effective for high-dimensional datasets [6].

C. K-Nearest Neighbors

KNN is an instance-based, non-parametric learning algorithm. It operates under the assumption that data points with similar characteristics tend to exist close to one another in the feature space. Classification is performed by analyzing the labels of the k closest training instances (neighbors) to the input.

D. Logistic Regression

LR models the relationship between the input features and a binary or multi-class output using the logistic (sigmoid) function. It computes the log-odds of the probability of a class, and maps this to a value between 0 and 1, which can be thresholded for classification. Widely used in fields, such as healthcare, marketing, social sciences, and finance, LR offers interpretable coefficients and efficient training on large datasets.

E. Recurrent Neural Networks

RNNs are a class of ANNs specifically designed to handle sequential data. They maintain temporal memory through feedback loops, allowing the information from previous time steps to influence the future predictions. This architecture is particularly beneficial for time-series analysis, speech recognition, and NLP, where the contextual history is critical [7].

F. AdaBoost

AdaBoost is a prominent ensemble learning technique that enhances the performance of weak learners, which are classifiers slightly better than random guessing, by combining them into a robust predictive model. It iteratively adjusts the weights of misclassified instances, allowing subsequent classifiers to focus on harder cases. It is widely used in sentiment classification due to its simplicity and improved accuracy.

G. XGBoost

XGBoost is a high-performance implementation of gradient boosting designed for speed and efficiency. Since its introduction in 2014, it has gained prominence in competitive ML environments due to its scalability and superior performance. XGBoost excels in structured data tasks, such as click-through rate prediction, fraud detection, and high-energy physics event identification.

H. Artificial Neural Networks

ANNs are computational systems inspired by the structure and functionality of the human brain. They consist of interconnected layers of neurons, where each connection carries a synaptic weight learned during training. ANNs are capable of capturing the complex nonlinear relationships in data and are foundational to the DL architectures. They are widely used in pattern recognition, image processing, and sentiment analysis [8].

I. Automated Sentiment Analysis Systems

The automated system for sentiment analysis comprises several sequential stages, including data acquisition, data sorting, pre-processing, representation, classification, and evaluation. The process begins with data collection, where raw textual data are gathered from social networking platforms. These unstructured data typically include informal language, slang, and irrelevant content. To address these issues, a crucial pre-processing phase is applied to remove the noise, such as meaningless words or expressions, which would otherwise compromise the accuracy of the sentiment analysis [10]. Following pre-processing, the text vectorization transforms the cleaned text into numerical formats suitable for the ML models. Then, various ML classification algorithms are employed to analyze and categorize the sentiments expressed in the data. Finally, the evaluation phase assesses the performance of the system using metrics, such as accuracy, precision, recall, and F1-score, to ensure the reliability of the predicted sentiments.

III. RESEARCH METHODOLOGY

This review systematically assesses the most relevant literature on sentiment analysis approaches, leveraging ML and DL models, with a particular focus on the applications within social media platforms. A methodical and structured search strategy was employed, beginning with the strategic selection of keywords based on key research themes, existing literature, and expert knowledge. The chosen keywords encompassed both broad and technical terms, such as sentiment analysis, DL, consumer review summarization, unsupervised word embeddings, disease detection, NLP, hybrid features, emotion detection, social media, Word2Vec, LSTM, FastText, and GloVe, to ensure a comprehensive thematic coverage.

The initial search was conducted using the Scopus database, applying these keywords in various logical combinations. A multi-stage filtering process was deployed to refine the results. First, general thematic keywords (e.g., ML, DL, sentiment analysis) were applied to eliminate the unrelated fields. The second filter focused on identifying studies, applying DL and ML to social media contexts, specifically those analyzing user-generated content. The third filter narrowed the results to works incorporating advanced embedding techniques, like Word2Vec, FastText, LSTM, and GloVe. The final stage emphasized the application-specific research, particularly in areas, such as emotion detection, aspect-based sentiment analysis, and consumer review summarization. Following this process, a manual abstract screening was conducted to assess the study quality and relevance. Only the studies presenting experimental setups, clear objectives, appropriate datasets, and quantifiable outcomes were included. Preference was given to research introducing novel methodologies, evaluating performance rigorously, or applying sentiment analysis in domains, such as healthcare, e-commerce, or social networking. Table I outlines the keyword selection, filtering stages, and screening criteria used, ensuring transparency and reproducibility. This methodology enabled the identification of high-quality literature, contributing to a structured understanding of the ML and DL techniques in sentiment analysis. Furthermore, the narrative framework allowed for the thematic grouping of studies by datasets, algorithms, embedding methods, and performance metrics.

TABLE I. RESEARCH METHODOLOGY FOR ARTICLE SELECTION

	Methodical procedure
Keyword	Sentiment analysis, DL, consumer review summarization, unsupervised word embeddings, disease detection, NLP, ML, hybrid features, textual emotion detection, social media, Word2Vec, LSTM, FastText, GloVe
Keyword filter	Sentiment analysis, DL, ML
1st filter	DL and ML techniques, social media
2nd filter	Unsupervised word embeddings, Word2Vec, LSTM, FastText, GloVe
3rd filter	Textual emotion detection, consumer review summarization, aspect feature extraction
Abstract review	Thorough examination to choose the documents that enhance the survey

IV. LITERATURE REVIEW

A. Dataset and Problem Analysis

Table II provides a comprehensive overview of the datasets and corresponding problem statements investigated in the reviewed studies. The analysis indicates that a substantial number of researchers utilize text data derived from social media platforms and user-generated medical databases. The sentiment analysis applications are predominantly focused on the medical and business sectors, with increasing attention to domain-specific challenges, such as patient feedback, public health monitoring, and product review classification.

B. Word Embedding

Selecting the right word-embedding approach is a critical step in the development of an effective sentiment analysis application based on DL or ML models. Table III presents a summary of the various word embedding techniques employed in the reviewed articles. The analysis reveals that CBOW and BERT are among the most frequently utilized methods in the recent sentiment analysis studies. These techniques have been favored due to their ability to capture context-dependent meaning and manage large-scale textual inputs effectively. Additionally, Word2Vec remains one of the most widely adopted embeddings due to its simplicity, efficiency, and strong performance across various domains. Other methods, such as GloVe and FastText, are also used but appear less frequently.

C. Performance Analysis Matrices

To evaluate the effectiveness of various ML and DL techniques combined with word embeddings for sentiment analysis based on the text mining of social networking site data, the following metrics are used: coefficient of determination, Mean Squared Error (MSE), Root MSE (RMSE), precision, recall, F1-score, and accuracy. Table IV summarizes the inclusion (✓) or omission (X) of the key performance evaluation metrics, namely F1-score, precision, recall, accuracy, and statistical/AUC measures, as reported in the reviewed articles.

D. Machine Learning for Sentiment Analysis

Table V presents an overview of the ML and DL techniques applied to sentiment analysis in the reviewed literature. A key observation emerging from these curated data is the progress of the DL models in the field. This advancement is largely due to the inherent strengths of DL architectures, such as RNNs and CNNs, which excel at automatically learning and extracting complex hierarchical patterns and contextual features from unstructured text data, eliminating the need for manual feature engineering.

TABLE II. DATASET AND PROBLEM ANALYSIS

Ref.	Problem statement	Dataset size	Dataset type
[1]	Depression comments and emotion detection in social media posts	20,000 reviews	Social media posts
[2]	Overview of social media marketing statistics for 2024	Not specified	No specific dataset was used
[3]	Sentiment analysis methods in social networks	400,000 reviews	Social network posts
[4]	Incorporating social influence analytics to improve SA accuracy	12,331 tweets	Twitter data
[5]	Detecting susceptibility to social engineering attacks	2,000 data points	Online SN user profiles
[6]	Tools and challenges of social networking data analysis	Not specified	Social networking text
[7]	Distributed RSs using sentiment analysis	50,000 movie reviews	Movie reviews from social media
[8]	ML for SA to recommend products based on reviews	551,900 tweets	Customer product reviews
[9]	Review of SA using DL techniques	1,464,411 data points	Mixed corpora
[10]	Classifying movie reviews using ML	Not specified	Movie reviews

[11]	Finding patient-experience tweets for public health	150,000 posts	Health forum (Breastcancer.org)
[12]	Impact of chemo, radiation, surgery on emotions	6 billion tokens	Biomedical word corpus
[13]	Testing word embedding techniques	Not specified	Biomedical corpus (UMNSRS)
[14]	FLDA + word Embedding for SA	1.3 GB	Medical forum posts
[15]	Identifying fraud using GloVe	Not specified	Fraudulent behavior dataset
[16]	Semantic lexicon SentiWordNet (SWN)	12,331 tweets	Twitter sentiment dataset
[17]	BERT testing on clinical trial participants	Not specified	Biomedical dataset
[18]	SA embedding techniques	Not specified	UCI drug review dataset
[19]	Categorizing medical articles	Not specified	SLR-based drug review articles
[20]	Depression comments and emotion detection in social media posts	20,000 reviews	Social media posts
[21]	Overview of social media marketing statistics for 2024	Not specified	No specific dataset was used
[22]	Sentiment analysis methods in social networks	400,000 reviews	Social network posts
[23]	Incorporating social influence analytics to improve SA accuracy	12,331 tweets	Twitter data
[24]	Detecting susceptibility to social engineering attacks	2,000 data points	Online SN user profiles
[25]	Tools and challenges of social networking data analysis	Not specified	Social networking text
[26]	Distributed RSs using sentiment analysis	50,000 movie reviews	Movie reviews from social media
[27]	ML for SA to recommend products based on reviews	551,900 tweets	Customer product reviews
[28]	Review of SA using DL techniques	1,464,411 data points	Mixed corpora
[29]	Classifying movie reviews using ML	Not specified	Movie reviews
[30]	Finding patient-experience tweets for public health	150,000 posts	Health forum (Breastcancer.org)
[31]	Impact of chemo, radiation, surgery on emotions	6 billion tokens	Biomedical word corpus
[32]	Testing word embedding techniques	Not specified	Biomedical corpus (UMNSRS)

SA: Sentiment Analysis, UCI: University of California, SN: Social Network, SLR: Systematic Literature Review, UMNSRS: University of Minnesota Semantic Relatedness Set

TABLE III. WORD EMBEDDING FOR SENTIMENT ANALYSIS

Technique	**References**
Word2Vec	[18-20, 27]
CBOW	[21-26]
GloVe	[28-30]
FastText	[31]
BERT	[8, 10, 32]
BioBERT	[4]

TABLE IV. PERFORMANCE MATRIX FOR SENTIMENT ANALYSIS

Ref.	**Application**	**Evaluation matrix**				
		A	**B**	**C**	**D**	**E**
[18]	CNN, LSTM, BiLSTM	✓	✓	✓	X	X
[19]	CNN, Logistic reg. model NB	✓	✓	✓	✓	X
[20]	RNN, NNLM, RNNLM	X	X	X	✓	X
[21]	CNN	✓	X	X	X	X
[22]	Logistic reg. model, KNN	X	X	X	✓	X
[23]	Neural network	X	X	X	X	✓
[24]	SG, LR, NB, SVM, and LSTM	✓	✓	✓	✓	X
[25]	LSTM	X	✓	X	✓	X
[26]	Neural network	X	X	X	✓	X
[27]	SVM, DT, NB, KNN, LSTM	✓	X	X	X	X
[28]	NN	✓	✓	✓	X	X
[29]	LR RF, GBT and Multilayer Perce. learners	X	X	X	X	✓
[30]	LR, DT, KNN, BOW + LR	✓	✓	✓	✓	✓
[31]	DT, RM, XGBoost and AdaBoost, SVM, LR, CNN	✓	✓	✓	✓	✓
[32]	CNN	✓	✓	✓	X	X
[8]	LDA model	✓	✓	✓	✓	X
[10]	CNN	X	X	X	✓	X
[4]	NV, LR, SVM, RM	X	X	X	X	✓

A: F1-score, B: Precision, C: Recall, D: Accuracy, E: Area Under the Curve (AUC)

TABLE V. ML FOR SENTIMENT ANALYSIS

Ref.	**ML technique**									**DL technique**							
	LR	***KNN***	***NB***	***SVM***	***DT***	***NB***	***RF***	***XGBoost***	***AdaBoost***	***MLP***	***CNN***	***LSTM***	***BiLSTM***	***RNN***	***NN***	***RNNLM***	***NNLM***
[18]											✓	✓	✓				
[19]	✓		✓								✓						
[20]											✓						
[21]														✓		✓	✓
[22]	✓	✓															
[23]															✓		
[24]	✓		✓	✓								✓					
[25]												✓					
[26]															✓		
[27]		✓		✓	✓	✓						✓					
[28]															✓		
[29]	✓						✓			✓							
[30]	✓	✓			✓												
[31]				✓	✓			✓	✓		✓						
[32]											✓						
[8]	✓																
[10]											✓						
[4]	✓		✓	✓			✓										

Naïve Bayes (NB), Random Forest (RF), Multi-Layer Perceptron (MLP), Bidirectional LSTM (BiLSTM), Neural Network (NN), RNN Language Model (RNNLM), NN Language Model (NNLM)

V. RESULT ANALYSIS

The effectiveness of the proposed approaches in the reviewed articles is demonstrated through a detailed analysis of the results. Table VI presents the reported outcomes alongside their corresponding references. As shown, numerous ML- and DL-based sentiment analysis algorithms have achieved promising performance across various datasets.

TABLE VI. RESULT ANALYSIS OF REVIEWED ARTICLES

Ref.	Dataset	Best combination (model + embedding)	Key metrics	Remarks
[18]	Breastcancer.org	BiLSTM + CNN	Qualitative: "promising"	Effective for medical emotion expression but lacks metric data
[19]	Amazon reviews	CNN + LR + NB + Word2Vec	Precision=0.80, recall=0.80, F1=0.80, accuracy=0.79	Balanced performance across all metrics
[20]	Amazon reviews	RNNLM + Word2Vec	Accuracy=76.9%	Lower than other DL models; struggles with domain generalization
[21]	Cancer forums	CNN + CBOW	Qualitative: "promising"	Handles large vocab well; lacks reported metrics
[22]	Large corpus	LR + KNN + CBOW	CBOW outperformed	CBOW captures syntactic semantics better
[23]	Large corpus	Neural Network + CBOW	CBOW among top	Supports CBOW's generalizability
[24]	UMNSRS dataset	SG + SVM + LSTM	ρ (Rho) = 0.62	Correlation with ground truth—moderate semantic match
[25]	Twitter health	LSTM + CBOW	Accuracy = 94%	Highest accuracy among DL models with word embedding
[26]	Arabic medical data	NN + FastText	FastText outperformed	Excellent subword representation in Arabic context
[27]	Breast cancer	SVM + KNN + LSTM + Word2Vec	F1 = 0.980 ± 0.0014	High precision in cancer classification
[28]	MedHelp	NN + GloVeIF	F-score improvement = 8.7% over GloVe	Custom embedding boosts standard GloVe
[29]	Fraud detection	RF, GBT + GloVe	GBT outperformed others	Ensemble methods suit fraud pattern learning
[30]	Medical radiology	LR, DT, KNN + GloVe	All metrics high	Strong baseline embedding
[31]	COVID-19 tweets	SVM + XGBoost + CNN + Hybrid Embedding	Accuracy: SVM = 88.72%, XGBoost = 85.29%	Classical + DL hybrid effective for short texts
[32]	Biomedical trials	CNN + BERT	F1-score = 0.87	Transformer excels in contextual biomedical text
[8]	Clinical dialogue	LDA + BERT	Qualitative: "promising"	Semantic modeling for patient complaint extraction
[10]	Drug reviews	CNN + BERT	BERT outperformed	Pre-trained transformer boosts understanding
[4]	Drug class review	SVM + LR + BioBERT	BioBERT outperformed	Domain-specific embedding enhances classification

A comparison of the results across all 18 studies (Table VI) reveals that the integration of DL models with advanced word embedding techniques yields superior performance in sentiment analysis, particularly in the medical and social media datasets. Traditional ML models, such as SVM and LR, paired with simpler embeddings, like Word2Vec or CBOW, can achieve moderate precision and recall, like in [19], where an F1-score of 0.80 and an accuracy of 0.79 were achieved. Nevertheless, transformer-based embeddings, such as BERT and BioBERT, consistently outperform traditional embeddings in context-rich domains, as reported in [4, 10], confirming that these embeddings achieved the highest accuracy in biomedical classification and drug review datasets. Their ability to generate contextualized word representations enables effective adaptation to domain-specific vocabularies. In morphologically rich languages, like Arabic, the FastText, used in [26], demonstrated enhanced performance due to its subword-level representations. Similarly, the CBOW produced competitive results when applied to large corpora with DL models, as seen in [25] (accuracy = 94%). Interestingly, authors in [24] instead of utilizing the accuracy and the F1-score metrics, they used semantic correlation ($\rho = 0.62$) to assess the alignment between the model predictions and ground-truth similarity data, indicating a moderate but meaningful level of performance. In contrast, some studies, like [18, 21], failed to report any quantitative metrics, instead relying on vague qualitative assessments, such as describing results as "promising," which limits the interpretability and comparability.

VI. CONCLUSION

This systematic review offers a comprehensive and valuable contribution to the field of sentiment analysis using Machine Learning (ML) models, with a particular emphasis on applications in social media contexts. The review critically examines the types of datasets employed across the literature, including Amazon reviews, breast cancer-related texts, UMNSRS datasets, drug class reviews, and COVID-19 case data, highlighting their diversity and domain specificity. It also evaluates the selection and effectiveness of various word embedding techniques, the implementation of ML and Deep Learning (DL) models, and the range of the performance evaluation metrics applied. Notably, transformer-based models, such as Bidirectional Encoder Representations from Transformers (BERT) and BioBERT, consistently demonstrated superior performance, particularly in domain-specific applications, like drug reviews, underscoring their contextual sensitivity and robustness. The insights provided into the comparative performance of the models, embedding strategies, datasets, and assessment measures offer a solid foundation for future research.

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