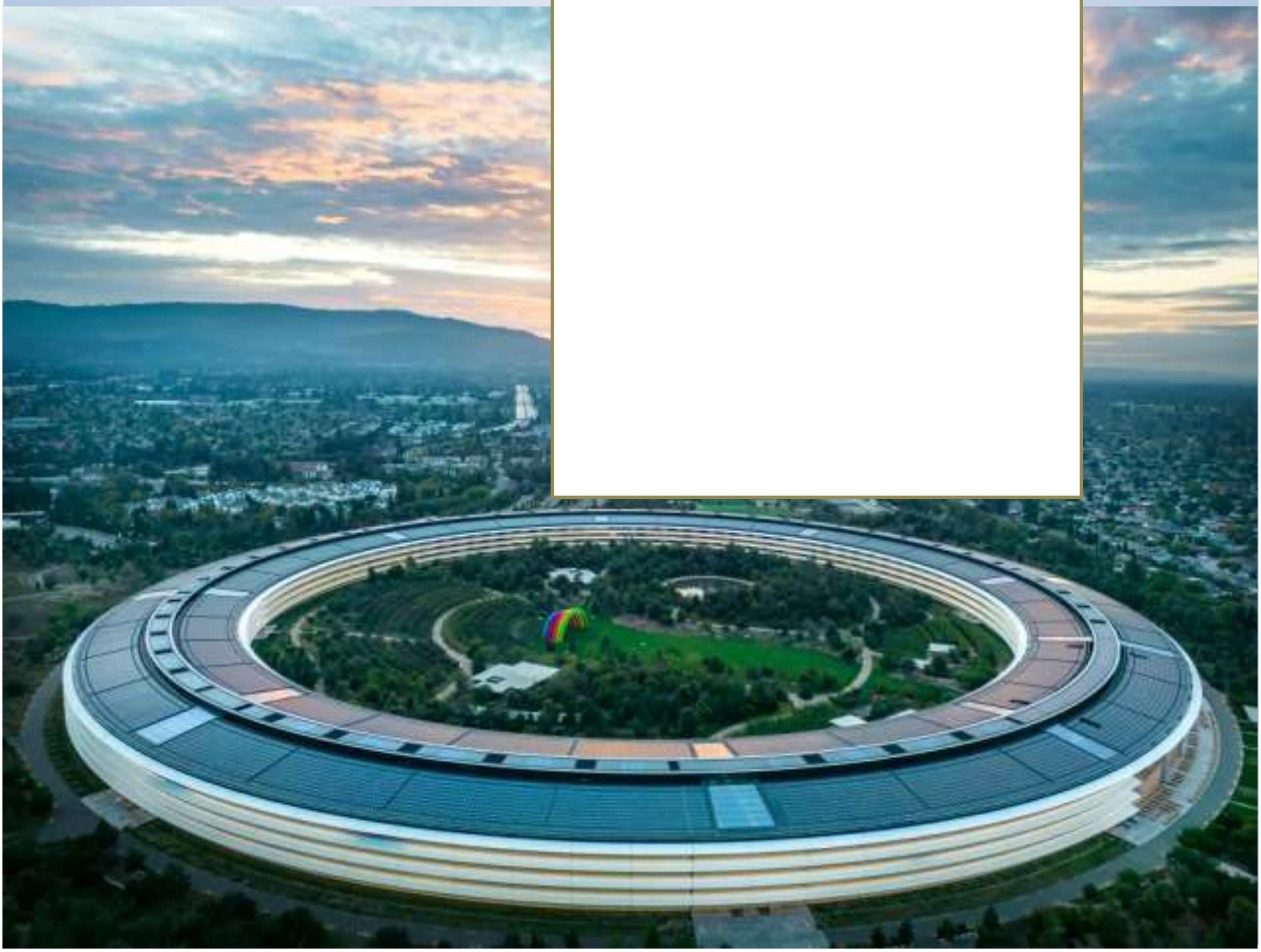
Silicon Valley Tech Review
Vol 1, No 1 (2022), Pages 35-47

Sentiment Analysis in IoT Data Streams: An NLP-Based Strategy for Understanding Customer Responses

Aditya Manikyala



Received on: 19 June 2022, **Revised on:** 02 August 2022, **Accepted on:** 14 August 2022, **Published on:** 25 August 2022

Cite as: Manikyala, A. (2022). Sentiment Analysis in IoT Data Streams: An NLP-Based Strategy for Understanding Customer Responses. *Silicon Valley Tech Review, 1*(1), 35-47.

Sentiment Analysis in IoT Data Streams: An NLP-Based Strategy for Understanding Customer Responses

Aditya Manikyala

Java AWS Developer, Dynamic Technology Inc., Ashburn, VA 20147, USA

Corresponding Contact:
Email: Aditya.manikyalaa@gmail.com

8/25/2022

Source of Support: None.
Conflicts of Interest Statement: No conflicts of interest have been declared by the author(s).

ABSTRACT

This research uses NLP to analyze IoT data streams for sentiment analysis to understand and react to consumer emotions and actions in real-time. This study investigates how NLP can handle multi-modal IoT data, including text, speech, and sensor measurements, to discover sentiment indicators and deliver customer satisfaction insights. The research addresses the problems of incorporating real-time sentiment analysis into IoT contexts via a secondary data assessment, including data volume, velocity, and multi-modal model computational complexity. The key results include multi-modal data integration, real-time processing frameworks, and edge computing for sentiment analysis. Contextual sensitivity and model improvement methods like distillation also improve sentiment accuracy. The paper also emphasizes explainability in AI models, particularly in sensitive applications, and recommends clear, ethical frameworks to protect data privacy and user trust. Policy implications show that IoT settings require strong data privacy and AI transparency policies to protect consumer data and promote ethical usage of AI-driven sentiment analysis technology. The study indicates that NLP-based sentiment analysis may improve IoT customer experience by providing real-time, data-driven insights into user preferences and behaviors.

Key words:
Sentiment Analysis, IoT Data Streams, Natural Language Processing (NLP), Customer Response, Real-Time Sentiment Detection, Multi-Modal Data, Edge Computing

INTRODUCTION

The Internet of Things (IoT) connects billions of devices worldwide and creates real-time, highly detailed data streams, changing how companies gather, analyze, and use data. IoT use is growing exponentially, giving companies across sectors a wealth of data on user interactions, preferences, and experiences (Ahmmed et al., 2021; Deming et al., 2021; Kommineni, 2020). These massive amounts of IoT data must be used to gather and interpret consumer attitudes as companies become more customer-centric (Devarapu et al., 2019). Processing this data to get valuable insights—especially about consumer emotions, preferences, and concerns—is difficult. NLP-based sentiment analysis can comprehend consumer replies in IoT data streams (Gade, 2019; Kundavaram et al., 2018).

NLP sentiment analysis extracts and classifies opinions, emotions, and subjective information from text. Initially used for organized feedback like customer reviews and social media postings, sentiment analysis is now used for unstructured and semi-structured IoT data (Gade et al., 2021; Kothapalli et al., 2019). Retail and automotive IoT devices may provide use records, voice conversations, or sensor data to indicate consumer pleasure. Businesses may improve customer experiences, develop goods, and anticipate difficulties using NLP-based sentiment analysis to understand client demands in real-time (Gummadi et al., 2020).

Sentiment analysis in IoT data streams has many obstacles. First, high-velocity, multi-modal, and continually created IoT data requires real-time or near-real-time processing for timely insights. Second, IoT data lacks clear, structured input like conventional sentiment analysis programs; instead, sentiment is inferred from indirect indications like natural language data via voice interfaces, chatbots, and intelligent assistants. In IoT contexts, sentiment analysis must account for context since environmental characteristics, user history, and other external circumstances might affect sentiment (Gummadi et al., 2021; Karanam et al., 2018; Kommineni, 2019; Roberts et al., 2020; Rodriguez et al., 2020; Talla et al., 2022; Onteddu et al., 2020; Richardson et al., 2021; Kommineni et al., 2020). These problems demand unique data preparation, model training, and deployment methodologies for continuous, context-aware analysis.

Deep learning, transformer-based models, and other machine learning and NLP advances have greatly enhanced sentiment analysis. BERT, GPT, and domain-specific extensions capture complex verbal patterns and contextual relationships for nuanced sentiment identification. These state-of-the-art models must be adapted to accommodate IoT-specific data restrictions such as restricted on-device processing, intermittent connection, and the necessity for lightweight, energy-efficient algorithms. Despite these obstacles, NLP-driven sentiment analysis in IoT systems has great promise. Businesses may acquire a more comprehensive and dynamic view of their consumers by improving sentiment extraction from customer-facing IoT data.

This paper discusses an NLP-based sentiment analysis technique for IoT data streams that addresses particular problems and maximizes user insights. We examine several NLP tool integration methods with IoT systems to give a complete framework for real-time customer answers and customer-centric decision-making. The article will apply these findings to consumer electronics, automotive, retail, and smart home applications, where customer sentiment may directly affect product development and service improvement. This investigation advances IoT-driven sentiment analysis as a novel option for improving customer experience in the IoT age.

Statement of the Problem

The integration of IoT technology into consumer goods and services has changed customer involvement in recent years. Companies may gather data from billions of linked devices to understand consumer preferences and activities. IoT has great potential, but deriving meaningful, sentiment-rich insights from raw data streams still needs to be mature (Thompson et al., 2019). IoT data is large, real-time, and typically unstructured, making it difficult to evaluate. The gap between IoT data insights and processing technologies has prevented IoT from comprehensively improving consumer experience.

Most sentiment analysis methods have focused on structured text sources like social media postings, product reviews, and survey replies, which are easy to interpret and categorize. Speech, behavioral signals, and device status logs are new unstructured or semi-structured IoT data forms requiring novel analytic methods (Venkata et al., 2022). These signals may include sentiment information but lack unambiguous indicators like text-based feedback. Understanding innovative assistant voice requests or connected appliance use patterns might suggest contentment or dissatisfaction, but it needs context-aware analysis. New models and techniques must be efficient, scalable, and context-sensitive to manage rapid, continuous IoT data streams. Traditional sentiment analysis algorithms need help to adapt (Talla et al., 2021).

This work develops an NLP-based sentiment analysis technique for IoT data streams to fill the research gap. This work investigates sentiment inference from various and dynamic IoT data sources, unlike standard sentiment analysis, which uses structured language inputs. This requires creating algorithms to interpret and categorize sentiment from unstructured data like speech recordings, sensor measurements, and use patterns. Given the temporal nature of IoT data, real-time or near-real-time analysis will be a priority to get insights and enable customer-centric solutions.

This research might turn IoT data into a strategic tool for customer experience analysis and improvement. This study advances sentiment analysis approaches for IoT devices, addressing the knowledge gap in processing and understanding IoT data streams. As organizations increasingly use IoT technology to communicate with customers, real-time sentiment recording and response will provide them a competitive edge. This research also benefits consumer electronics, automotive, retail, and smart home technology businesses where client sentiment is crucial to service delivery.

This study addresses a significant gap in sentiment analysis by concentrating on IoT data, which has usually been ignored. Thus, this work shows how NLP may be adapted and developed for IoT-based consumer sentiment analysis to progress in both domains. This research develops practical frameworks and algorithms to help businesses maximize IoT data, transforming customer interactions and providing deeper, data-driven insights into customer preferences and satisfaction.

Methodology of the Study

This secondary data-based research synthesizes sentiment analysis, NLP, and IoT data processing literature and advances. It reviews earlier research, theoretical frameworks, and contemporary implementations to understand how sentiment analysis may be applied to IoT data streams. NLP models for unstructured data, real-time sentiment extraction from high-velocity data streams, and IoT contextualization difficulties are examined. A complete evaluation using peer-reviewed publications, conference proceedings, and technical papers on NLP algorithms, sentiment analysis, and IoT analytics. NLP for speech, sensor data, and behavioral analytics studies are emphasized to identify IoT-specific gaps and trends. NLP-based sentiment analysis is used to uncover proven methods and research paths that improve customer experience insights from IoT data.

FOUNDATIONS OF SENTIMENT ANALYSIS IN IOT DATA

Internet of Things (IoT) devices have generated unprecedented data that may reveal user habits, preferences, and emotional reactions. Sentiment research may help firms analyze client experiences and customize offerings. Due to the nature of IoT data, sentiment analysis in IoT data streams differs from structured text from social media postings, reviews, or polls. This chapter discusses the sorts of data used in IoT sentiment analysis, the applicability of Natural Language Processing (NLP) to these situations, and the unique problems and needs for evaluating this data (Park et al., 2018).

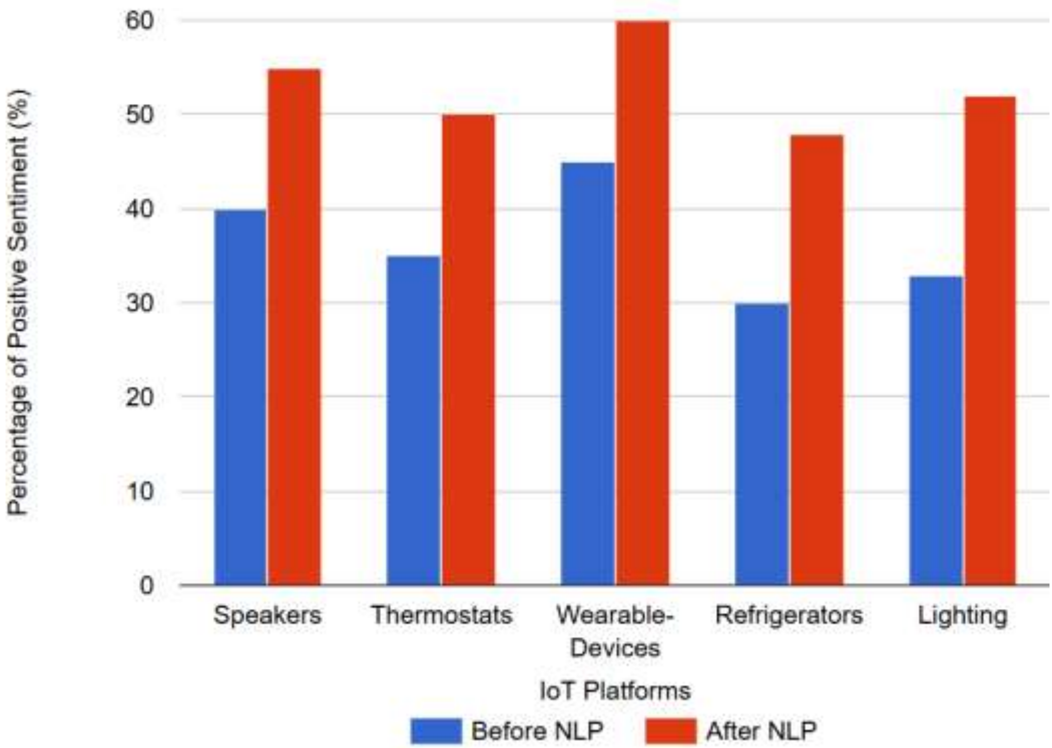


Figure 1: Positive Sentiment Analysis Results Before and After NLP Implementation

This double-bar graph in Figure 1 shows the proportion of favorable sentiment found on five IoT platforms—smart speakers, smart thermostats, wearable technology, smart refrigerators, and bright lighting—before and after using NLP methods. The comparison shows how NLP enhances the ability to detect positive sentiment in user interactions with various IoT devices.

Sentiment analysis, a branch of NLP, classifies textual views and feelings as positive, negative, or neutral. NLP has proved effective in text-based applications like product evaluations and social media comments where opinions are explicit. Sentiment analysis for IoT data must go beyond textual expressions to infer sentiments from other data kinds. Sensor measurements, device logs, user interactions, voice commands, and ambient elements might indicate consumer happiness or displeasure. A rise in smart thermostat temperature readings may indicate user discomfort, while repeated voice requests to an intelligent assistant may indicate device response irritation. These signals, however less direct than text-based feedback, might indicate sentiment if analyzed properly (Jarwar et al., 2017).

NLP approaches are essential for processing complex, multi-modal data in IoT environments, including behavioral or sensor-based sentiment indicators. Modern NLP models can capture linguistic and contextual subtleties in text input, especially deep learning architectures like CNNs, RNNs, and transformers like BERT or GPT. Using transfer learning and fine-tuning, these models may extract sentiment-related variables in non-traditional forms for IoT data. CNNs identify patterns in time-series sensor data, whereas transformer models interpret speech interaction text. Due to their versatility, these algorithms can recognize emotion cues in textual and non-textual IoT data (Tutubalina & Nikolenko, 2018).

Due to IoT data's unique properties, sentiment analysis with IoT data is complex. IoT data is high-volume and fast, requiring real-time or near-real-time processing to get meaningful insights. Computer models that can handle streaming data are needed since IoT devices create data continually. Streaming data processing frameworks and edge computing may be better than batch-based sentiment analysis techniques. IoT data is multi-modal; therefore, sentiment analysis systems must combine text, voice, and sensor data into a single framework to interpret context-specific sentiment indicators (Noori & Maktoubian, 2019).

To overcome these problems, IoT-based sentiment analysis must create strong, context-aware models to manage varied data sources and real-time data processing. Researchers may improve IoT sentiment analysis accuracy and relevance by integrating NLP models with edge-based sentiment categorization and adaptive model retraining. As IoT technologies advance, sentiment analysis in this sector must be strengthened to support customer-centric initiatives that use fast, data-driven insights on customer responses and experiences.

NLP Techniques for Real-Time Sentiment Detection

Real-time sentiment recognition is essential for organizations seeking to increase customer happiness and user experience as IoT devices create data. Advanced NLP algorithms are needed for real-time sentiment analysis in IoT environments to handle high-velocity, multi-modal input and provide sentiment insights rapidly enough to inspire response actions (Mallipeddi, 2022; Narsina et al., 2019). We examine the major NLP approaches and tactics for real-time sentiment detection, their adaption for IoT data streams, and the difficulty of obtaining fast, accurate sentiment categorization in such dynamic situations.

NLP models must handle and interpret IoT device data, such as voice commands and chat inputs, and use trends and biometric or environmental sensor data for real-time sentiment identification. NLP models like CNNs, RNNs, and transformers like BERT and GPT have shown promise in evaluating sentiment in conventional text sources, but IoT data is continuous and context-rich. NLP-based speech-to-text conversion and sentiment analysis pipelines can handle sentiment data from IoT devices with voice interfaces like smart speakers and virtual assistants. NLP models can identify customer irritation, happiness, and bewilderment in real-time by transcribing spoken requests and classifying the generated text. This allows service replies to be adjusted immediately (Wang & Youn, 2019).

Transformers like BERT and GPT can capture contextual subtleties and analyze complicated language connections, making them ideal for real-time sentiment analysis in IoT data streams. These algorithms can detect tiny emotional signals by focusing on important content.

Transformers are computationally demanding, making real-time processing difficult in IoT applications where data must be handled on-device or at the edge to reduce latency. Distillation, which compresses huge transformer models into smaller, quicker ones without losing accuracy, is an efficient transformer deployment method in IoT contexts. DistilBERT, a distilled variant of BERT, balances computational economy and model performance for speedier real-time sentiment detection on low-resource platforms (Sabra et al., 2018).

Table 1: Comparison of NLP Sentiment Detection Models

Model	Training Time	Inference Speed	Memory Usage	Real-Time Suitability
Naive Bayes	Low	Very Fast	Low	High (suitable for simple tasks)
SVM (Support Vector Machine)	Moderate	Moderate	Moderate	Moderate (limited in high-volume IoT applications)
LSTM (Long Short-Term Memory)	High	Slow	High	Low to Moderate (suitable with optimizations)
BERT (Bidirectional Encoder Representations from Transformers)	Very High	Moderate to Slow	Very High	Moderate to Low (suitable only with edge computing or optimization)
Logistic Regression	Low	Fast	Low	High (suitable for fundamental sentiment analysis)
RoBERTa	Very High	Moderate to Slow	Very High	Low (challenging for real-time applications)
FastText	Low	Fast	Moderate	High (ideal for real-time, low-latency environments)
TextBlob (Rule-Based)	Very Low	Very Fast	Very Low	High (suitable for lightweight real-time applications)

Table 1 shows model alternatives based on application needs, such as processing power and sentiment data complexity.

Naive Bayes and Logistic Regression suit real-time IoT applications that value simplicity and speed above model depth.

FastText is fast and accurate for real-time emotion recognition with moderate memory.

BERT and RoBERTa are accurate but need much processing power and memory, making them unsuitable for real-time applications.

LSTM models are suitable for sequential data processing but may impede inference in high-volume IoT data streams.

Continuous data processing and low-latency analysis using streaming data frameworks like Apache Kafka and Apache Flink are promising for real-time sentiment analysis in IoT. These frameworks and NLP models allow sentiment analysis systems to handle IoT data streams as they come, eliminating batch processing delays. NLP models may be linked into real-time data pipelines to identify sentiment indicators that need quick attention using these frameworks.

In IoT sentiment analysis, multi-modal data needs complex NLP approaches to combine text, voice, and sensor signals. Multi-modal models may simultaneously assess different kinds of data to provide a comprehensive perspective of user sentiment. A sentiment detection algorithm may utilize voice sentiment and behavioral data like frequent device resets to assess user displeasure with a device function. Multi-modal transformers and attention processes help the model integrate various inputs for better sentiment interpretation (Wang et al., 2018).

Finally, memory, processing power, and networking issues complicate NLP model deployment in IoT applications. Edge computing, which processes data locally rather than on cloud servers, is critical for real-time IoT sentiment detection. When initial sentiment analysis is done locally on the device or adjacent edge nodes, latency is decreased, and user reactions are rapid. Edge computing enables sentiment analysis to continue independently while the connection is interrupted, syncing with cloud resources for model updates or more advanced processing.

NLP must balance accuracy and computational efficiency to identify real-time sentiment in IoT data streams. Distillation, streaming data framework integration, and edge computing may let these NLP models gather consumer sentiment in real-time. Real-time NLP-based sentiment detection in IoT devices might change consumer interactions by making proactive, sentiment-driven modifications that boost user pleasure and engagement.

Challenges and Future Directions in IoT Sentiment Analysis

The sentiment analysis problems for IoT data streams go beyond text-based sentiment analysis. Due to IoT data's amount, pace, and diversity, adopting NLP approaches to this domain requires solving technological, operational, and contextual issues. Despite these challenges, NLP and machine learning are enabling IoT sentiment analysis. This chapter examines IoT sentiment analysis's main difficulties and prospects that might improve sentiment detection and analysis in real-time, customer-facing applications (Xie et al., 2018).

Managing IoT device data's volume and velocity is a significant difficulty in sentiment analysis. In an extensive IoT network, devices continually communicate data, which must be analyzed in real-time to get insights. Traditional batch-processing sentiment analysis algorithms cannot handle such data streams quickly enough to provide timely insights. This challenge highlights the need for advanced streaming data processing frameworks like Apache Kafka and Apache Flink to process large volumes of IoT data in real-time. However, these frameworks must be integrated with NLP models to ensure accuracy without compromising speed.

IoT data's multi-modality is another issue. IoT sentiment analysis must analyze voice commands, biometric measurements, environmental sensor data, and behavioral signals like device use trends, unlike conventional sentiment analysis, which uses textual input. These data formats may include implicit user sentiment indicators, but interpreting them in a unified model needs extensive multi-modal fusion. Multi-modal transformer models and cross-modal attention processes are promising answers, but computational restrictions make real-time analysis difficult, especially on edge devices with low resources (Wang et al., 2018).

This stacked bar graph in Figure 2 shows the distribution of the main obstacles that five IoT systems must overcome—privacy concerns, latency difficulties, interpretability limitations, and data volume constraints. Each bar represents an IoT platform, with segments indicating the percentage of each difficulty. This graphic illustrates common difficulties on specific platforms, such as increased data volume issues in smart cities and privacy concerns in healthcare IoT.

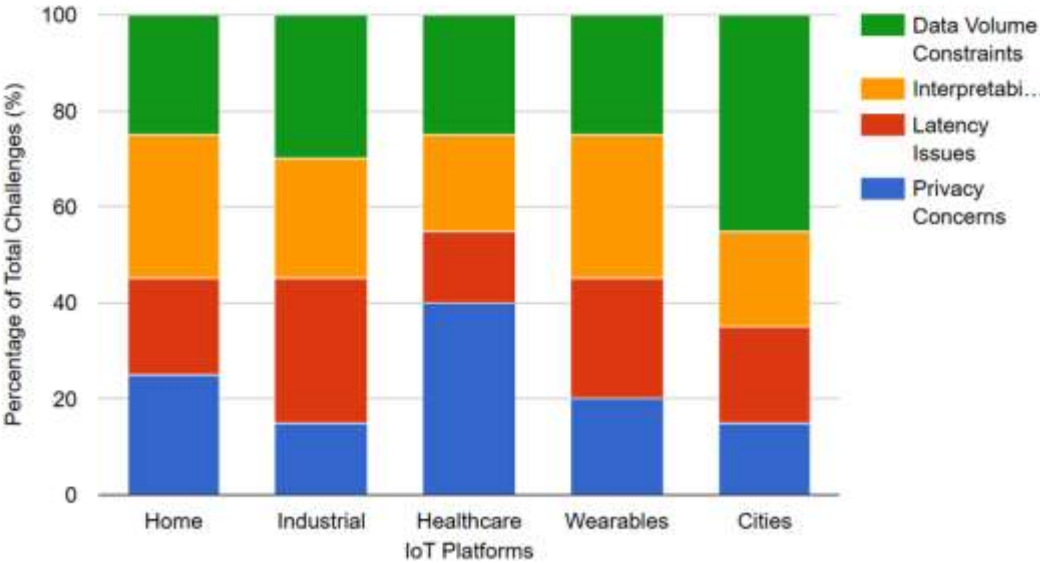


Figure 2: Composition of Challenges in IoT Sentiment Analysis across Platforms

IoT sentiment analysis also faces contextual sensitivity issues. IoT data sentiment is modified by time, location, user history, and external environmental circumstances. Customers may feel differently about linked appliances based on the time of day or season. Accurate sentiment classification requires contextually aware sentiment analysis models, but integrating them into NLP models, particularly in real-time, is difficult. Recurrent neural networks (RNNs) and context-aware embeddings are promising temporal dependency capture methods, but more research is required to integrate them into IoT systems (Alam & Yao, 2018).

Edge computing might improve IoT sentiment analysis in the future. Process data closer to IoT devices at the edge to minimize latency and do sentiment analysis without cloud access. This is crucial in low-bandwidth or intermittent network conditions. NLP models on edge devices must be lightweight and efficient owing to limited computing power and memory. Model compression methods like distillation and quantization will enable edge-based IoT sentiment analysis (Chen et al., 2018).

Advanced multi-modal architectures are another critical area. Future models may combine text, voice, and sensor data for more accurate and extensive sentiment insights. Voice sentiment, environmental data, and device use patterns may give a comprehensive perspective of consumer happiness, enabling organizations to adapt to user experience adjustments proactively. Multi-modal transformers and hybrid neural networks are intriguing, but more study is required to make them real-time-efficient.

Finally, explainable AI drives sentiment analysis models that categorize and explain decision-making. Explainability helps boost user confidence in IoT applications, especially in sensitive fields like healthcare and finance, where IoT sensors are widely deployed. Creating sentiment analysis models with interpretable insights helps users and developers understand sentiment categorization and ensures they meet user expectations and ethical standards.

NLP, machine learning, and edge computing technologies may help IoT sentiment analysis overcome data velocity, multi-modality, contextual sensitivity, and computational restrictions. Future research in sentiment analysis may enable real-time, customer-centric IoT applications and improve enterprises' customer understanding and response.

Major Findings

Sentiment analysis on IoT data streams combines NLP and IoT technologies to help businesses understand and respond to customer emotions and preferences in real-time. Several significant discoveries have arisen from integrating previous research and developing trends in this domain, illustrating both the progress gained and the obstacles in applying sentiment analysis to IoT data. These results demonstrate how NLP may be utilized to get insights from varied IoT data sources and enhance consumer experiences.

Multi-Modal Data Integration Matters: It was found that IoT sentiment analysis involves multi-modal data integration, including text (voice commands and user interactions), sensor data (temperature, use patterns), and environmental elements. NLP models developed for text data must be modified to accommodate IoT streams' heterogeneous, unstructured, and indirect signals. This requires complex multi-modal models that simultaneously evaluate textual and non-textual input and identify speech, behavior, and sensor patterns to estimate consumer sentiment reliably. Text-based NLP hybrid models with sensor data processing and behavioral analysis seem promising for this integration.

Real-Time Processing is a Key Challenge: This research recognized real-time sentiment recognition as a significant difficulty. Continuous, high-velocity IoT data streams need NLP capabilities to analyze data as it is created. Traditional batch-processed sentiment analysis approaches need to be revised for real-time IoT analysis. To allow instant sentiment categorization, Apache Kafka and Apache Flink, which handle high-speed data, must be coupled with NLP models. Research and development must focus on low-latency processing while maintaining accuracy.

Edge Computing Improves Real-Time Sentiment Analysis: Edge computing's potential to solve real-time sentiment analysis problems is exciting. Organizations may cut latency and get sentiment insights quickly by processing data on devices or edge nodes. In distant or bandwidth-constrained IoT contexts, edge-based processing is crucial. Lightweight NLP models on edge devices enable real-time sentiment detection without cloud computing, improving sentiment analysis efficiency and responsiveness.

Contextual Sensitivity Enhances Accuracy: Another result is that sentiment analysis requires contextual awareness. Time of day, user history, and external variables affect IoT customer sentiment. An intelligent appliance user's irritation may differ by location, such as home or work. Thus, contextually-aware sentiment models are necessary for correct sentiment categorization. Recurrent neural networks (RNNs) and attention mechanisms, which capture temporal and contextual correlations, improve sentiment accuracy in dynamic, real-world IoT applications.

Challenges with Multi-Modal Model Deployment: Although multi-modal data for sentiment analysis has advanced, applying these models in real-world IoT applications takes time and effort. While promising, multi-modal transformers are computationally demanding and challenging to execute on resource-constrained IoT devices. These models must be optimized for real-time applications via distillation and quantization. Scaling multi-modal sentiment analysis in IoT contexts requires balancing model complexity and resource efficiency, which is still being studied.

Explainability in Sentiment Analysis Models is Crucial: Explainable AI (XAI) is becoming more critical in IoT sentiment analysis. Transparent and interpretable models build trust with end users and developers as organizations employ sentiment information to steer customer interactions. Ethical and responsible usage of AI technology in IoT systems requires the capacity to explain sentiment classifications, particularly in sensitive fields like healthcare and finance.

This research found that applying sentiment analysis to IoT data streams presents problems and potential for innovation. Multi-modal data, real-time processing, edge computing, contextual sensitivity, and model explainability improve IoT sentiment detection accuracy and efficacy. Real-time sentiment analysis will shape customer experience in the IoT age as these technologies develop to boost customer happiness and promote proactive service enhancements.

Limitations and Policy Implications

Despite its potential, sentiment analysis in IoT data streams has some drawbacks. Real-time processing is complex, especially in high-data-velocity contexts with limited computing resources. NLP model integration with IoT systems involves significant infrastructure, which may need to be more practical for small or resource-constrained enterprises. Multi-modal sentiment analysis is functional yet computationally demanding, making it challenging to implement on edge devices with low processing capacity. Finally, contextual intricacies of sentiment detection, impacted by external influences, make sentiment categorization difficult and biased. Policy-wise, NLP-based sentiment analysis in IoT contexts demands data protection and ethical norms. GDPR requires organizations to anonymize and safeguard user data. AI algorithms must be transparent and explainable to build confidence and use consumer data ethically.

Conclusion

IoT data stream sentiment analysis using NLP is a revolutionary way to analyze and react to real-time consumer emotions and actions. As IoT devices multiply and provide massive volumes of data, the opportunity to understand consumer happiness, preferences, and complaints has never been more significant. NLP algorithms are improving in interpreting complex, dynamic user sentiment signals by integrating text, speech, and sensor data. Applying NLP to IoT data takes a lot of work. Real-time analysis, high data velocity, and volume need modern streaming data frameworks and edge computing solutions. Additionally, multi-modal sentiment analysis models' computational needs, particularly on resource-constrained devices, require model optimization approaches like distillation and quantization. Sentiment recognition accuracy depends on contextual sensitivity, which requires models to adapt to different user contexts and scenarios. Despite these obstacles, IoT sentiment analysis has great potential. With advances in NLP, machine learning, and edge computing, firms may gain consumer knowledge and provide more customized, proactive service. As sentiment analysis tools become more common, authorities must address ethical issues, including data privacy, transparency, and model explainability, to promote trust and responsible AI usage in IoT contexts. The future of consumer experience will depend on NLP and IoT.

References

Ahmmed, S., Narsina, D., Addimulam, S., & Boinapalli, N. R. (2021). AI-Powered Financial Engineering: Optimizing Risk Management and Investment Strategies. Asian Accounting and Auditing Advancement, 12(1), 37–45. https://4ajournal.com/article/view/96

Alam, S., Yao, N. (2018). Probabilistic Neural Network and Word Embedding for Sentiment Analysis. *International Journal of Advanced Computer Science and Applications*, *9*(7). https://doi.org/10.14569/IJACSA.2018.090708

Chen, H., Du, L., Lu, Y., Gao, H. (2018). Improved Convolutional Neural Network for Chinese Sentiment Analysis in Fog Computing. *Wireless Communications & Mobile Computing (Online)*, *2018*. https://doi.org/10.1155/2018/9340194

Deming, C., Pasam, P., Allam, A. R., Mohammed, R., Venkata, S. G. N., & Kothapalli, K. R. V. (2021). Real-Time Scheduling for Energy Optimization: Smart Grid Integration with Renewable Energy. *Asia Pacific Journal of Energy and Environment*, *8*(2), 77-88. https://doi.org/10.18034/apjee.v8i2.762

Devarapu, K., Rahman, K., Kamisetty, A., & Narsina, D. (2019). MLOps-Driven Solutions for Real-Time Monitoring of Obesity and Its Impact on Heart Disease Risk: Enhancing Predictive Accuracy in Healthcare. *International Journal of Reciprocal Symmetry and Theoretical Physics*, *6*, 43-55. https://upright.pub/index.php/ijrstp/article/view/160

Gade, P. K. (2019). MLOps Pipelines for GenAI in Renewable Energy: Enhancing Environmental Efficiency and Innovation. *Asia Pacific Journal of Energy and Environment*, *6*(2), 113-122. https://doi.org/10.18034/apjee.v6i2.776

Gade, P. K., Sridharlakshmi, N. R. B., Allam, A. R., & Koehler, S. (2021). Machine Learning-Enhanced Beamforming with Smart Antennas in Wireless Networks. *ABC Journal of Advanced Research*, *10*(2), 207-220. https://doi.org/10.18034/abcjar.v10i2.770

Gummadi, J. C. S., Narsina, D., Karanam, R. K., Kamisetty, A., Talla, R. R., & Rodriguez, M. (2020). Corporate Governance in the Age of Artificial Intelligence: Balancing Innovation with Ethical Responsibility. *Technology & Management Review*, *5*, 66-79. https://upright.pub/index.php/tmr/article/view/157

Gummadi, J. C. S., Thompson, C. R., Boinapalli, N. R., Talla, R. R., & Narsina, D. (2021). Robotics and Algorithmic Trading: A New Era in Stock Market Trend Analysis. *Global Disclosure of Economics and Business*, *10*(2), 129-140. https://doi.org/10.18034/gdeb.v10i2.769

Jarwar, M., Abbasi, R., Mushtaq, M., Maqbool, O., Aljohani, N. (2017). CommuniMents: A Framework for Detecting Community Based Sentiments for Events. *International Journal on Semantic Web and Information Systems*, *13*(2), 87-108. https://doi.org/10.4018/IJSWIS.2017040106

Karanam, R. K., Natakam, V. M., Boinapalli, N. R., Sridharlakshmi, N. R. B., Allam, A. R., Gade, P. K., Venkata, S. G. N., Kommineni, H. P., & Manikyala, A. (2018). Neural Networks in Algorithmic Trading for Financial Markets. *Asian Accounting and Auditing Advancement*, *9*(1), 115–126. https://4ajournal.com/article/view/95

Kommineni, H. P. (2019). Cognitive Edge Computing: Machine Learning Strategies for IoT Data Management. *Asian Journal of Applied Science and Engineering*, *8*(1), 97-108. https://doi.org/10.18034/ajase.v8i1.123

Kommineni, H. P. (2020). Automating SAP GTS Compliance through AI-Powered Reciprocal Symmetry Models. *International Journal of Reciprocal Symmetry and Theoretical Physics*, *7*, 44-56. https://upright.pub/index.php/ijrstp/article/view/162

Kommineni, H. P., Fadziso, T., Gade, P. K., Venkata, S. S. M. G. N., & Manikyala, A. (2020). Quantifying Cybersecurity Investment Returns Using Risk Management Indicators. Asian Accounting and Auditing Advancement, 11(1), 117–128. https://4ajournal.com/article/view/97

Kothapalli, S., Manikyala, A., Kommineni, H. P., Venkata, S. G. N., Gade, P. K., Allam, A. R., Sridharlakshmi, N. R. B., Boinapalli, N. R., Onteddu, A. R., & Kundavaram, R. R. (2019). Code Refactoring Strategies for DevOps: Improving Software Maintainability and Scalability. *ABC Research Alert*, *7*(3), 193–204. https://doi.org/10.18034/ra.v7i3.663

Kundavaram, R. R., Rahman, K., Devarapu, K., Narsina, D., Kamisetty, A., Gummadi, J. C. S., Talla, R. R., Onteddu, A. R., & Kothapalli, S. (2018). Predictive Analytics and Generative AI for Optimizing Cervical and Breast Cancer Outcomes: A Data-Centric Approach. *ABC Research Alert*, *6*(3), 214-223. https://doi.org/10.18034/ra.v6i3.672

Mallipeddi, S. R. (2022). Harnessing AI and IoT Technologies for Sustainable Business Operations in the Energy Sector. *Asia Pacific Journal of Energy and Environment*, *9*(1), 37-48. https://doi.org/10.18034/apjee.v9i1.735

Narsina, D., Gummadi, J. C. S., Venkata, S. S. M. G. N., Manikyala, A., Kothapalli, S., Devarapu, K., Rodriguez, M., & Talla, R. R. (2019). AI-Driven Database Systems in FinTech: Enhancing Fraud Detection and Transaction Efficiency. *Asian Accounting and Auditing Advancement*, *10*(1), 81–92. https://4ajournal.com/article/view/98

Noori, M., Maktoubian, J. (2019). Business Improvement Approach Based on Sentiment Twitter Analysis: Case Study. *EAI Endorsed Transactions on Cloud Systems*, *5*(14). https://doi.org/10.4108/eai.13-7-2018.158417

Onteddu, A. R., Venkata, S. S. M. G. N., Ying, D., & Kundavaram, R. R. (2020). Integrating Blockchain Technology in FinTech Database Systems: A Security and Performance Analysis. Asian Accounting and Auditing Advancement, 11(1), 129–142. https://4ajournal.com/article/view/99

Park, W., You, Y., Lee, K. (2018). Detecting Potential Insider Threat: Analyzing Insiders' Sentiment Exposed in Social Media. *Security and Communication Networks*, *2018*. https://doi.org/10.1155/2018/7243296

Richardson, N., Manikyala, A., Gade, P. K., Venkata, S. S. M. G. N., Asadullah, A. B. M., & Kommineni, H. P. (2021). Emergency Response Planning: Leveraging Machine Learning for Real-Time Decision-Making. *Technology & Management Review*, *6*, 50-62. https://upright.pub/index.php/tmr/article/view/163

Roberts, C., Kundavaram, R. R., Onteddu, A. R., Kothapalli, S., Tuli, F. A., Miah, M. S. (2020). Chatbots and Virtual Assistants in HRM: Exploring Their Role in Employee Engagement and Support. *NEXG AI Review of America*, *1*(1), 16-31.

Rodriguez, M., Sridharlakshmi, N. R. B., Boinapalli, N. R., Allam, A. R., & Devarapu, K. (2020). Applying Convolutional Neural Networks for IoT Image Recognition. *International Journal of Reciprocal Symmetry and Theoretical Physics*, *7*, 32-43. https://upright.pub/index.php/ijrstp/article/view/158

Sabra, S., Malik, K. M., Alobaidi, M. (2018). Prediction of Venous Thromboembolism Using Semantic and Sentiment Analyses of Clinical Narratives. *Computers in Biology and Medicine*, *94*, 1. https://doi.org/10.1016/j.compbiomed.2017.12.026

Talla, R. R., Manikyala, A., Gade, P. K., Kommineni, H. P., & Deming, C. (2022). Leveraging AI in SAP GTS for Enhanced Trade Compliance and Reciprocal Symmetry Analysis. *International Journal of Reciprocal Symmetry and Theoretical Physics*, *9*, 10-23. https://upright.pub/index.php/ijrstp/article/view/164

Talla, R. R., Manikyala, A., Nizamuddin, M., Kommineni, H. P., Kothapalli, S., Kamisetty, A. (2021). Intelligent Threat Identification System: Implementing Multi-Layer Security Networks in Cloud Environments. NEXG AI Review of America, 2(1), 17-31.

Thompson, C. R., Talla, R. R., Gummadi, J. C. S., Kamisetty, A (2019). Reinforcement Learning Techniques for Autonomous Robotics. *Asian Journal of Applied Science and Engineering*, *8*(1), 85-96. https://ajase.net/article/view/94

Tutubalina, E., Nikolenko, S. (2018). Exploring Convolutional Neural Networks and Topic Models for User Profiling from Drug Reviews. *Multimedia Tools and Applications*, *77*(4), 4791-4809. https://doi.org/10.1007/s11042-017-5336-z

Venkata, S. S. M. G. N., Gade, P. K., Kommineni, H. P., Manikyala, A., & Boinapalli , N. R. (2022). Bridging UX and Robotics: Designing Intuitive Robotic Interfaces. *Digitalization & Sustainability Review*, *2*(1), 43-56. https://upright.pub/index.php/dsr/article/view/159

Wang, Y., Kim, K., Lee, B., Youn, H. Y. (2018). Word Clustering Based on POS Feature for Efficient Twitter Sentiment Analysis. *Human-centric Computing and Information Sciences*, *8*(1), 1-25. https://doi.org/10.1186/s13673-018-0140-y

Wang, Y., Youn, H. Y. (2019). Feature Weighting Based on Inter-Category and Intra-Category Strength for Twitter Sentiment Analysis. *Applied Sciences*, *9*(1). https://doi.org/10.3390/app9010092

Xie, J., Song, Z., Li, Y., Zhang, Y., Yu, H. (2018). A Survey on Machine Learning-Based Mobile Big Data Analysis: Challenges and Applications. *Wireless Communications & Mobile Computing (Online)*, *2018*. https://doi.org/10.1155/2018/8738613

--0--