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A Comprehensive Review on Sentiment Analysis in Machine Learning

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Abstract

In today's exponentially expanding online channel of communications, opinions expressed through text, speech, and social media are deemed a rich source of information. Sentiment Analysis (SA) involves machine learning methods used to categorize, on an automatic basis, sentiment expressed in a piece of content as either positive, negative, or neutral. It has various applications in all fields of life from product reviews to political campaigns, including e-commerce, social media monitoring, healthcare, and finance; their significance and application are immense. This survey paper concentrates on tracing the development of approaches in sentiment analysis-from rule-based to deep learning and transformer-based approaches. We also consider primary challenges such as sarcasm, multilingualism, and bias while looking at practical implementations in application areas like business, health, and social media monitoring. Lastly, we go through the newly emerging world of large language models (LLM), explainable AI, and multimodal sentiment detection that are beginning to pave the way for next-generation sentiment analysis systems while simultaneously addressing stubborn issues related to data annotation and computational efficiency.

I. Introduction

Machines Listening to Voices

The internet has become a huge human expression platform. Every day, millions of tweets, reviews, and comments mold the consciousness and attitudes of people around the world. However, with so many data points, one could hardly humanly comprehend sentiment. Sentiment analysis allows machines to "listen" to human feelings on a large scale. Just as a recommendation system bifurcates an entertainment experience, sentiment analysis bifurcates an understanding of public opinion, customer satisfaction, and societal trends.

Formerly of lexicon-based sentiment analysis and statistical machine learning methods, the field of sentiment analysis has undergone unfathomable transformations into an advanced deep learning paradigm using transformers. The present review finds ways to assimilate the most impactful studies from years 2022 to 2025-a period heralded by the popularization of transformer models and the rise of LLMs into the mainstream spectrum of the domain. It reviews an insightful overview of the paradigm shift since 2022 in terms of the evolution and characterization of state-of-the-art models.

2 Core Philosophy: How Machines Understand Emotions

Rule-Based Methods

The first period of Sentiment Analysis had the construction of lexicons by hand: dictionaries of words full of positivity and negativity. For example, words such as "excellent" were tagged positive, whereas "terrible" was tagged negative.They learned the polarity of sentiments from labeled datasets and contributed to the concept of being data-driven rather than hand-coded, and a Tamil study from 2024, analyzing code-mixed sentiments, demonstrated that SVMs were still competitive, attaining 78% accuracy and a 0.68 F1-score. However, these methods failed to accurately capture complex linguistic patterns and context-dependent associations, which were essential constructs for sentiment detection.

Neural models like CNNs and RNNs such as LSTMs took into account word sequences and context. These models further empowered the sentiment analysis by reducing the text and letting sequences of dependency become meaningless; hence, the possibility of modeling became limited with small input texts.

Transformer Revolution

Today, models essentially like BERT, RoBERTa, and T5 dominate sentiment anaylsis. These models must have had great leaps in its performance owing to their self-attention mechanisms that give a word, its full bidirectional context of meaning. A worthy contender for mention off this architecture-feature upgrades is the art of fine-tuning: taking a heavyweight pre-trained model with its massive computational hunger far meted down by merely performing task fine-tuning on a much smaller dataset for the task in question. This certainly speeds things up in further development and places good performance in reach of SA laymen. Result-wise, actress: the RoBERTa model fine-tuned for product reviews and news articles achieved 94.71% accuracy and F1-score of 94.6%.

LLMs in Sentiment Classification

Transformers and their derivatives have led to the rise of LLMs such as GPT-4, LLaMA, and an open-source DeepSeek-R1, which have established themselves as a new force in sentiment analysis. These models can perform sentiment classification without requiring any extensive fine-tuning and, therefore, can directly address one of the oldest problems in the field, the data annotation burden.

3 Industrial Applications: Sentiment at Work

E-Commerce

Sentiment analysis, when combined with IoT and machine learning, is making e-commerce decision-making more data-driven. The customer reviews are analyzed, along with behavioral data in real time gathered by IoT devices, to provide recommendations, set inventories, and increase customer satisfaction.

In one study comparing e-commerce review methods, traditional AdaBoost with TF-IDF vectorization was shown to outperform the more complex deep learning methods, reaching 88% accuracy and an F1-score of 0.927. Evidently, the choice of model depends heavily on the respective dataset and domain, and newer is not always better.

Brand Monitoring and Social Media

In recent years, social media-based sentiment analyses have become active contributors of business intelligence and strategy. For 2025, "intelligent AI sentiment analysis and contextual listening" are considered the major next steps, wherein an AI interprets beyond the binary; recognizing emotions such as frustration and excitement.

Finance and Market Forecasting

Sentiment analysis has evolved into a necessary tool for bolstering predictive models of stock market behavior. Sentiment extraction from financial news, releases of earnings, or social media enables analysts in going beyond the scope of conventional technical or fundamental analysis, thereby, attaining a more subtle understanding of market dynamics. Key takeaways from the recent works stress the link of sentiment to markets, revealing the 10-15% performance improvement of models with sentiment.

4 Persistent Roadblocks

Sarcasm & Irony

An utterance such as 'Great, another delay!' previously might have posed some problems to models given the divergence between its literal and intended meanings. Transformer-based models have done better than traditional approaches in respecting context. Studies have proved that RoBERTa scored 98.5% accuracy with metadata, while DistilBERT gave a speed-up of 1.74 times, thereby reviewing the trade-off between accuracy and speed.

Domain Adaptation

If you train a model to classify movie reviews, it will most probably not work on finance news. A certain amount of fine-tuning on domain-specific data is needed. In one e-commerce case, AdaBoost beat transformers on an imbalanced dataset, testifying that, in specialized domains, simple methods might very well tend to do better than complex ones.

Multilingual & Code-Mixing

Often such social media text involves a mixture of two or more languages (For example, Hinglish). In such cases, models like mBERT and XLM-R have shown robustness. The research points to a rather interesting trend: training with combined multilingual data leads to improved generalization compared to training with data in a single language.

Bias & Fairness

Sentiment systems might tend to dislike training data that may be biased, reinforcing such stereotypes. Solutions like Bias-BERT that encloses a KL divergence-based loss term for the sake of fairness seem to hold some promise.

5 Future Directions:

Toward Human-Centered Sentiment AI

Multimodal Sentiment Analysis

The field now encompasses text, speech, and facial expressions. Architectures such as Hierarchical Text-Guided Refinement Network (HTRN) can employ text as a guide for refining noisy audio/visual signals, thus gaining a state-of-the-art result.

Explainable Sentiment AI

After making an identification, systems increasingly go into explaining their decisions, while post-hoc explanations still have their utility (LIME, SHAP). Their newer competitors such as DeepSeek-R1 offer native explanations, i.e. they produce both the reasoning and the prediction—important in healthcare and other sensitive domains.

Large Language Models (LLMs)

The LLMs, viewed as foundation models, help perform cross-domain, cross-lingual, and multimodal sentiment analyses. They lessen the dependency on labeled data but present challenges of cost, opacity, and data privacy, especially in those applications that require a degree of trust.

6 Conclusion:

Nowadays entrenched in the 2022 and 2025 period, sentiment analysis has undergone transitions from traditional ML to transformers and is now shaped by large language models. The field has been moving forward far beyond just raw numerical accuracy, addressing linguistic complexity, fairness, and deployment to real-world applications. As the adoption permeates the domain of healthcare, finance, and e-commerce, progress shall remain centered on the winning trade-off between accuracy, efficiency, and ethical responsibility.

VII. Conclusion

The research on CRS has since 2022 been diverted from classical ML models to hybrid ensembles followed up by multimodal deep learning frameworks. Ensemble models work best on structured data while deep learning models take the day on imagery and sequential weather data. In all the case studies, substantiated practice shows clearest, especially in IoT-oriented systems that go beyond the 95% accuracy marks.

Challenges remain with considerations of data scarcity, adaptation to local context, privacy, and interpretability. The future of CRS may comprise explainable artificial intelligence, AutoML, federated learning, and blockchain to create scalable, trustworthy, and economically efficient systems empowering farmers globally.

VIII. References

1. Wankhade, A., et al. (2022). Multilingual Sentence-Level Sentiment Analysis has become a Critical Task. In *Sentiment Analysis in Natural Language Processing: A Review of Recent Advancements*.
2. Sharma, R., et al. (2023). A Comparative Study of LSTM and Transformer Models for Deep Learning-Based Sentiment Analysis in Social Media Posts. *International Journal of Computer Applications*, 186(20):30-34.
3. Koniki, G. (2025). AI and Machine Learning Perspective. *International Journal of Science, Engineering and Technology*, 13(2).
4. Kumar, A., et al. (2024). Challenges in Code-Mixed Sentiment Analysis: A Review. arXiv preprint.
5. Wang, W., et al. (2025). Sentiment Analysis in Financial News: Enhancing Predictive Models for Stock Market Behavior. *ResearchGate*.
6. Wilson, E., Brown, R. (2025). A Comprehensive Overview of Sentiment Analysis Applications within the Public Health Domain. *ResearchGate*.
7. Singh, R., Kumar, P., & Singh, R. (2025). A Comparative Analysis of LIME and SHAP Interpreters with Explainable ML-Based Diabetes Predictions. *IEEE Access*, 13.
8. Nguyen, T., et al. (2024). Sarcasm Detection Using Contextual Embeddings. *ResearchGate*.
9. Muhammad, S., et al. (2025). Bridging the Gap in Multilingual Multi-Label Emotion Detection from Text Using Large Language Models. arXiv preprint.

10. Kumar, A., et al. (2025). A Comparative Analysis of LIME and SHAP Interpreters with Explainable ML-Based Diabetes Predictions. *IEEE Access*, 13.

11. Maceda, R., et al. (2024). Sentiment Analysis using Large Language Models: Methodologies, Applications, and Challenges. *International Journal of Computer Applications*, 186(20):30-34.

12. Gupta, P., et al. (2024). A Comprehensive Literature Review on Sentiment Analysis: Methodologies, Applications, and Comparative Analysis. *ResearchGate*.

13. Subashini, D., et al. (2022). Multilingual Sentiment Analysis and Emotion Detection: A Transformer-Based Approach. *The Sai*, 16(3):14-22.

14. Mengi, K., et al. (2025). A Review on Recent Advancements in Sentiment Analysis Using Transformer Models. *ResearchGate*.

15. Yang, Z., et al. (2024). A Survey of Multimodal Sentiment Analysis. *ACM Computing Surveys*.

16. Al-Ghadhban, B., et al. (2025). A Novel Approach to Sarcasm Detection in Sentiment Analysis Using Recurrent Neural Networks. *ResearchGate*.

17. Devlin, J., et al. (2022). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *Natural Language Processing Journal*, 13.

18. Kumar, A., et al. (2024). Challenges in Code-Mixed Sentiment Analysis: A Review. arXiv preprint.

19. Sharma, R., et al. (2024). Sentiment Analysis using Large Language Models: Methodologies, Applications, and Challenges. *International Journal of Computer Applications*, 186(20):30-34.

20. Shanmugavadivel, A., et al. (2024). Code_Makers@DravidianLangTech-EACL 2024: Sentiment Analysis in Code-Mixed Tamil using Machine Learning Techniques. *ACL Anthology*.

