**A Literature Review on Real Time Sentiment analysis Dashboard**

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**Abstract**

Sentiment analysis of social media platforms, especially Twitter, plays a vital role in understanding public opinions, brand perceptions, and social dynamics. This paper reviews recent studies that apply machine learning, deep learning, and big data techniques to analyze sentiment from Twitter data. Drawing insights from ten significant papers, this literature review explores current methodologies, applications, and the challenges faced in analyzing Twitter sentiment. It aims to provide a comprehensive overview of state of the art sentiment analysis practices and identifies future research directions.

Keywords: Sentiment Analysis, Twitter, Machine Learning, Deep Learning, Text Mining, Big Data, Social Media Analytics.

**1. Introduction**

Social media platforms such as Twitter generate an enormous volume of usergenerated content, making it a rich source of realtime public sentiment. Sentiment analysis of Twitter data aims to classify tweets into categories such as positive, negative, or neutral, allowing for insights into people's emotions, opinions, and perceptions. The challenge of accurately analyzing Twitter data arises from its informal and noisy nature, including abbreviations, slang, and emojis.

Machine learning (ML), deep learning (DL), and big data technologies have emerged as powerful tools for handling the complexities of sentiment analysis on Twitter. This paper surveys key research works that highlight advancements in these areas, discussing their methodologies, findings, and applications in sentiment classification.

**2. Review of Literature**

**2.1 Application of Machine Learning to Data Mining**

One early study [DOI: 10.1109/ACCESS.2017.2672677] focuses on the use of machine learning algorithms to mine sentiment from Twitter data. The research compares traditional models, including Support Vector Machines (SVM), Naive Bayes, and decision trees, for sentiment classification tasks. Among these, SVM showed superior performance in classifying sentiments due to its ability to handle high dimensional data efficiently. The paper also discusses the importance of preprocessing steps, such as tokenization and feature selection, for improving model accuracy.

**2.2 Deep Learning for Sentiment Analysis of Social Media**

The work presented in [DOI: 10.1109/TKDE.2019.2913641] delves into the use of deep learning techniques for sentiment analysis of Twitter data. The study highlights the use of Convolutional Neural Networks (CNNs) and Long ShortTerm Memory (LSTM) networks to capture complex patterns in textual data. LSTM networks, in particular, were found to outperform traditional machine learning approaches, offering improved performance in understanding sequential dependencies and contextual meanings in tweets. This paper emphasizes the significance of deep learning models in addressing challenges posed by informal language and noise in Twitter content.

**2.3 Predictive Modeling for Sentiment Classification**

A study by [DOI: 10.1109/ACCESS.2017.2776930] investigates the application of predictive modeling for sentiment analysis, with a focus on ensemble methods. The paper explores hybrid models that combine multiple classifiers, such as Random Forests and Gradient Boosting, to enhance sentiment prediction accuracy. The results show that these ensemble methods reduce overfitting and improve robustness by leveraging the strengths of different algorithms. The paper also discusses the importance of model evaluation metrics like accuracy, precision, and recall in ensuring the reliability of sentiment analysis systems.

**2.4 Reinforcement Learning for Improving Sentiment Models**

Reinforcement learning (RL) is traditionally used in decisionmaking problems, but [DOI: 10.1109/ACCESS.2020.2983859] explores its application in sentiment analysis. The authors propose a method where RL agents are trained to classify sentiments through a feedback loop, where they improve their performance over time based on the rewards or penalties associated with their predictions. This approach could be valuable for dynamic sentiment analysis in realtime scenarios, such as monitoring public opinion during elections or product launches on Twitter.

**2.5 Big Data Techniques in Sentiment Analysis for Smart Cities**

[DOI: 10.1109/ACCESS.2018.2876674] investigates the integration of big data analytics in understanding public sentiment related to urban issues through social media. The study focuses on how sentiment analysis on Twitter can inform city planning, such as optimizing transportation and addressing public concerns. By leveraging distributed computing frameworks like Hadoop and Spark, the study demonstrates how big data technologies can process large volumes of tweet data, providing valuable insights into public opinions on various city related topics.

**2.6 AI Driven Healthcare Sentiment Analysis**

Although the primary focus of [DOI: 10.1109/JBHI.2021.3133103] is healthcare data, it offers useful insights for sentiment analysis on social media platforms like Twitter. This paper reviews AI techniques in medical data analysis and emphasizes the role of NLP in understanding public sentiment regarding healthrelated issues. The same techniques used in healthcare sentiment analysis, such as text preprocessing and sentiment lexicons, can be applied to analyze Twitter data to gauge public sentiment during health crises or evaluate the public's reaction to healthcare policies.

**2.7 IoT and Sentiment Analysis in Health Monitoring**

While primarily discussing IoT based health monitoring, [DOI: 10.1109/ACCESS.2019.2961100] highlights the role of sentiment analysis in understanding public sentiment toward health campaigns or emerging health issues. Using Twitter sentiment analysis alongside IoT data could provide a comprehensive view of public opinion and emotional responses during healthrelated events, such as outbreaks or vaccination drives. The paper illustrates how sentiment analysis can aid in tracking and responding to public concerns in real time.

**2.8 Big Data and Machine Learning in Healthcare Sentiment Monitoring**

The study [DOI: 10.1109/ACCESS.2020.3013933] discusses how big data and machine learning can be used to analyze sentiments expressed in social media, particularly in healthcare. The paper highlights the potential of combining ML models with largescale healthrelated Twitter data to monitor public reactions to health policies or track the progression of healthrelated events, such as pandemics. Machine learning models can be used to identify shifts in public sentiment, providing valuable insights for decisionmakers in healthcare systems.

**2.9 Blockchain for Enhancing Data Security in Sentiment Analysis**

[DOI: 10.1109/ACCESS.2023.3320738] examines the potential for blockchain technology to improve the security and integrity of healthcare data. While focused on medical records, this concept can be extended to sentiment analysis on social media. Blockchain’s decentralized and immutable nature could be used to verify the authenticity of social media posts, ensuring that the data used for sentiment analysis on platforms like Twitter is accurate and trustworthy. This is particularly important in areas where misinformation can influence sentiment, such as political events or crisis situations.

**2.10 Biomedical Applications and Text Mining Techniques**

The paper [DOI: 10.1109/ACCESS.2019.2923275] discusses data mining techniques for biomedical applications, many of which can be applied to sentiment analysis. It emphasizes the use of text classification methods such as Naive Bayes and support vector machines, which are commonly used for sentiment classification in Twitter data. The paper further highlights the importance of feature extraction and preprocessing in enhancing the performance of sentiment analysis models, which is crucial for handling the noisy and unstructured data found in tweets.

**3. Discussion**

The reviewed studies demonstrate the growing importance of machine learning, deep learning, and big data technologies in improving sentiment analysis on Twitter. Traditional methods such as SVM and Naive Bayes continue to be effective for basic sentiment classification, especially when combined with feature engineering techniques. However, deep learning approaches, particularly LSTM networks, have proven more successful in handling the complexities of informal language on Twitter, such as slang, hashtags, and emojis.

Furthermore, the integration of big data processing frameworks like Hadoop and Spark has enabled the handling of massive volumes of Twitter data, making realtime sentiment analysis more feasible. Hybrid models that combine various machine learning techniques, as well as novel applications of reinforcement learning, provide additional avenues for improving the accuracy and adaptability of sentiment models.

Despite these advancements, challenges remain, particularly regarding data quality, noise, and the dynamic nature of language on social media. Future research could explore hybrid approaches, enhanced preprocessing techniques, and novel frameworks like blockchain for ensuring data integrity.

**4. Conclusion**

Twitter sentiment analysis offers a valuable tool for understanding public opinion across a range of topics. The papers reviewed in this survey illustrate the progress made in applying machine learning, deep learning, and big data technologies to analyze Twitter data. While traditional methods still hold value, deep learning models and hybrid approaches are at the forefront of research, offering superior performance in dealing with the complexities of social media language.

Future research should focus on further optimizing existing models, exploring new algorithmic strategies, and addressing the challenges of data privacy and security to improve the effectiveness of sentiment analysis tools.

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