

Problem Statement: Finding the Balance Between Accuracy and Adaptability in Sentiment Analysis

Social media has become a powerful place for expressing opinions, reactions, and emotions. Understanding these sentiments is crucial for businesses, policymakers, and researchers looking to analyze the public's opinion and trends. Sentiment analysis, powered by deep learning, has significantly improved in recent years, yet challenges remain—specifically in adapting to new trends, slang, and delving into topics like the COVID-19 pandemic (Alsayat, 2022). While deep learning models are highly effective, they often struggle to maintain accuracy across different datasets and real-world situations (Seo et al., 2020).

One of the most promising approaches to sentiment analysis is hybrid deep learning models. Studies show that combining Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVMs) leads to better sentiment classification than using any single method alone (Li & Li, 2023). Advanced word embedding techniques, such as BERT and Word2Vec, also play a key role in improving accuracy by capturing deeper contextual meaning (Zhang et al., 2024). However, there is no single method that works perfectly in every scenario, and each approach has its limitations. Some models work well on short texts like tweets but would struggle with long reviews, while others may perform well in general sentiment classification but fail to detect sarcasm or complex emotions (Dang et al., 2020).

Another area of interest in recent research is the impact of user-specific data on sentiment prediction. Some studies suggest that analyzing a user's past comments can improve the accuracy of sentiment analysis by considering their typical tone (Li & Li, 2023). For example, a user who frequently uses sarcastic language may be better understood by a model that takes their history into account. However, other research argues that sentiment analysis models can still achieve high accuracy without user-specific data, making this an ongoing debate (Alsayat, 2022).

Recent experiments have shown that hybrid deep learning models outperform traditional methods, especially when trained on diverse datasets from social media platforms like Twitter, Yelp, and Amazon (Seo et al., 2020). For example, CNN-BiLSTM models have proven effective at detecting emotions such as joy, anger, and sadness, while aspect-based sentiment analysis techniques help identify the sentiment toward specific topics like customer service or product quality (Zhang et al., 2024). However, there are still major challenges, including handling multilingual data, identifying sarcasm—as previously mentioned—and making models efficient enough for real-time applications (Dang et al., 2020).

Despite these obstacles, sentiment analysis continues to develop, driven by the need for more adaptable and accurate models. The key to future improvements lies in developing more flexibility and understanding the bigger picture in deep learning techniques.

By refining hybrid models, improving word embeddings, and striking a balance between complexity and efficiency, researchers can create more powerful sentiment analysis tools that work across different domains and real-world applications (Li & Li, 2023).

Research objective

This research aim is to enhance the sentiment analysis for social media by improving its accuracy, adaptability, and efficiency in processing diversity and complex language patterns. Sentiment analysis plays an important role in understanding the public's opinion, keeping up with trends, and detecting emotions in online interactions. But deep learning models face significant challenges in handling developing languages, sarcasm, aspect-based sentiment, and large-scale real-time applications. The objectives of this research are designed to systematically improve sentiment classification by integrating hybrid deep learning models, optimizing feature extraction techniques, and refining user-specific sentiment predictions.

1. Incorporating ensemble deep learning models to enhance sentiment classification accuracy by combining advanced word embedding techniques with Long Short-Term Memory (LSTM) networks (Alsayat, 2022). This objective focuses on improving contextual understanding in sentiment analysis, specifically for trending topics such as the COVID-19 pandemic. The ensemble approach takes advantage of multiple state-of-the-art models to boost accuracy across various datasets, including Twitter, Amazon, and Yelp.
2. Developing hybrid deep learning frameworks that integrate Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and LSTM models to improve sentiment analysis reliability (Seo et al., 2020). This objective focuses on evaluating the adaptability of hybrid models across multiple datasets with different sizes and structures. By combining multiple deep learning techniques and feature extraction techniques, this research focuses on developing robust models that perform consistently across diverse domains.
3. Conducting a comparative analysis of deep learning architectures to determine the optimal model structure for sentiment classification (Dang et al., 2020). This objective involves evaluating different model types, including CNNs and Recurrent Neural Networks (RNNs), using word-level and character-level embeddings. By analyzing model performance on multiple datasets, this study seeks to identify the most effective architecture for sentiment classification in different social media contexts.
4. Enhancing emotion recognition in sentiment analysis by developing models that can accurately detect specific emotions such as joy, anger, and sadness in social media text (Li & Li, 2023). This objective aims to improve the ability of sentiment analysis systems

to capture emotional expressions using CNN-BiLSTM architectures combined with advanced feature extraction techniques such as Latent Dirichlet Allocation (LDA).

5. Refining aspect-based sentiment analysis (ABSA) by incorporating user behavior data to enhance sentiment classification at a more granular level (Zhang et al., 2024). This objective focuses on developing models that consider user-specific sentiment tendencies and historical comment patterns, improving accuracy in identifying sentiment related to specific aspects such as product reviews or service experiences.
6. Developing lightweight and computationally efficient sentiment analysis models that can handle large-scale social media data in real-time (Seo et al., 2020). This objective seeks to optimize hybrid models that balance high accuracy with reduced computational costs, ensuring practical implementation in fast-evolving online environments.

By tackling these objectives, this research helps improve sentiment analysis techniques, making deep learning models more flexible, efficient, and accurate in understanding user opinions and emotions on social media.

References:

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