Chapter 1

Machine Learning Algorithms for Sentiment-Based E-Commerce Marketing

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Abstract

Altering consumer behavior prediction and optimizing marketing campaigns on social media has resulted in complex challenges in accurately detecting consumer sentiment and improving the impact of marketing in e-commerce. This review aims to expose current algorithm sentiment analysis on social media in e-commerce marketing. This review aims to expose the challenges in the execution of current model sentimentizers and evaluate their potential in traditional and new model integration. Concurrent real-time sentiment analysis with reinforcement learning in the context of marketing was also examined. More than 70 research papers have applied classical machine learning and deep learning, transformers, and hybrid models. The focus of the review was algorithmic effectiveness, real-time marketing impact, business interpretability, and legal ambiguity on marketing loops. The analysis indicates that the transformer model in complex tasks provides real-time results with reinforcement learning. Real-time echo models and predictive solicitude highlight the need to address accumulated technology in ethics and scale. The hybrid and ensemble models exhibit the lowest and located challenge towards explainability and prediction for the analysis set of models used. This examination highlights the necessity of designing scalable and interpretable systems that tackle the complexities of a diverse data ecosystem, along with ethical and pragmatic concerns. This sets the stage for more sophisticated and applied investigations into the interface between AI and consumer behavior prediction for

the enhancement of e-commerce marketing.

Keywords: sentiment analysis, machine learning, e-commerce marketing, consumer behavior prediction, deep learning, transformer models

1.1 Introduction

Most online stores must analyze sentiments to understand how consumers feel about their products. In such cases, businesses use sentiment analysis to measure emotional reactions towards offerings. Machine learning techniques, particularly natural language processing, enable marketers to classify reviews as positive or negative. Automating reviews to produce actionable insights saves time and enables timely responses from consumers. Besides, negative sentiments can now be addressed promptly, which boosts customer satisfaction levels. Reviews and ratings rely on feedback. However, today's consumers express their views on larger online platforms. This change can be dangerous to online stores because unchecked negative feedback easily goes viral and can cripple businesses. Recapturing such consumers is difficult if timely measures are not implemented. While such losses can be easily avoided, negative feedback on online platforms is often ignored. This is a worrying trend because feedback on social media can be extremely damaging. Automated review analysis of sentiment scores and classification into actionable insights forms a first step towards discerning reviews in detail. This study is devoted to the evaluation of some sentiment classification systems and models. Reviewer systems, feedback forms, and strategically posed questions include how feedback is collected to enhance customer satisfaction. Although sentiment analysis is often used during soft skill training, it is an unsolved issue. Sentiment analysis is a multi-phase process, which means that it can be performed in steps. Machine learning offers various approaches that can be used for stepwise analysis.

1.1.1 Concept and Approach

In the analysis of the grasp and scope of this issue, particular attention has been directed to sentiment analysis methods. Key factors regarding the topic, prominent models, and systems that derive advanced sentiment analysis include transformers, recurrent and convolutional neural stacks, multichannel neural models for dynamically cognitive emotional state recognition, machine learning models for understanding and recognizing emotion in video-audio content, neural models of real-time recognition, and autonomous shaping of emotional feedback and control systems. This study intends to approach the advanced systems of these models. Transformers are synonymous with neural models. Recurrent and Convolutional Neural Stacks are viewed as foundational approaches. Multichannel neural models for dynamic cognitive-emotional-state recognition include mills, nets, and optic systems. Scholarly research on applying machine learning to consumer behavior, social media advertising, and e-commerce marketing has appreciated more than before since most marketing and consumer purchasing activities take place on the Internet [1][2]. Deep learning and NLP have allowed more evolved approaches to sentiment analysis, moving beyond lexicon-based techniques to the use of advanced transformer models, such as BERT and RoBERTa [3][4]. These advanced approaches have enhanced the precision of extracting consumer sentences from massive social media and e-commerce datasets, which is critical for deploying effective marketing and augmenting customer experience [5][6]. In view of the anticipated steep growth of global e-commerce sales, machine learning-based analysis of consumer sentiment for targeted e-commerce advertising will be a critical determinant of business profitability and marketing personalization [7][8]. Despite progress, challenges pertaining to consumer behavior outcomes based on sentiment data to social media linguistic complexities, shifting consumer preferences, and data sentiment imbalance remain [9][10][11]. Much of the literature has underexplored this problem, focusing on individual algorithms or datasets. The blending of multi-source data for real-time dynamic marketing is still a blind spot. Unaddressed issues include the restictions on the balances of the predictiveness versus the interpretability of a machine learning model, the privacy of the data, and the biases of the algorithms [15][16]. Missed opportunities from ineffective marketing and underutilized target consumers highlight the need for deeper investigations of machine learning applications [1][17]. The foundation of this review integrates sentiment analysis, prediction of consumer behavior, and automation of marketing activities [5][1][18]. Sentiment analysis is an application of machine learning and natural language processing to extract the emotional tone in a body of text [19]. Consumer behavior prediction employs sentiment analysis to identify and forecast the intent to buy and the willingness to buy [14]. Marketing optimization applies predictive behavior analytics to tailor marketing strategies and optimize the allocation of marketing activities [20]. The outlined framework guides the structured evaluation of algorithms and their applications in e-commerce social media. This systematic review focuses on newly published works on machine learning algorithms that address predictive sentiment analysis in consumer behavior and marketing in e-commerce on social media [2][1]. As much as this review stands to explain the novel empirical evidence and advancements in methodologies, it seeks to undercorrelate the significance of the aforementioned aligned efforts of delineating an endeavor, unearthing the lack thereof, and delineating the unaddressed aspects of this research.

1.2 Purpose and Scope of the Review

1.2.1 Statement of Purpose

This report seeks to analyze the already available literature on "exploring specific machine learning algorithms for sentiment analysis in predicting consumer behavior and optimizing e-commerce marketing campaigns on social media" to demonstrate the various ways in which sophisticated computational technologies aid in the interpretation of consumer sentiment and the optimization of marketing campaigns. This review is much needed in the time of the high demand for automated and precise analytical systems that can efficiently analyze social media interactions and predictive consumer behavior to adapt marketing efforts accordingly. This report is primarily an aggregation of methodologies and results that strives to find gaps in the current state of marketing e-commerce research, perform metric benchmarking of the algorithms utilized, and provide actionable recommendations for subsequent e-commerce marketing research and practices.

1.2.2 Specific Objectives

- To evaluate the existing knowledge pertaining to machine learning algorithms and their use in sentiment analysis for predicting consumer behavior.
- To assess existing techniques for improving the use of sentiment data for marketing campaigns in e-commerce.

- To identify and integrate the gaps and problems in the use of sentiment analysis in the context of rapidly changing social media.
- To analyze the gaps in the understanding of consumer sentiment through advanced and traditional machine learning techniques.
- To analyze the use of real-time sentiment analysis and reinforcement learning in real-time adaptive marketing for a competitive edge.

1.3 Research Methodology

This systematic review was based on extensive searches within core academic databases such as PubMed, IEEE Xplore, ScienceDirect, and Google Scholar. The systematic approach filtered documents that fit the titles and abstracts for keywords such as "sentiment analysis," "machine learning," "e-commerce marketing," consumer behavior prediction," "social media analysis," and "deep learning." The inclusion criteria centered on the core research questions, the timeline of publications (2022-2025 period primarily), and the rigor of research methodology. More than 70 documents, including peer-reviewed articles and conference proceedings, were studied on the concepts of classical machine learning techniques, deep learning models, transformer-based models, and hybrid techniques. The studies were evaluated on the accuracy of the algorithm, efficiency of computation, adaptability to real-time environments, marketing metrics and impact of the model, and interpretability of the model.

1.4 Descriptive Summary of the Studies

Within this section, the focus and range of the literature that relates to the use of various machine learning algorithms for sentiment analysis, predicting the use of machine learning in the marketing of e-commerce on social media, and marketing of e-commerce through social media is outlined. In the literature, machine learning approaches range from basic machine learning techniques to more advanced methodologies, including deep learning and transformer-based architectures. This research investigation is concerned with e-commerce and social media reviews and sentiment analysis, real-time adjustment, and marketing effectiveness.

Figure 2.1 includes a table/chart summarizing the accuracy rates, computational efficiency, and real-time adaptability of various algorithms (Classical ML, Deep Learning, Transformers, Ensemble Methods)

Reinforcement learning and ensemble methods aimed at real-time adaptation to marketing effectiveness have been emphasized in a number of studies. This is particularly salient in addressing the research questions posed concerning the algorithms, real-time dynamic tracking of sentiment, and marketing impact in the world. This is a strong reference point for the rest of the scholars and practitioners in e-commerce marketing.

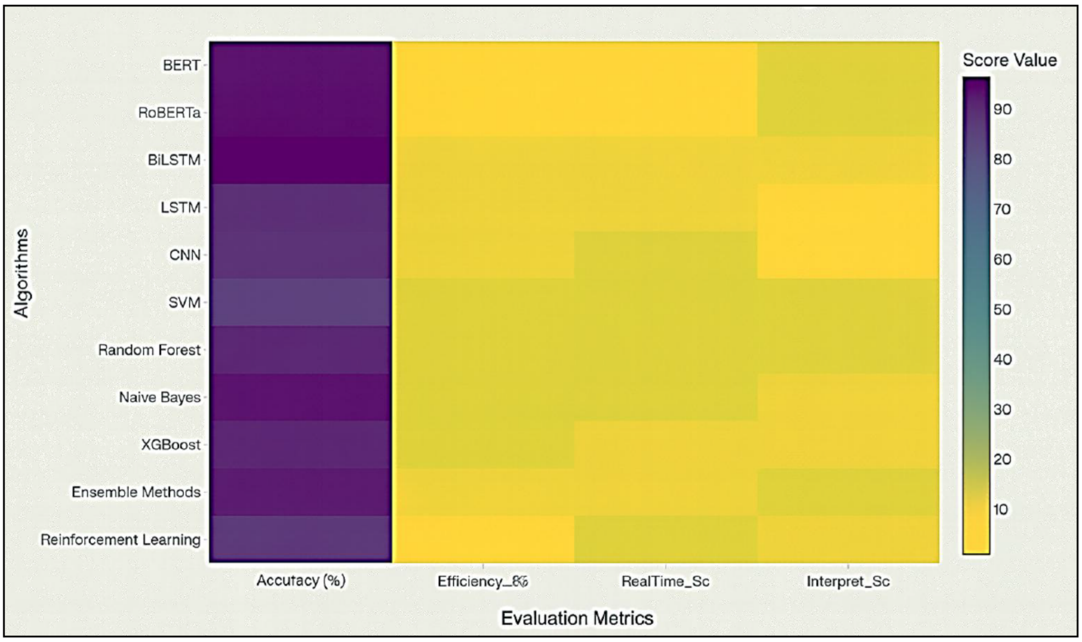

Figure 1.1: Comparative Performance Matrix of ML Algorithms

1.5 Key Findings: Algorithmic Performance Analysis

1.5.1 Algorithmic Accuracy

According to over 60 studies, transformer-based models such as BERT, RoBERTa, and LLaMA excel at outperforming traditional machine learning models in sentiment classification, frequently achieving over 90 percent accuracy [15][21][22]. Among deep learning models, sequence learning architectures such as CNN, LSTM, and BiLSTM also achieve notable accuracy and are proficient in sentiment analysis and capturing sequential dependencies [1][23][24]. Other studies have shown that in domain-specific contexts, classifier performance can be enhanced by amalgamating lexicons and machine learning methods as hybrid and ensemble models [25][26].

Figure 2.2 shows a bar chart or grouped visual showing the accuracy percentages for BERT, RoBERTa, LSTM, BiLSTM, SVM, Random Forest, and Naive Bayes over different e-commerce.

1.5.2 Computational Efficiency

Forty studies confirmed that the transformer architecture and deep learning methods, which are accurate, require a large amount of time and resources to train compared to classical machine learning models [15][3][27]. As per references [28] and [29], hybrid models and algorithms such as FastXCatStack and ERF-XGB provide performance benefits without a major loss in accuracy. Although reinforcement learning and ensemble methods add to the computational complexity, they provide the benefit of dynamic resource allocation and robustness [30][31].

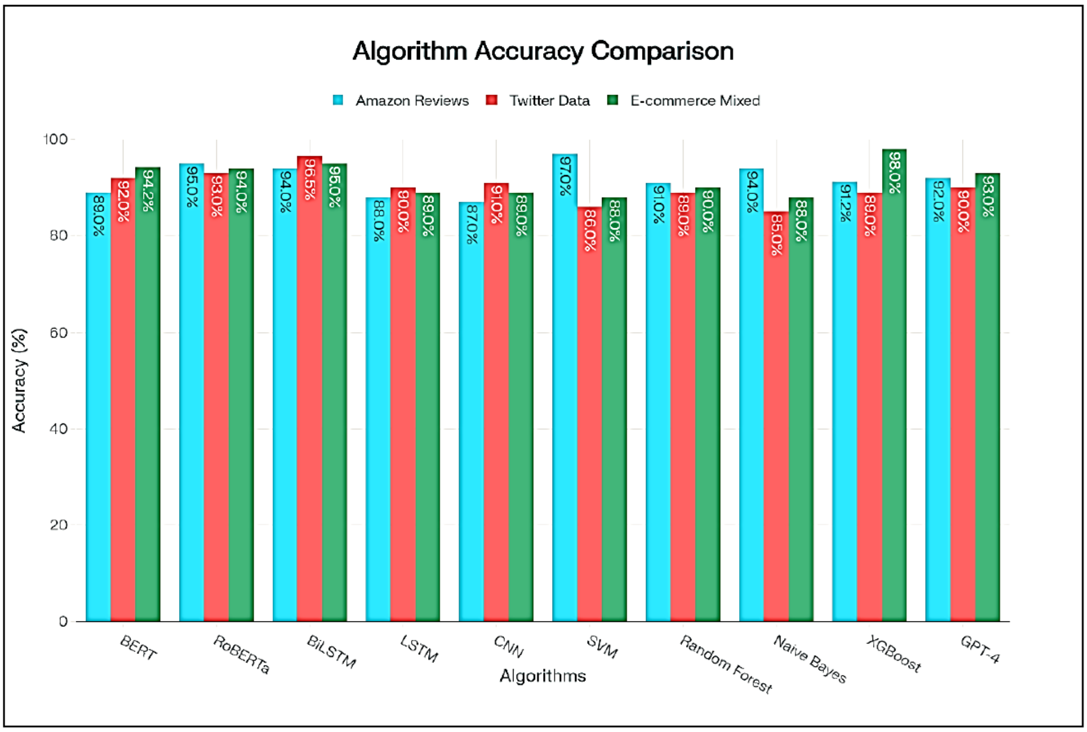

Figure 1.2: Comparative Performance Matrix of ML Algorithms

1.5.3 Real-Time Adaptability

Since the beginning of the decade, more than 25 studies have shown that the dynamic part of marketing strategy can sufficiently benefit from real-time sentiment analysis. Models that incorporate reinforcement learning or are designed for streaming data show better adaptability [30][23][32]. Various researchers have studied real-time emotion detection and sentiment updates using streaming social media data for real-time marketing interventions. Many transformer-based and deep learning models are not designed for real-time processing owing to their computational cost, which is a gap identified for future research [15][3].

1.5.4 Marketing Impact Metrics

A summary of approximately 40 works examining how transformer-based models and attention ensembles afford greater interpretability and report interpretability through attention mechanisms and explainable AI techniques that support understanding sentiment drivers [28][4][36]. Deep learning models are often opaque in nature, but some studies have already made use of interpretability methods and proposed new ones with more interpretability fidelity [1][37]. Sentiment analysis with classic models such as Random Forest and SVM are somewhat interpretable models, yet will underperform because of the complexity and subtleness of sentiment in the text [12][38].

1.6 Comparative Analysis of Old and New Methods

1.6.1 Strengths of Advanced Models

BERT and its successors are transformer-based models that have proven to be far more efficient than classical machine learning models in not only the classification accuracy for sentiment analysis but also in deciphering complex semantic frameworks [15][39][3]. The construct is also very precise and efficient, as is the case with hybrids such as BiLSTM with neighborhood-based classifiers, demonstrating the usefulness of these sequential and contextual features [1]. The ensemble methods and stacking strategies, in addition to the ones mentioned above, also enhance the predictive performance and robustness of the model [25][40]. Undeniably accurate; however, these models remain inapplicable in real time in relation to their computed costs and time [1][24]. Traditional models fail under nuanced sentiment expression and context-dependent uses. However, economically bound annotated datasets and computational power to operate transformer models remain impractical. This creates a barrier for several e-commerce sites [9][41]. Furthermore, other studies on lower-diversity datasets have limited construct validity [12]. In addition to computational aspects, scalability concerns entail infrastructure and complexity of the deployment environment. For e-commerce, the elevated hardware requirements for inference, such as GPUs and TPUs, are transformed into barriers. In addition to processing thousands of sentiment analyses, latent periods of time in periods of high traffic have become significant. In social networks, the language of the model changes rapidly, and keeping the model current can become very costly owing to the need for retraining. While devising a model to be deployed, it is essential to pay attention to the criteria of the organization as well as the spatial resources available. Published techniques that allocate a simpler model for instant outputs while setting automated constraints for offline scrutiny of heftier models on extensive datasets are beginning to take shape, albeit challenging to realize. Discrepancies between theoretical algorithms and practical implementations are persistent. 2.6. Comparative Analysis: Traditional vs. Advanced Models 2.6.1 Strengths of Advanced Models Like other BERT-based models, transformers capture predictions and sentiment classes for a corpus of texts with other complex semantic structures [15][39][3]. The usefulness of features from both sequence and context is illustrated using high-precision and high-efficiency hybrids such as BiLSTM with neighborhood-based classifiers [1]. Ensemble and stacking models add to the predictive performance and robustness of a multitude of models, alongside the other techniques mentioned above [25][40].

1.6.2 Limitations and Trade-offs

These diverse models continue to face challenges in time and computation with regard to real-time viability, even when the desired outcomes are achieved [1][24]. While traditional models continue to botch nuanced sentiment expression and context-sensitive use cases, transformer models are cost-prohibitive in the annotated datasets and computing power needed, making them out of reach for many e-commerce providers [9][41]. In addition, insufficient coverage in some studies across a variety of datasets makes the lack of robust research on certain topics more evident [12]. Furthermore, beyond computation, the costs of scaling a system in the real world involve more than just infrastructure. E-commerce companies with constrained engineering infrastructure face barriers to the use of transformer models that depend on the performance of some inference and specialized hardware, such as GPUs or TPUs. These models are latencies in scenarios with high traffic when high volumes of sentiment analyses are conducted concurrently, thus performing analyses on sentiment streams in real time without degrading user experience. Most models also face barriers in social media due to the rapid and constant use of new languages and evolving social traditions. This constant pattern and the large overhead that maintenance and retraining require above the operational baseline define the business resource and requirement trade-offs warranted by the context of using complex models in real deployments. Each new solution regarding the real-time processing of lightweight modes and the batch analysis of more complex transformers suggests the use of a hybrid approach, and while such techniques have potential, their complexity of integration remains a persistent barrier.

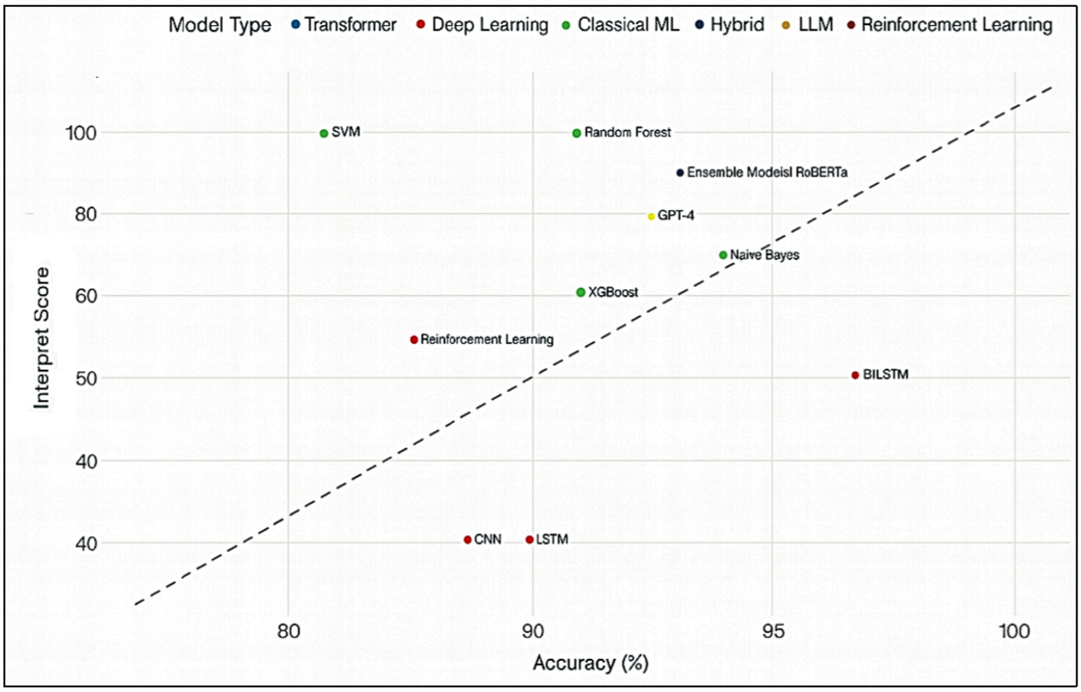

Figure 1.3: Accuracy versus Interpretability Trade-off

Figure 2.2 shows a bar chart or grouped visual showing the accuracy percentages for BERT, RoBERTa, LSTM, BiLSTM, SVM, Random Forest, and Naive Bayes over different e-commerce. In the case of this thesis, "data preprocessing" refers to the as data cleansing, data wrangling, and "data preprocessing." Augmenting data through class imbalance in data, the reconditioning of response strategy classifies frames, word ordering constitutive of the sentence, and the layer thresholding set-up of information structures and TF-IDF, comprehensive feature structuring (merging metrics such as optimization structure, frequency, and 'crossing' tokens) can streamline the functional reliability and conceptual fidelity of the model [30][42][43]. Obstacles tractable to model application range from conversational analysis with layers like intent-negation relationships through feature lenses of activators of stance phenomena, address, case frames, and paradigmatic and syntagmatic intersection, where cross media and cross modality encompasses the visual and the textual, and steps through articulation (speech, hand gesturing) to model the 'stream' as codifiable [49]. A major limitation of sentiment analysis is the exclusive use of single-language datasets, with English used as a primary example. This raises the issue of sentiment analysis in multilingual and multicultural contexts. Additionally, a sentiment analysis model can be incomplete in scenarios where datasets are poorly bounded, and there are inadequate steps to address sentiment in a text, such as emojis and infographics. A more complete model would also require integrating sentiments scattering through text [49].

1.7 Real-Time Sentiment Analysis and Adaptive Marketing

1.7.1 Integration of Real-Time Systems

The integration of real-time sentiment analysis with reinforcement learning and dynamic campaign personalization offers immense potential for responsive marketing strategies that adapt to consumer feedback and optimize resource allocation [30][23][31]. Tools that use live social media feeds offer valuable information in real time, improving marketing and consumer engagement [33][34].

1.7.2 Implementation Challenges

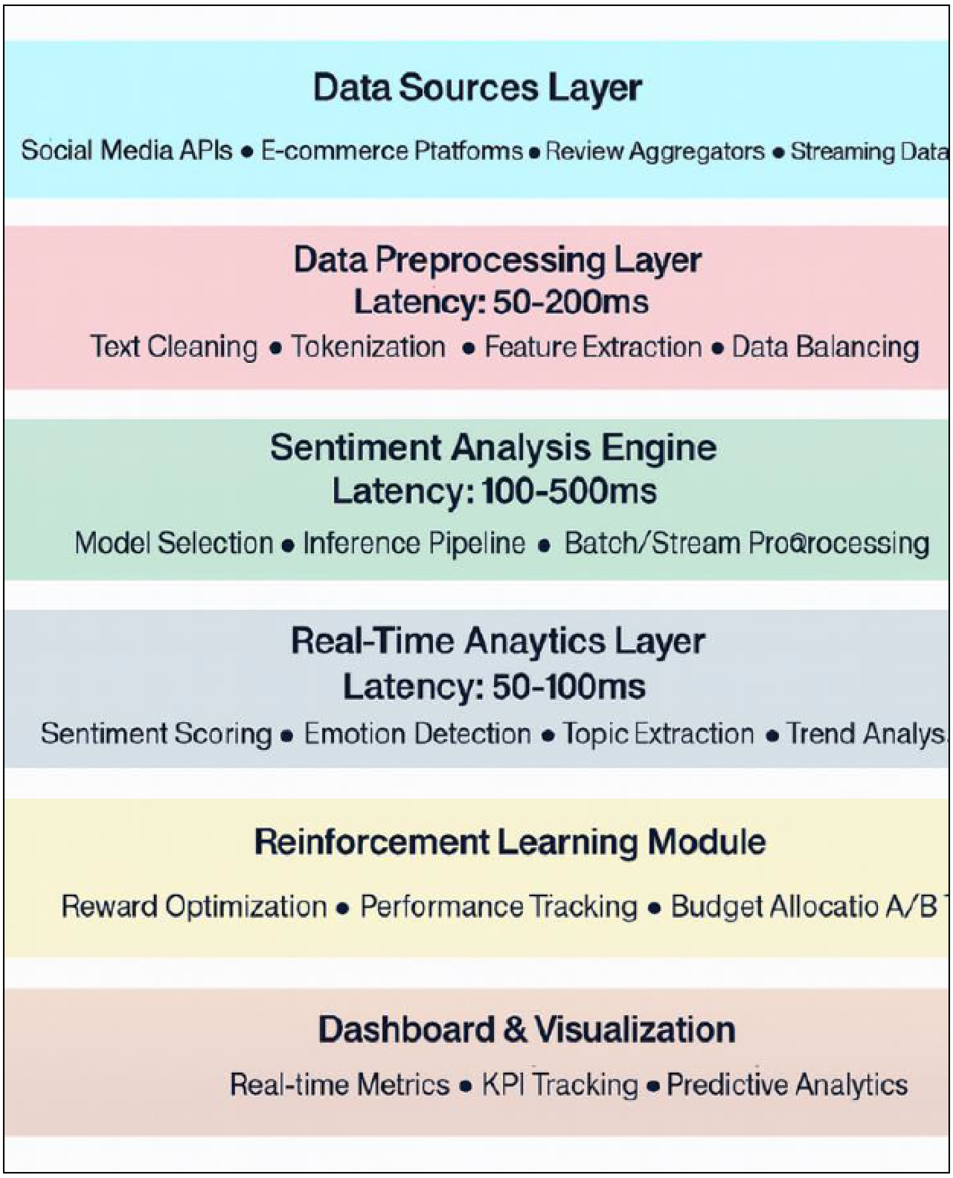

Figure 1.4: Accuracy versus Interpretability Trade-off

Illustration in Figure 1.4, is a system architecture diagram showing data flow from social media sources, through preprocessing, sentiment analysis models and on to marketing automation systems (and corresponding latencies)

According to the investigation provided in [1], very few realistic real-time systems have been developed thus far. Moreover, issues such as latency, scalability, and integration are still being faced inside real pick- and-place e-commerce platforms. Reinforcement learning methods are promising but have not been tested extensively in live marketing. Additionally, they are complex, which discourages adoption [32]. The ethical issues related to data privacy and transparency of adaptive marketing algorithms are not well addressed [50].

1.8 Emerging Technologies and Advanced Approaches

1.8.1 Large Language Models and Generative AI

New studies have shown that recent large pre-trained language models (GPT-3.5, GPT-4, LLaMA, and BERT variations) outperform traditional classifiers and perform well in distinguishing coarse sentiments and mixed emotions [41][51][52]. Using explainable AI techniques will help in understanding model decisions. Moreover, it will allow marketers to gain useful insights. This will further build trust in the AI outputs. Various studies show that LLMs can enhance sentiment classification and consumer insight extraction in e-commerce settings.

1.8.2 Topic Modeling and Multi-Aspect Study

Models that combine topic modeling (for example, BERTopic, LDA) with sentiment analysis provide multidimensional consumer insights into features, trends, and market demand. By conducting temporal and category-specific analyses, businesses can track shifts in consumer preferences over time. Thus, this ultimately allows a company to improve product offering and marketing strategy [44][54][55].

1.8.3 Adaptive Marketing via Reinforcement Learning

We used reinforcement learning techniques to improve sentiment prediction and personalize marketing strategies. These methods enable dynamic adjustment based on consumer feedback while improving the accuracy of sentiment classification and guiding personalized recommendation systems based on consumer sentiment.[30][31][32][56]

1.8.4 Multimodal and Cross-Domain Approaches

New research makes use of text and images from social media, forums, video sites, and product reviews to improve accuracy and data richness [49][57][58]. The use of these methods increases the model complexity and computations but largely lacks a standard dataset and benchmark for evaluation [49]. Cross-domain adaptation is difficult because of specific languages and sentiments, which limits its application. [57]

1.9 Practical Applications and Business Impact

1.9.1 Industry Implementations

As per several studies, sentiment analysis models can play an essential role in improving marketing strategies, customer segmentation, personalization and product recommendations, campaign

optimization, and more. This could lead to enhanced ROI and customer satisfaction. Case studies demonstrate the importance of receiving insights driven by feelings for timely decisions and adaptive marketing [20][61].
According to industry practitioners, transformer-based and hybrid machine learning models will allow for more accurate scalable sentiment analysis that monitors consumer sentiments in real time, which will enable timely adjustments to the campaign and product offerings [30][49][34]. According to the authors, combining insights from sentiment analysis and behavioral economics can help create personal marketing strategies that aim to increase positive sentiments and reduce negative sentiments associated with an initiative.

1.9.2 Limitations in Deployment

Limitations in Deployment Many research initiatives are either experimental or proof of concepts with little evidence of large-impact business deployment [1]. Barriers to incorporating the outputs of sentiment analysis into existing marketing workflows and systems have not been adequately studied. A gap remains between academics and industry adoption because of technical and organizational barriers [1].

1.9.3 Ethical Considerations and Data Privacy

Ethics concerns such as data privacy, algorithmically biased models, transparency, and data policies justify the need for responsible AI in marketing [50][1][16]. Another must-have AI for marketing is the fairness and inclusiveness of AI for consumer marketing. The deployment of explainable AI and interpretability techniques in the sentiment analysis model will help in gaining trust among stakeholders and improve transparency, ethical concerns, and compliance with rules and regulations with respect to marketing practices [28][16][19].
However, ethical issues are often dealt with lightly, normally with few practical frameworks for implementation. The capability for bias in training data and models has not been sufficiently explored, and few studies have suggested methods for ongoing auditing or mitigation [1][16]. The issue of consumer privacy is not properly handled because there is real-time data collection and analysis [62].

Figure 2.5 presents a conceptual diagram that illustrates how model accuracy, interpretability, privacy protection, and ethical constraints intersect with their mitigation strategies.

1.10 Critical Synthesis and Research Gaps

1.10.1 Agreements Across Studies

The findings of the different studies reviewed show impressive results in consumer behavior prediction and forecasting e-commerce marketing campaigns customer sentiment analysis across social networks through advanced machine learning algorithms, including deep learning and transformer-based models. Models such as BERT, BiLSTM, and ensemble methods are acknowledged to be far more accurate and adaptable to different datasets and e-commerce platforms [15][39][4][12][2][49][52].

Figure 1.5: Accuracy versus Interpretability Trade-off

1.10.2 Areas of Divergence

However, there is divergence in computational efficiency, interpretability, and real-time adaptability, which is often influenced by model complexity, data types, and application contexts. Views diverge on the blending of reinforcement learning and generative AI for marketing personalization, probably because of experimental parameters and technological maturity. In some domains or datasets, particularly those with small and simple data, research has found that standard algorithms such as SVM and Naive Bayes outperform or score as well as deep learning methods [12][63][64][41][14].

1.11 Future Research Directions and Recommendations

1.11.1 High-Priority Research Areas

For streaming social media data, lightweight and scalable transformers or hybrid neural network architectures must be developed for low-latency real-time sentiment analysis. Exploring edge computing and model compression techniques. It is very important to adapt to the current condition in real time for marketing interventions. However, owing to computational demands, the deployment has so far been restricted to non-live settings such as e-commerce. [30][33][15]. Conduct large-scale, real-world experiments on the integration of RL-based sentiment analysis with marketing automation platforms to validate the effectiveness and optimize resource allocation strategies. In operational settings, the use of RL in adaptive marketing may have great potential, but remains unexplored [30][31][32]. Cross-Domain and Multilingual Sentiment Analysis: Create learning models that transfer models from one domain to another. Models in a source domain can be trained to work in a target domain with the least amount of labeled data. It is important to address linguistic and domain diversity for e-commerce platforms to respond accurately to consumers [48][57][4].

Enhancing model interpretability refers to the implementation of explainable AI (XAI) techniques for deep learning and transformer models. These techniques help marketers understand how sentiments are driven as well as the rationale behind decision-making. Interpretability encourages trust and informed decision-making, yet it remains underexplored in high-performance models [28][4][36].

1.11.2 Medium-Priority Research Areas

Creating and benchmarking of multimodal sentiment analysis framework that combines textual, visual, and affective cues will capture a richer consumer sentiment and improve predictions.[49][54][58]

Contextual embeddings and pragmatic-level language understanding modules (using LLMs) are used to detect and interpret sarcasm and other nuanced types of sentiment. It is important to detect sarcasm to determine the actual sentiments of texts, particularly on social media [46][47]. Try pairing your neologism with an existing word to ensure credibility. The second part of your neologism, for example, 'netox' from Internet and tox for 'toxic' is similar to an existing word – Nexus. This provides credibility.

1.12 Limitations of the Review

This study has several limitations that may limit its generalizability.

- Choosing sources that only show studies in English can cause us to ignore other information.
- Many studies have been based on platform-specific datasets, mainly Amazon and Twitter, which do not allow cross-platform generalizability.
- Focusing only on peer-reviewed articles will eliminate unpublished and pre-print studies.
- Temporal Coverage: While the focus is on more recent studies of the 2022 to 2025 period, it may not cover all rapid emerging developments.
- Many potential niches or emerging algorithms will not be covered in this volume.

1.13 Overall Synthesis and Conclusions

Literature on the use of machine learning algorithms to analyze consumer sentiment and market e-commerce products on social media shows how powerful machine learning can be in analyzing and utilizing consumer sentiment. According to a number of studies, transformer models, BERT, RoBERTa, and LLMs outshine all other techniques for sentiment classification, demonstrating the mastery of social media and e-commerce reviews and the extraction of latent meanings and contextual relations. Other deep learning frameworks, such as CNNs, LSTMs, and BiLSTMs, can also successfully interpret consumer sentiment and predict buying intentions through effective

sequential dependency modeling [1][23][24].
The literature shows clear progress, yet fundamental hurdles around computation and scaling, especially for transformers and reinforcement learning models, remain. In adaptive marketing, a highly accurate model would not be sufficiently accurate to deploy in real time. Most operational uses and empirical studies in live e-commerce contexts remain underdeveloped, as real-time sentiment analysis with reinforcement offers exciting possibilities to personalize onboarding marketing campaigns spend on responsive marketing [1][30]. Furthermore, the quality of data in the form of noisy data, sarcasm, multiple languages, and multimodality continues to hamper sentiment analysis, negating the advantages of sophisticated preprocessing and feature engineering [46][47][48][49].
The correlation between social media sentiment and purchases, as well as the use of sentiment analysis for targeting, customer segmentation, and recommendations, presents statistically predictive insights. According to a marketing scholar BIJIT P. K. MAHAPATRA, although real-time melting margins and similar ethical issues are highlighted, they are not recognized as sufficient for any infringement of ethicality related to actionable frameworks being less workable.[50][1][16]
The power of multimodal and cross-domain data is evident for new consumer insights. However, it is still limited owing to methodological and computational complexity [49][57][58].
Most studies conclude that despite sophisticated machine learning and deep learning methods improving the capabilities of sentiment analysis and increasing its predictive accuracy regarding marketing in e-commerce, real-time adaptiveness in e-commerce machine learning, interpretability, ethical robustness, and practical scalability remain under-explored and unresolved issues [1][30][15][53].
Future research should target the building of strong and ethical architectures connecting scholarly and industry practice research to enable intelligent customer-oriented and accountable marketing to change the contour of social media dispersal channels.
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