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The Role of AI in Customer Sentiment Analysis for Strategic Business Decisions

Direesh Reddy Aunugu[1], Vijayalaxmi Methuku[2], Rahul Manche[3]
[1] Independent Researcher - Irving, Texas
[2] Independent Researcher - Leander, Texas
[3] Independent Researcher - Hyderabad, India

ABSTRACT: Customer sentiment analysis has become a vital tool for businesses seeking to understand consumer emotions, preferences, and feedback in real-time. Traditional sentiment analysis methods often struggle with scalability, contextual interpretation, and processing unstructured data from diverse sources such as social media, customer reviews, and survey responses. Artificial Intelligence (AI) has revolutionized this domain by leveraging advanced Natural Language Processing (NLP) techniques, including transformer-based models (e.g., BERT, GPT), recurrent neural networks (RNNs), and sentiment-aware embeddings, to extract nuanced insights with higher accuracy and efficiency. AI-driven sentiment analysis enhances customer experience, optimizes marketing strategies, and informs strategic business decisions in areas such as product development and risk management. However, challenges such as algorithmic bias, data privacy concerns, and model interpretability remain critical hurdles. This paper explores these challenges while discussing potential solutions, such as debiasing techniques, federated learning for privacy-preserving sentiment analysis, and explainable AI approaches. Furthermore, it highlights future advancements that could improve the accuracy, reliability, and ethical application of AI in sentiment analysis, ultimately strengthening data-driven decision-making for businesses in dynamic market environments.

KEYWORDS: Artificial Intelligence (AI), Business Intelligence, Customer Sentiment Analysis, Machine Learning (ML), Natural Language Processing (NLP).

I. INTRODUCTION

In today's digital age, customer feedback is the lifeblood of successful businesses, driving strategic decisions and fueling continuous improvement. With the proliferation of online platforms, including social media, e-commerce reviews, and customer support interactions, businesses now have access to vast amounts of unstructured data that contain valuable insights into consumer sentiment. However, extracting actionable intelligence, such as identifying emerging trends, pinpointing customer pain points, and gauging the effectiveness of marketing campaigns, remains a significant challenge. Traditional sentiment analysis methods, such as lexicon-based and rule-based approaches, often struggle with scalability, contextual understanding, and accuracy.

Artificial Intelligence (AI) has revolutionized sentiment analysis by leveraging Natural Language Processing (NLP) and Machine Learning (ML) techniques to process, interpret, and categorize customer emotions with greater precision (Liu 2022), (Cambria et al. 2017). Advanced deep learning models, particularly transformer-based architectures like Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019) and Generative Pre-trained Transformers (GPT) (Brown et al. 2020), have significantly improved sentiment classification by capturing contextual nuances. AI-driven sentiment analysis empowers businesses to optimize customer experience, personalize marketing campaigns, enhance brand monitoring, and support real-time decision-making (Pang et al. 2008).

Despite these advancements, AI-driven sentiment analysis presents several challenges, including algorithmic bias, data privacy concerns, and model interpretability (Chang et al. 2019). Ensuring ethical and unbiased sentiment analysis requires advancements in explainable AI (XAI), privacy-preserving AI techniques like federated learning, and debiasing methodologies to promote fairness in automated decision-making (Myakala et al. 2024).

The remainder of this paper is organized as follows: Section 2 provides an overview of AI methodologies used in sentiment analysis. Section 3 discusses practical applications across industries. Section 4 highlights key challenges and mitigation strategies. Finally, Section 6 explores future directions for improving AI-driven sentiment analysis.

II. AI METHODOLOGIES FOR CUSTOMER SENTIMENT ANALYSIS

The rapid advancements in Natural Language Processing (NLP) and Machine Learning (ML) have significantly improved sentiment analysis techniques, enabling businesses to analyze customer emotions with higher accuracy and contextual understanding (Liu 2022), (Cambria et al. 2017). AI-based sentiment analysis systems typically follow a structured pipeline consisting of data collection, preprocessing, feature extraction, model training, and sentiment classification.

A. Data Collection and Preprocessing

Sentiment analysis begins with the collection of large-scale textual data from various sources such as social media platforms, online reviews, surveys, and customer support interactions (Pang et al. 2008), (Chang et al. 2019). However, raw text data is often noisy, requiring preprocessing techniques to improve its quality and suitability for analysis.

Key Preprocessing Techniques

- ***Tokenization***: Splitting text into individual words or subwords. For example, the sentence "AI-powered sentiment analysis is transformative." would be tokenized into ["AI-powered", "sentiment", "analysis", "is", "transformative"].
- ***Stopword Removal***: Filtering out frequently occurring words (e.g., “the,” “is,” “and”) that do not contribute significantly to sentiment analysis.
- ***Stemming and Lemmatization***: Reducing words to their root form to normalize variations. For example, “running,” “runs,” and “ran” would be reduced to “run.” This ensures that different forms of the same word are treated consistently, improving sentiment classification accuracy.
- ***Named Entity Recognition (NER):*** Identifying named entities such as names, locations, brands, and products to provide deeper contextual understanding. For instance, recognizing that “Apple” refers to a company rather than a fruit in a given text.

B. Feature Engineering and Representation

Once the data is pre-processed, it is transformed into numerical representations suitable for ML models. Traditional methods include Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) (Liu 2022), (Pang et al. 2008). However, modern AI-driven sentiment analysis leverages advanced techniques such as:

- ***Word Embeddings***: Vectorized word representations such as Word2Vec, GloVe, and FastText that capture semantic relationships (Cambria et al. 2017). For instance, the words "happy" and "joyful" would have similar vector representations in a well-trained embedding space.
- ***Contextualized Embeddings***: Unlike static embeddings, deep learning models such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pretrained Transformers (GPT) generate word representations dynamically based on surrounding context (Devlin et al. 2019), (Brown et al. 2020). For example, in BERT, the word “bank” would have different vector representations in the sentences “He went to the river bank” and “She deposited money in the bank.”

C. Machine Learning and Deep Learning Models

Various machine learning and deep learning techniques are employed for sentiment classification:

- ***Traditional Machine Learning***: Algorithms such as Naïve Bayes, Support Vector Machines (SVM), and Random Forests have been widely used for sentiment analysis (Pang et al. 2008). These models rely on handcrafted features and statistical techniques to classify sentiment.
- ***Deep Learning Approaches***: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are effective for analyzing sequential text data and capturing dependencies between words (Chang et al. 2019).
- ***Transformer-Based Models***: Recent advancements, such as BERT and GPT, use attention mechanisms to capture complex linguistic patterns, improving sentiment classification accuracy (Devlin et al. 2019), (Brown et al. 2020).

D. Sentiment Classification Techniques

Once features are extracted, sentiment classification is performed using the following techniques:

- ***Binary Classification***: Classifying sentiment as either positive or negative, commonly used in basic sentiment analysis applications.

- ***Multi-Class Classification***: Identifying multiple sentiment categories, such as positive, negative, and neutral, to provide a more nuanced understanding of sentiment.
- ***Fine-Grained Sentiment Analysis***: Assigning sentiment scores on a continuous scale to capture sentiment intensity. For instance, a 1-5 star rating system used in product reviews, where 1 represents very negative sentiment and 5 represents very positive sentiment.

This section has provided an overview of AI methodologies used in customer sentiment analysis, emphasizing data processing, feature extraction, and machine learning techniques. The next section explores the real-world applications of AI-powered sentiment analysis across various industries.

III. APPLICATIONS OF AI-DRIVEN SENTIMENT ANALYSIS

The integration of Artificial Intelligence (AI) in sentiment analysis has transformed multiple industries by enabling businesses and organizations to extract actionable insights from large volumes of unstructured textual data. AI-driven sentiment analysis is widely applied in marketing, customer service, finance, healthcare, and political analysis, improving decision-making and operational efficiency (Liu 2022), (Cambria et al. 2017). While sentiment analysis offers numerous advantages, ethical concerns such as algorithmic bias, data privacy, and misinformation detection must also be addressed.

A. Marketing and Brand Management

Sentiment analysis plays a crucial role in marketing and brand management by enabling businesses to monitor customer opinions, track brand reputation, and optimize advertising strategies. Companies analyze consumer sentiment from social media, product reviews, and customer surveys to gauge public perception (Pang et al. 2008), (Chang et al. 2019). AI-powered sentiment analysis helps businesses tailor marketing campaigns based on audience sentiment, detect potential public relations crises early, and refine brand messaging for improved engagement.

For instance, real-time sentiment tracking on platforms like Twitter and Facebook allows brands to respond promptly to customer concerns and capitalize on positive feedback. Research suggests that businesses using AI-powered sentiment analysis for marketing have seen an increase in customer engagement by up to 25\% and improved brand loyalty due to personalized interactions (Devlin et al. 2019).

B. Customer Service and Experience Optimization

AI-powered sentiment analysis enhances customer service by improving interactions between businesses and consumers. Companies analyze product reviews, support tickets, and chatbot interactions to assess customer satisfaction levels (Cambria et al. 2017).

Sentiment-aware chatbots and virtual assistants can detect frustration in a customer's tone and escalate the issue to human agents for personalized support (Devlin et al. 2019). Studies indicate that AI chatbots have reduced customer service response times by 40% and increased resolution efficiency in call centers (Pang et al. 2008). Additionally, businesses evaluate call center transcripts to identify recurring customer issues and enhance agent training programs, leading to more efficient and empathetic customer service.

C. Financial Market Sentiment Analysis

The finance industry leverages sentiment analysis to assess investor sentiment, predict stock market trends, and manage risks. AI-driven models analyze financial news, earnings reports, and social media discussions to identify shifts in market sentiment (Pang et al. 2008), (Chang et al. 2019).

For instance, a surge in negative sentiment regarding a company's performance could indicate declining investor confidence, influencing stock prices (Myakala et al. 2024). In cryptocurrency markets, sentiment analysis provides insights into price volatility by evaluating online discussions and sentiment fluctuations (Brown et al. 2020). Given the rapid nature of cryptocurrency trading, where market sentiment can shift dramatically within minutes, AI-driven sentiment analysis enables traders to make informed decisions in high-frequency trading environments. A recent study found that incorporating sentiment analysis into cryptocurrency trading strategies improved prediction accuracy by approximately 18% (Chang et al. 2019).

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D. Healthcare and Patient Experience Analysis

In healthcare, sentiment analysis is used to evaluate patient feedback, monitor public health trends, and enhance medical research. Hospitals and healthcare providers analyze online patient reviews, survey responses, and telemedicine interactions to identify areas for service improvement (Cambria et al. 2017).

Sentiment analysis also plays a role in mental health monitoring, where AI models analyze social media posts and digital interactions to detect early signs of depression or anxiety (Chang et al. 2019). In drug safety monitoring, pharmaceutical companies use AI to analyze discussions about medication side effects and patient experiences. However, ethical considerations arise when analyzing sensitive health data, particularly concerning patient privacy and the potential for AI bias in diagnostic assessments. Ensuring transparency and accountability in AI-driven healthcare sentiment analysis is crucial for ethical implementation.

E. Political and Social Analysis

Governments and policymakers use sentiment analysis to assess public opinion, predict election outcomes, and monitor societal trends. AI-driven models process sentiment from news articles, public speeches, and social media to gauge political sentiment and voter inclinations (Pang et al. 2008), (Liu 2022).

During elections, real-time sentiment analysis helps political campaigns understand voter sentiment and refine their strategies (Devlin et al. 2019). Additionally, sentiment analysis is used in detecting misinformation and fake news, aiding in the fight against disinformation campaigns (Brown et al. 2020). However, the use of sentiment analysis in political decision-making raises concerns about potential bias in AI models, the ethical implications of influencing public opinion, and the risks of misinterpreting sentiment data. Ensuring transparency in AI methodologies and mitigating bias are essential to maintaining fairness in political sentiment analysis (Kamatala et al. 2024).

This section has outlined the diverse applications of AI-driven sentiment analysis in various industries, demonstrating its impact on business intelligence, financial decision-making, healthcare optimization, and political analysis. While sentiment analysis provides valuable insights, ethical concerns such as bias, data privacy, and misinformation must be carefully addressed to ensure responsible AI implementation. The following section discusses key challenges and limitations associated with AI-powered sentiment analysis.

IV. CHALLENGES AND LIMITATIONS OF AI-DRIVEN SENTIMENT ANALYSIS

Despite the significant advancements in AI-driven sentiment analysis, several challenges and limitations remain. These challenges include algorithmic bias, contextual misinterpretation, data privacy concerns, and the complexity of sentiment analysis in multilingual and multimodal data. Addressing these issues is crucial for improving the reliability, fairness, and ethical application of AI in sentiment analysis (Liu 2012), (Cambria et al. 2017), (Kamatala et al. 2024).

A. Algorithmic Bias and Fairness

One of the major concerns in AI-based sentiment analysis is algorithmic bias, which can result in unfair or inaccurate sentiment classifications (Zhang et al. 2020). Bias in training data, imbalanced class distributions, and model design flaws can lead to systematic errors, disproportionately affecting certain demographics or viewpoints.

For instance, sentiment models trained primarily on Western social media data may fail to accurately interpret sentiment in diverse cultural contexts. Additionally, biases in word embeddings, such as associations between gender and sentiment polarity, have been widely documented (Devlin et al. 2019). Mitigating these biases requires techniques such as debiasing word embeddings, employing diverse training datasets, and incorporating fairness-aware learning algorithms.

B. Contextual Understanding and Sentiment Ambiguity

AI-driven sentiment analysis struggles with understanding complex linguistic nuances, sarcasm, irony, and implicit sentiment. While transformer-based models such as BERT and GPT have improved contextual awareness, they still face difficulties in correctly interpreting sentiment in ambiguous scenarios (Pang et al. 2008), (Zhang et al. 2020).

For example, in the sentence "I love waiting in long queues—such a great experience!", traditional sentiment models may misclassify the sentiment as positive due to the presence of "love" and "great." Context-aware models attempt to resolve such ambiguities but remain imperfect. One promising approach is the integration of knowledge graphs, which provide structured representations of real-world relationships between entities, concepts, and contexts. By incorporating external knowledge from

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sources such as ConceptNet and WordNet, sentiment analysis models can gain a better understanding of sarcasm, contextual references, and domain-specific sentiment nuances.

C. Data Privacy and Ethical Concerns

The collection and analysis of user-generated content raise concerns about data privacy, consent, and ethical AI usage (Cambria et al. 2017), (Brown et al. 2020). Many sentiment analysis applications process sensitive user data, including personal opinions, health-related discussions, and financial sentiments, which may violate privacy regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA).

Ensuring ethical sentiment analysis requires implementing privacy-preserving techniques such as federated learning, which enables model training without directly accessing user data. Differential privacy methods can also be applied to anonymize text while maintaining analytical utility. Businesses leveraging sentiment analysis must prioritize transparent data policies and obtain user consent to comply with ethical standards.

D. Multilingual and Multimodal Sentiment Analysis

Sentiment analysis in multiple languages remains a significant challenge due to linguistic variations, differing grammatical structures, and the lack of high-quality annotated datasets (Pang et al. 2008), (Devlin et al. 2019). Many sentiment analysis models perform well in English but struggle with languages that have limited training data or rely on different sentiment expressions.

Furthermore, modern sentiment analysis must extend beyond text to multimodal data, including images, audio, and videos. Sentiment expressed through voice tone, facial expressions, and gestures provides valuable cues that text-based models may overlook (Zhang et al. 2020). Multimodal sentiment analysis integrates NLP with computer vision and speech processing techniques to enhance accuracy. However, building effective multimodal sentiment models requires large-scale labeled datasets and computationally intensive architectures.

E. Scalability and Real-Time Processing Constraints

AI-driven sentiment analysis models require substantial computational resources, particularly when processing high volumes of real-time data from social media, financial markets, or customer service interactions (Pang et al. 2008), (Brown et al. 2020). Deploying deep learning models such as transformers can be computationally expensive, limiting their scalability in production environments.

One promising solution is Edge AI, which refers to running AI models directly on edge devices such as smartphones and IoT devices instead of relying on cloud-based infrastructure. By processing sentiment data locally, Edge AI reduces latency, enhances privacy, and minimizes bandwidth usage. Optimizing model efficiency through techniques like knowledge distillation, quantization, and low-rank matrix factorization can further reduce computational overhead while maintaining accuracy.

F. The Role of Interdisciplinary Research

Overcoming the challenges in sentiment analysis requires collaboration across multiple disciplines. While computer scientists focus on improving AI models, insights from linguists help refine language representation, ethicists contribute to fairness and privacy frameworks, and cognitive scientists assist in modeling human-like sentiment perception. Interdisciplinary research integrating expertise from these fields is essential for building robust, context-aware, and ethically responsible sentiment analysis systems.

G. Mitigation Strategies and Future Directions

Addressing these challenges requires continuous advancements in AI methodologies, ethical AI frameworks, and interdisciplinary research. Several promising strategies include:

- Developing fairness-aware AI models that minimize bias through adversarial training and balanced datasets.
- Enhancing contextual understanding by incorporating knowledge graphs and commonsense reasoning into sentiment models.
- Implementing privacy-preserving AI techniques such as federated learning and differential privacy to protect user data.
- Advancing multimodal sentiment analysis by integrating NLP with computer vision and speech recognition.
- Improving model efficiency and scalability through Edge AI deployment, lightweight architectures, and real-time inference optimizations.

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- Encouraging interdisciplinary collaboration between AI researchers, linguists, ethicists, and policymakers to ensure responsible sentiment analysis applications.

While sentiment analysis has made remarkable progress, addressing these limitations will be critical for its responsible and widespread adoption. The next section explores future research directions and emerging trends in AI-driven sentiment analysis.

V. FUTURE DIRECTIONS AND EMERGING TRENDS IN AI-DRIVEN SENTIMENT ANALYSIS

The field of AI-driven sentiment analysis is evolving rapidly, with ongoing research focused on enhancing contextual understanding, improving ethical AI practices, and integrating multimodal data sources. As businesses and researchers strive for more accurate, interpretable, and privacy-aware sentiment models, several emerging trends are shaping the future of sentiment analysis (Cambria et al. 2017). This section discusses key future directions in sentiment analysis research.

A. Enhancing Contextual and Commonsense Understanding

One of the primary challenges in sentiment analysis is accurately interpreting context-dependent sentiment, sarcasm, and implicit meaning. Future sentiment analysis models will increasingly rely on commonsense reasoning and external knowledge sources to improve contextual awareness

Integrating knowledge graphs such as ConceptNet and WordNet into sentiment analysis pipelines allows models to infer real-world relationships between words and concepts (Devlin et al. 2019). Additionally, advancements in self-supervised learning techniques are enabling models to develop richer representations of sentiment nuances without requiring large labeled datasets.

Another promising direction is the application of causal inference in sentiment analysis, which aims to identify the underlying factors driving sentiment instead of merely associating words with predefined labels. By adopting causal reasoning frameworks, sentiment models can move beyond surface-level text analysis and develop deeper interpretative capabilities.

B. Privacy-Preserving Sentiment Analysis

With growing concerns about data privacy, future sentiment analysis research is focusing on privacy-preserving AI techniques (Pang et al. 2008), (Zhang et al. 2020).

Federated learning is a promising approach that enables sentiment models to learn from distributed data without transferring user information to centralized servers. This ensures privacy compliance with regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Additionally, techniques such as differential privacy and homomorphic encryption are being explored to anonymize sentiment data while maintaining analytical accuracy.

Future research will focus on developing robust frameworks for balancing privacy, interpretability, and analytical performance in sentiment analysis applications.

C. Advancements in Multimodal Sentiment Analysis and Standardization

Current sentiment analysis models primarily focus on textual data, but future research is moving towards multimodal sentiment analysis, which integrates multiple data sources such as text, speech, images, and video (Cambria et al. 2017), (Brown et al. 2020). By combining Natural Language Processing (NLP) with computer vision and speech recognition, sentiment models can capture sentiment cues from facial expressions, voice tone, and visual elements. For example, sentiment analysis of video-based customer feedback can provide deeper insights by analyzing both textual responses and facial micro-expressions.

Transformer-based multimodal models, such as VisualBERT and MMFT-BERT, are being developed to effectively process multimodal sentiment signals (Devlin et al. 2019). However, as multimodal sentiment analysis advances, a major challenge is the lack of standardization in multimodal datasets and evaluation metrics. Current datasets often vary in annotation methodologies, making it difficult to compare model performance across studies. Future research should focus on developing benchmark datasets with unified sentiment labels and creating standardized evaluation metrics to ensure consistency in multimodal sentiment model assessment.

D. Real-Time and Low-Latency Sentiment Analysis

As sentiment analysis is increasingly applied to high-speed domains such as financial markets, social media monitoring, and customer service, the need for real-time sentiment processing is growing (Pang et al. 2008).

Edge AI will play a significant role in enabling low-latency sentiment analysis by running models directly on edge devices instead of relying on cloud-based processing (Brown et al. 2020). Deploying optimized deep learning models on mobile devices and IoT hardware will allow real-time sentiment analysis in applications such as smart assistants, wearable health devices, and in-car sentiment monitoring systems.

To improve computational efficiency, future research will explore quantization techniques, pruned neural networks, and knowledge distillation to reduce model size without sacrificing accuracy.

E. Ethical AI and Bias Mitigation

The ethical implications of AI-driven sentiment analysis are gaining increasing attention, with researchers focusing on mitigating algorithmic bias and improving interpretability. Future work will explore adversarial debiasing techniques, fairness-aware sentiment models, and transparent AI frameworks to ensure that sentiment classification does not reinforce societal biases (Devlin et al. 2019). Another critical area of research is explainable AI (XAI) for sentiment analysis, where models provide justifications for their sentiment classifications in human-understandable formats (Cambria et al. 2017). Future sentiment models will integrate self-explaining architectures that highlight the key linguistic features influencing sentiment predictions, increasing transparency and trustworthiness.

F. Cross-Domain and Transfer Learning Approaches

Sentiment expressions vary significantly across different domains such as healthcare, finance, and social media. A sentiment model trained on product reviews may not generalize well to financial market sentiment analysis (Pang et al. 2008).

To address this, future research will focus on cross-domain sentiment adaptation, where models transfer knowledge from one domain to another using transfer learning and domain adaptation techniques. Pre-trained sentiment analysis models fine-tuned on specific industry datasets will enable more accurate cross-domain applications.

Additionally, low-resource language adaptation is a growing research focus, aiming to develop sentiment analysis models that perform well in languages with limited training data.

G. Interdisciplinary Research for Future Sentiment Analysis

The future of sentiment analysis will require collaboration across multiple disciplines. Linguistics will continue to play a crucial role in improving sentiment lexicons and discourse analysis techniques. Ethicists and policymakers will help shape AI governance frameworks to ensure responsible sentiment analysis applications. Cognitive scientists will contribute insights into human emotional processing, aiding in the development of more psychologically aware sentiment models.

VI. CONCLUSION

AI-driven sentiment analysis is evolving towards more context-aware, privacy-preserving, multimodal, and real-time applications. By integrating knowledge graphs, federated learning, multimodal transformers, Edge AI, and fairness-aware frameworks, sentiment analysis will continue to become more accurate, ethical, and interpretable.

While significant progress has been made, addressing the existing challenges and embracing interdisciplinary research will be essential for the widespread and responsible adoption of sentiment analysis technologies. As sentiment analysis continues to shape business intelligence, healthcare, finance, and social interactions, ongoing research and innovation will define the next generation of sentiment-aware AI systems.

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