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Decoding Customer Sentiments in E-Commerce: A Review of Machine Learning and Deep Learning Approaches

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***Abstract*— *E-commerce has been growing exponentially, creating a wave of user-generated content, which includes product reviews, ratings, and social media feedback in the process. Data streams from such analyses will be helpful for businesses to understand better the sentiments of customers, enhance decision-making, and improve customer engagement. Sentiment analysis is one of the critical branches of NLP, where insights are derived from textual data. Some of the classical approaches involve lexicon-based models and Naïve Bayes and Support Vector Machines from the machine learning area. More advanced techniques rely on deep learning approaches, for instance, LSTM, CNN, BERT, GPT-like transformer-based models.Techniques in Sentiment Analysis in E-commerce: A Comparison between Machine Learning and Deep Learning Approaches. This work encompasses major issues, such as sarcasm detection, spam review detection, and aspect-based sentiment analysis. It also includes popularly used datasets, such as Amazon Reviews and Yelp Reviews, and real-world applications, such as personalized recommendation systems and automated customer services. Furthermore, it introduces future research avenues: Explainable AI, multimodal learning, and federated learning for private sentiment analysis. The paper focuses on the review, analysis, methodologies, challenges, and applications in the effort of guiding researchers and industry professionals toward developing more effective sentiment analysis solutions for the e-commerce industry.*

I. INTRODUCTION

E-commerce has greatly changed the way consumers interact with companies by gradually integrating online shopping into the model of modern retail. Because customers increasingly rely on digital platforms, such as Amazon, eBay, Flipkart, and Alibaba, for various purposes, huge chunks of textual data are generated through everyday products in reviews, ratings, social media comments, and customer feedback [1]. This vast repository of user-generated content acts as an important asset for businesses in efforts to understand consumer behavior, preference, and market trends. However, the practicality of analyzing this amount of data is impossible; hence, techniques to automatically extract meaningful insights must be developed [1].

Sentiment analysis [2] forms a subdiscipline of natural language processing in which consumer attitudes, views, and feelings regarding goods and services are most important. Here, the company can measure client happiness, predict buy patterns, and even change its marketing strategy. Sentiment analysis is also important for reputation management because it lets brands address the concerns of the customers proactively and improve the overall consumer experience. With the advent of advanced machine learning and deep learning techniques, from simple rule-based methods, advanced models can understand contextual meanings and sarcasm plus nuanced emotions within the scope of sentiment analysis [2].

This review has aimed to do a comprehensive survey of the different methodologies used within the field of sentiment analysis towards e-commerce data, traditional approaches using machine learning, and then the newer more advanced deep architectures. It discusses the key challenges of fake review detection, aspect-based sentiment analysis, and multilingual sentiment interpretation [4]. The paper further explores benchmark datasets, real-world applications, and future research directions in sentiment analysis. This review aims to guide researchers and industry professionals toward more effective and efficient sentiment analysis solutions for e-commerce platforms by pointing out the progress and limitations in this field.

A. Scope of the Review

The paper takes into consideration the history, methodologies, challenges, and applications of sentiment analysis within the e-commerce context. Today, as dependence on customer opinions to guide the direction of businesses increases, a key tool has become essential: that is sentiment analysis in ascertaining consumers' preferences to ensure the maximization of customer satisfaction. It starts from the most classical approaches in machine learning: Naïve Bayes, Support Vector Machines, and Random Forest to the latest deep learning techniques, which include Recurrent Neural Networks, Convolutional Neural Networks, and Transformer-based models such as BERT and GPT [4].

In addition, a review is carried out for critical challenges in sarcasm detection, fake review filtering, aspect-based sentiment analysis, and multilingual sentiment interpretation. Other datasets freely available for the benchmarking of sentiment analysis models are also considered, including the Amazon Reviews dataset, Yelp Reviews dataset, and IMDB Sentiment Dataset. Among real-world applications, the paper addresses product recommendation systems, customer service automation, and brand reputation management. Ultimately, trends such as Explainable AI (XAI), multimodal sentiment analysis, and federated learning have been presented as future research directions [4].

B. Objectives of the Review

The primary objective of this literature review paper is to:

- Collectively discuss all the techniques for sentiment analysis adopted in e-commerce, including classical machine learning models and deep learning models;
- Contrast the strengths and weaknesses of various approaches to sentiment analysis, including precision, scalability, and relations to the real world;
- Identify at least one of the critical challenges of using e-commerce for sentiment analysis: detecting sarcasm, spam reviews, and adaptation to a new domain.
- Explore the existing public datasets and benchmarking practices of the field in sentiment analysis research.
- Focus on how applications are generated within the scope of e-commerce based on the sentiments that may involve personal recommendation systems, customer service automation, or even managing brand portfolios.
- To elaborate, recent trends, opportunities for future work in this line, including a particular role from Explainable AI, multimodal learning, or federated learning.

The paper will accomplish this objective by serving as a resource for researchers, data scientists, and industry professionals in search of avenues to use sentiment analysis to enhance their e-commerce platforms and improve customer engagement.

Fundamentals of Sentiment Analysis in E-Commerce

Sentiment analysis, also known as opinion mining, is a powerful natural language processing technique that analyzes text and determines the emotions, opinions, or attitudes expressed within it [5]. This technique is widely applied in various fields, including business intelligence, social media monitoring, customer feedback analysis, and market research. There are different types of sentiment analysis that provide varying levels of insight into textual data depending on the granularity of analysis. There are three basic kinds of sentiment analysis: polarity-based sentiment analysis, emotion-based sentiment analysis, and aspect-based sentiment analysis. Each of the methods is very important for understanding human sentiments and opinions, thereby making it possible to enable businesses and researchers to extract the most valuable insights [5].

Polarity-based sentiment analysis [6] is the most widely used method, which categorizes sentiments into three broad categories, being either positive, negative, or neutral. This type of analysis helps to determine the general sentiment toward a product, service, or topic. The process involves analyzing the words, phrases, and overall sentence structure to identify the polarity of the text. Traditionally, lexicon-based approaches have been used to detect sentiment by matching words with predefined sentiment dictionaries. The words "amazing," "excellent," and "fantastic" are considered positive, whereas the words "terrible," "bad," and "horrible" are classified as negative

[6]. But it sometimes falls short when dealing with complex structures, sarcasm, and context-dependent meaning. Other approaches such as Support Vector Machines (SVM), Naïve Bayes, and deep learning-based models like BERT and LSTMs have been able to get better results in sentiment classification with more and more large labeled datasets. However, the polarity-based approach for sentiment analysis is not fully suitable when a sentence can contain mixed sentiments or contains implicit opinions or cannot state the opinions clearly [7].

Emotion-based sentiment analysis [8] goes further than the normal sentiment classification of identifying specific emotions expressed in text. Instead of just classifying sentiments as being positive or negative, this detects emotions such as joy, anger, sadness, surprise, fear, or disgust. This analysis is particularly important in applications where deeper understanding of human emotion is required. Such applications include mental health monitoring, personalized marketing, and automation of customer services. Emotion-based sentiment analysis draws its foundations from theories behind human emotions, such as Plutchik's wheel of emotions or Ekman's six basic human emotions. From a traditional stand, lexicon-based approaches take advantage of specific word lists that elicit emotions. Modern deep learning models, however, rely on neural networks for the extraction of nuances in text to infer emotional cues. For example, where "I am overjoyed with my purchase" does convey joy, "I feel so frustrated with the delay in service" infers anger. This is still limited in many ways: not able to understand mixed emotions of a sentence in one sentence, closely related emotions, and changes in expressions through culture [8].

The more subtle or fine-grained approach would be aspect-based sentiment analysis, finding the sentiment on specific aspects about a product, service, or entity. ABSA does not produce a universal score, unlike polarity-based sentiment analysis. Instead it breaks a text into multiple aspects and determines which aspect contains which sort of sentiment against it. For instance, if one provides a product review that reads "The camera quality is excellent but the battery life is bad", then a general classifier of sentiment cannot tag that with either a positive or negative sentiment tag. ABSA would report "camera quality" to be positive and "battery life" to be negative. This level of granularity makes ABSA incredibly useful in providing insight for any business looking into specific customer concerns or improving key areas in their offering [9]. To extract aspects and associate with sentiment, ABSA uses advanced NLP techniques such as dependency parsing, word embeddings, and attention mechanisms. The major problems of ABSA are handling implicit aspects in which the feature is not explicitly mentioned, managing domain-specific terminology, and accurately interpreting ambiguous opinions [9].

Each of the techniques mentioned above has its strengths and challenges: their application depends on the specifics of the task. Polarity-based analysis provides a high-level overview of trends in sentiment, while emotion-based analysis offers deeper insights into user emotions. This helps businesses pull out in-depth feedback about attributes of a specific product or service. The maturity of deep learning and NLP has dramatically changed the accuracy and applicability of sentiment analysis to become a gold standard for applications in several fields. The AI-driven sentiment analysis holds much promise as it progresses with the capability to alter the ways companies engage with their customers, understand public opinion, and make informed decisions based on data.

Machine Learning Techniques for Sentiment Analysis

Sentiment analysis is a very vital tool in public opinion, customer feedback, and social media trend analysis. It has been significantly important in machine learning for automated sentiment classification using pattern recognition from textual data through model training. Machine learning approaches for sentiment analysis can be divided into two main categories: traditional machine learning techniques and feature engineering techniques [10]. Traditional machine learning comprises algorithms that can classify feelings over any text through features extracted from text, but feature engineering encompasses techniques for the transformation of raw text into numeric representations that may be processed over machine learning models.

A. Traditional Methods of Machine Learning

Traditionally, machine learning is used before deep learning is applied in the process of sentiment analysis. These are statistical methods and based on supervised learning models with labeled datasets where the dataset is labeled with the sentiment either as positive, negative, or neutral. The most widely applied algorithms include Naïve Bayes, Support Vector Machines, Decision Trees, and Random Forest [11].

Naïve Bayes is a probabilistic classifier based on Bayes' theorem and is used especially for the text classification problem, including the sentiment analysis problem. It presumes that a certain word occurring in a sentence is independent of the occurrence of other words; hence, the term "naïve" is used in its name. Although it looks simple and trivial, it is still surprisingly efficient for the task of sentiment classification when used along with the methods of Laplace smoothing and feature selection. Still, it faces problems with the complex sentence structure, sarcasm, and context [11].

The most widely used algorithm for sentiment analysis is SVM. It tries to find a hyperplane that is best in discriminating between different categories of data points. SVM has excellent performance in high-dimensional data and is well-suited for text classification, where thousands of words can be used as features. The use of kernel functions, including linear, polynomial, and radial basis function (RBF) kernels, further improves its ability to capture non-linear relationships in text data. However, SVM requires careful parameter tuning and can be computationally expensive for large datasets [12].

Decision Trees are hierarchical models where text is classified based on rules derived from the values of the features. The internal nodes describe a decision about a feature and the branches, the possible outcome. Decision trees are easy to interpret and are computationally very efficient but may overfit-the model does not generalize well on unseen data. To counter such overfitting, ensemble methods like Random Forest are used [12].

Random Forest is an ensemble learning technique that constructs multiple decision trees and combines their outputs to improve classification accuracy. It reduces overfitting by averaging the predictions of multiple trees, making it a robust choice for sentiment analysis. However, Random Forest can be computationally expensive and may not perform as well as deep learning approaches on large-scale datasets [12].

B. Feature Engineering Techniques

Feature Engineering is, in fact the most crucial step in sentiment analysis as it converts raw textual data into a more structured format that computer models can then understand. Several techniques represent text as numerical features: the Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and Word2Vec [13].

One of the simplest feature extraction techniques is the Bag of Words (BoW). It represents text as a collection of words, ignoring grammar and word order but keeping track of word frequencies. Each unique word in the dataset forms a feature, and the presence or absence of words in a document determines the feature values. Though simple, BoW suffers from sparsity issues and fails to capture semantic relationships between words [13].

TF-IDF, short for Term Frequency-Inverse Document Frequency, extends the BoW method by weighting the words based on their importance in a document compared to the whole corpus. Words that occur more frequently in the document but infrequently in the corpus are stressed, which are useful for removing common words not contributing to the sentiment. It enhances text representation but does not capture word meaning or contextual relationship [13].

Word2Vec is a neural network-based technique for representing words as dense vectors in a continuous vector space. Word2Vec does not have any problems of semantic and syntactic relationships between words because it has been trained on huge text corpora. The method of word embedding using CBOW and Skip-Gram can provide words that share similar meanings to have close vector representations. It greatly enhances the performance of sentiment analysis especially if used together with deep learning models [13].

Traditionally, the primary approach to this task is Naïve Bayes and SVM and recently has used advanced features engineered using methods like Word2Vec; in fact, these are part of deep learning. The appropriateness of a method depends much on the dimensions like how many samples the computational resources allow and the inherent complexity of the patterns found in sentiments expressed in a piece of text.

Deep Learning for E-Commerce Sentiment Analysis

With e-commerce platforms now booming, analyzing the sentiment of a customer has gained more importance because companies need to understand how people behave and have to improve the products and their customer services accordingly. Traditional methods of machine learning are effective; however, capturing complex language structures, contextual meanings, and long-range dependencies in texts is quite challenging with traditional methods. Among the deep learning methods, the RNN, LSTM networks, CNNs, and Transformer-based models like BERT, GPT, and T5 have made significant progress in sentiment analysis with more context-aware and precision classification.Hybrid models, which have a combination of traditional machine learning and deep learning, have further steered itself in the right direction in the domain of sentiment analysis for the e-commerce space [14].

This model of deep learning is essentially recurrent neural nets used to manage sequential data; they are particularly helpful in the sense of doing a sentiment analysis. Unlike feedforward neural nets, in the RNN, there is this unit of memory, where all previous inputs are kept and can be reused for realizing the context within a sentence so that it would understand the whole thing.The vanishing gradient problem makes it challenging for typical RNNs to learn long relationships in the text; this is one of the major drawbacks [14].

The problem was able to be solved when LSTMs introduced memory cells to store and selectively update information along a lengthy sequence.In particular, LSTMs are very useful for sentiment analysis tasks since they can capture word dependencies even if they appear quite far apart in a sentence. Take a simple example based on an e-commerce review for instance, such as, "The product quality was superior to my expectation, though it has been delivered very late," an LSTM would see that the negative phrase at first, the final sentiment is however positive. In this sense and capacity for modelling long-range dependency, LSTMs are rather valuable in working with product review and customer responses in e-commerce [14].

A. Convolutional Neural Network (CNN) for Text-based Sentiment Analysis

CNNs were originally developed for computer vision applications but have also been adopted and showed remarkable success in text-based sentiment analysis. CNNs will extract hierarchical features on text represented by convolutional filters and then identify n-grams and some important sentiment-carrying phrases. Unlike RNNs, the way that CNNs can process a sequence of text is in parallel rather than sequential, thus being computationally efficient and fast in training [15].

Very useful in classifying short texts like product reviews, customer comments, and social media mentions in e-commerce sentiment analysis. For example, in a broken-up review, the CNN model would come out with phrases that have high content of a sentiment like "terrible service" or "highly recommended.". This can be implemented through multiple convolutional layers and max-pooling operations, automatically extracting features related to the sentiment with minimum manual feature engineering. Yet since CNNs do not capture such long-term dependencies, they are not as effective in the analysis of complicated sentence structures or lengthy customer reviews [15].

B. Transformer-Based Models for Context-Aware Sentiment Analysis

One of the emergent lines of transformer-based models has transformed NLP by introducing self-attention and positional encoding mechanisms into training models to better grasp context compared to their RNN or CNN-based counterparts. Transformers require huge amounts of text data for training and can be fine-tuned for fine-grained sentiment analysis with high accuracy [16].

BERT is a current transformer model, where it makes sense to consider words in terms of their contexts and surrounding words rather than isolating them. Most approaches in text processing proceed either from left to right or vice versa. In this sense, BERT captures the context both ways; therefore, it has proven very effective for sentiment classification. In e-commerce, it lets one accurately make an analysis about product reviews given the understanding of nuances in the expressions of sentiments such as, "The product itself is great, but the packaging was damaged." [16]

Another model with extremely high capabilities in generating text and in sentiment-aware responses is GPT. Unlike BERT which is an optimized version for classification, GPT excels at conversational AI, and this makes it quite useful in the e-commerce world, like in chatbots, customer support automation, or even personalized recommendations based on trends in sentiment [17].

Yet another versatile transformer model, T5 addresses each NLP task as a text-to-text problem. For example, for sentiment analysis, scores for sentiment can be generated or even customer reviews summarized or responded to based on the tone of sentiment. It is highly useful for companies seeking to automate sentiment-based decision-making when fine-tuned for e-commerce scenarios [17].

C. Hybrid Models Integrating the Conventional Approach of Machine Learning with Deep Learning

Deep learning models have allegedly shown better results in sentiment analysis. The hybrid model that involves using traditional techniques of machine learning with deep learning-based approaches promises better improvements than that. These are a perfect integration of both classical machine learning efficiency and the strength of deep learning, which hence reflects an improvement in the precision of the classification of sentiments [18].

Some common hybrid approaches involve feature engineering techniques like TF-IDF or Word2Vec for transforming text into numerical vectors and then applying deep learning models such as LSTMs or CNNs for classification. The other is by using traditional machine learning models such as Random Forest or SVM, as an ensemble layer over deep learning models for fine-tuning the predictions [18].

For instance, when doing sentiment analysis on e-commerce, a hybrid model will first apply BERT-based transformer to extract contextual embeddings from text and then send the final call about the sentiment to a Random Forest classifier. Here again, this combination would exploit the context-awareness of transformers and would combine robust decision-making capabilities of ensemble learning that could further lead towards making an even better and more understandable classification system for sentiment [18].

Deep learning has improved the sentiment analysis of the e-commerce industry significantly with more accurate, context-aware, and scalable solutions. RNNs and LSTMs are best suited for sequential dependencies, whereas CNNs efficiently extract sentiment features from short texts. Models like BERT, GPT, and T5 advance the sentiment analysis, capturing bidirectional context and generating insightful sentiment-aware responses. Hybrid models, which combine the traditional machine learning approach with deep learning, have also been shown to provide optimal performance for the task of sentiment classification. E-commerce platforms continue to grow; hence, adopting advanced deep learning techniques will become crucial in order to improve the customer experience, enhance product recommendation, and support data-driven business strategies.

II. METHODOLOGY

This review paper presents an overview of the latest techniques developed in the domain of e-commerce in terms of sentiment analysis. Additionally, this work specifically targets two subfields in the field: machine learning and deep learning approaches. The research methodology for this paper is adopted with the use of a systematic literature selection method, allowing relevant, high-quality sources to be included but filtering out the rest that are less relevant and obsolete. Here's a more elaborate description on how this methodology applies to the review:

A. Databases/Resources

The literature for this review was drawn from a modest but thoughtfully chosen list of academic databases and journals well recognized for having very large collections of peer-reviewed studies in machine learning, NLP, sentiment analysis, and e-commerce. The list of those academic databases and journals appears below:

- IEEE Xplore
- Springer
- Elsevier
- Wiley Online Library
- Google Scholar
- ACM Digital Library

These databases were selected based on a strong collection of researches regarding machine learning, deep learning, and NLP, particularly for applications related to e-commerce and sentiment analysis. Furthermore, the best contributions out there in some of the leading conferences like NeurIPS, which is known as the Conference on Neural Information Processing Systems; ICML, International Conference on Machine Learning; and ACL, Association for Computational Linguistics were included in this review to capture the most current studies that pertain to applications in the realm of sentiment analysis for e-commerce.

B. Inclusion criteria

ONLY research paper of good quality and relevant in the review is taken in by strict inclusion criterion. The selected studies were assessed with the help of the following parameters:

- **Time Frame:** Only research published over the last five years, which means between 2019 and 2024, was taken into account to review the recent developments in sentiment analysis of e-commerce. Yet, if it had any founding paper that delivered critical insights or background necessary for understanding more recent developments, older papers were incorporated.The studies relevant to these papers in regard to the e-commerce sentiment analysis are product reviews, customer feedback, social media sentiment, and market analysis based on e-commerce. Papers which were not strictly related to any of these applications but just some general sentiment analysis were excluded in this review.
- **Machine Learning and Deep Learning Methods:** Only articles using machine learning or deep learning methodology for analyzing sentiments are accounted for. Naïve Bayes, SVMs, Random Forests, CNNs, RNNs, and various transformer models- BERT, GPT among others are encompassed in those studies. It is excluded here since only studies used traditional method but did not consider ML/ DL methodology were considered.
- **Textual Data and Multimodal Approaches**: The literature review encompasses works that base their research on textual data retrieved from e-commerce sites, which include product descriptions, customer reviews, and ratings. Other papers are based on multimodal approaches where text data are complemented by images and audio for improved sentiment classification. Works on non-textual sentiment analysis alone or which have no direct relationship with the use of textual data were not included.

D. Key Words

A focused and targeted keyword strategy was used to ensure an efficient and thorough literature search. The following key words were used in the search process:

- E-commerce sentiment analysis
- Machine learning for sentiment analysis in e-commerce
- Deep learning in e-commerce
- Customer sentiment analysis
- Sentiment classification models (CNN, RNN, Transformer)

- Product review analysis
- Social media sentiment in e-commerce
- Multi-modal sentiment analysis
- NLP for sentiment analysis

Combination with Boolean operators in literature searching involved using AND or OR to bring up focused though all-inclusive retrieval of texts and limit relevant articles to mainly the most crucial articles for use in the literature review.

E. Step-wise Selection

Stepwise selection of relevant literature to include only high-quality and highest impact studies were included in it. The entire process is detailed as follows

- **Main Collection:** In the first stage, it was initiated with a free search of the described key words on all the selected databases for retrieving articles. The preliminary search returned about 50 review articles. The background work included citation tracking besides database searching to identify further relevant studies, which were cited very frequently in influential works.
- **Shortlisting:** In the second stage, the abstracts and titles of the retrieved papers were carefully screened to ensure whether they met the inclusion criteria or not. This evaluation led to the shortlisting of 25 papers based on their relevance with e-commerce sentiment analysis, ML and DL application, and a focus on analyzing customer feedback.
- **Final Review** This was a deeper review of the shortlisted 15 papers, which were considered the most influential and impactful works. These papers were reviewed to see what actually they did for the techniques in sentiment analysis, innovation in deep learning, and practical application in the field of e-commerce. The studies that significantly advanced in sentiment classification, social media sentiments, and multimodal data usage were preferred to include.

F. State-of-the-art and Comprehensive Literature Review

The approach will help the review paper to be contemporary and comprehensive while discussing the state-of-the-art developments in applications of machine learning and deep learning for sentiment analysis in e-commerce. A systematic selection process was followed, making the review identify recent developments along with ongoing issues in the domain, such as dealing with sarcasm, context-aware sentiment analysis, and integrating multimodal data.

The review is also focused on innovation research areas, like explainable AI, which would improve the interpretability of models related to sentiment and federated learning for privacy-preserving sentiment analysis. These elements ensure that the review is not only encompassing but also leads to future research directions in the field of sentiment analysis and its practical applications to the e-commerce sector.

Table 1. Selection Process of Literature Review

Stage	Number of Papers	Description
Initial Collection	100	Papers identified through database searches and citation tracking using defined keywords related to sentiment analysis in e-commerce.
Shortlisting	25	Papers reviewed for relevance based on inclusion criteria (machine learning and deep learning models, customer sentiment analysis, product reviews, and social media sentiment).
Final Review	15	In-depth review of selected papers that focus on CNN-based models, transformer models (BERT, GPT), and multimodal AI approaches for sentiment analysis in e-commerce.

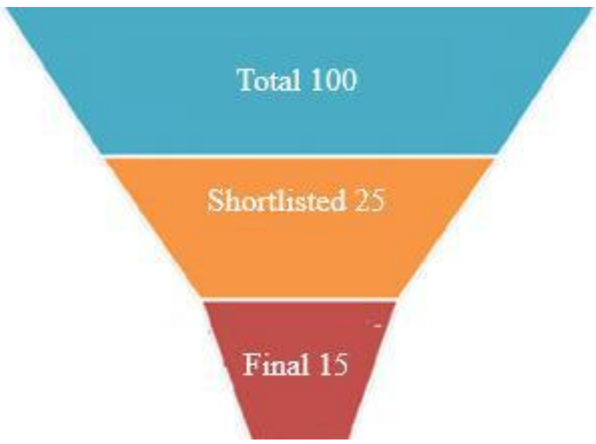

Fig.1. Funnel Diagram for Literature Review

III. LITERATURE REVIEW

The final selected papers for literature review are as follows,

A hybrid model, RoBERTa-1D-CNN-BiLSTM, was presented by Rana, **M. R. R., et al. (2024) [19],** which attempted to find the intricacies of the complexities involved in short, unstructured, and emotive reviews' interpretation.

Herein, feature extraction is done with pre-trained RoBERTa, 1D-CNN refines the features, and classification is done using BiLSTM. The proposed system achieves an accuracy of 92.33% with cross-domain datasets, outperforming the state-of-the-art sentiment analysis techniques.

Purnamasari, D., et al. (2024) [20] also assessed the customers' reviews of the Indonesian e-commerce platforms during the COVID-19 pandemic by determining if sentiment analysis would influence the MSME decisions. They found that the LSTM model had the highest rating at 94%, thus proving its advantage in analyzing sentiment compared with other machine learning and deep learning techniques for the determination of product development.

Ma, X., Li, Y., & Asif, M. (2024) [21] developed the model BERT-LSTNet-Softmax in which NLP comes with sentiment analysis which helped to analyze consumer trust, perceived benefit, and purchase intention. Their results illustrate that this model really works toward forecasting the time-series trends in sentiment and extracting insights into consumer behavior of e-commerce.

Wu, Y., et al. (2024) [22] focused on the application of deep learning to sentiment analysis. This includes BERT. Their work described the architecture of BERT, optimization strategies, and experimental validations. Fine-tuned BERT models improve significantly in performance on sentiment analysis tasks. It also covered future research directions and applications of BERT in sentiment analysis.

Wan, B., et al. B. in 2024 [23] proposed Emotion-Cognitive Reasoning integrated BERT (ECR-BERT) for emergency online public opinion analysis. ECR-BERT integrates emotion models and deep learning, using OCC's self-adaptive fusion algorithm to reduce knowledge noise. Their evaluation over four datasets proved that ECR-BERT is indeed better than the traditional BERT model and details reasons describing the reasons for deriving sentiments.

Yi, G., et al. 2024 [24]. Development of the Disentanglement Translation Network with Slack Reconstruction. Unfortunately, multimodal sentiment analysis still suffers from some problems. The model disentangles modality-specific and common features, removes redundancy, and aligns feature distributions. Experiments confirmed that DTN can improve the accuracy of sentiment analysis; codes were published.

Li, X., Li, Q., & Kim, J. (2023)[25] proposed the CNN-TRI model for review helpfulness prediction by incorporating text and star ratings features. It performed better than other models in terms of reducing information overload and enhancing decision-making ability, especially when analyzing reviews on Amazon.

Li, H., et al. (2023) [26] proposed the BiLSTM-CNN Model with Attention mechanism to perform Chinese e-commerce sentiment analysis. The authors used three-class sentiment classification with a weighted attention mechanism for better feature vectorization and elevated model performance.

Mahmud, F. A. M., et al. in 2023[27] used NLP and machine learning to analyze reviews of women's clothing. Out of the numerous models experimented upon, the accuracy was the maximum at 96.51% with the use of Random Forest classifier, thus depicting the mutual association between different aspects of a product and consumers' attitude towards the product of customers that enable merchants to improvise their service.

AlzahraniM. E. et al. (2022) [28] focused on fraudulent review detection using CNN-LSTM and LSTM models for the classification of sentiment. Both their models performed with an accuracy of 94% and 91% for different categories of Amazon products.

Fang, L., et al. (2022) [29] proposed Sense-aware BERT (SenBERT) for multimodal sentiment analysis with multi-head attention and auxiliary tasks. Their model outperformed baselines on CMU-MOSI and CMU-MOSEI datasets, especially in balancing modality attention for improved sentiment classification.

Ye, J., et al. (2022) [30]designed SMP for multimodal sentiment analysis. In the SMP framework, they used cross-modal contrastive learning with sentiment-specific objectives, outperforming capture of sentiment signals, especially from multimodal datasets.

Zou, W., et al. (2022) [31]explored the importance of BERT’s intermediate layers in multimodal fusion for sentiment analysis. Their Hierarchical Fusion Model incorporated fine-grained sentiment features, outperforming previous approaches on the CMU-MOSI and CMU-MOSEI benchmark datasets.

Yang B. et al. in 2022 [32] proposed Two-Phase Multi-task Sentiment Analysis (TPMSA) to optimize pre-trained models for multimodal sentiment analysis. The two-phase training strategy proposed herein permits effective multi-task learning but still achieves strong performance on the CMU-MOSI and CMU-MOSEI datasets.

Wang, D., et al. (2022) [33] Introduce Cross-modal Enhancement Network (CENet) for multimodal sentiment analysis, aiming to enhance text representations with visual and acoustic cues. Benchmark datasets with high gains over state-of-the-art methods can be achieved under dealing with differences of modality distribution.

Table 1. Literature Review Findings

Author Name (Year)	Main Concept	Findings	Limitations
Rana, M. R. R., et al. (2024)	Hybrid model: RoBERTa-1D-CNN-BiLSTM	Achieved 92.33% accuracy on cross-domain datasets, outperforming state-of-the-art techniques	Does not address all possible complexities of short, unstructured reviews
Purnamasari, D., et al. (2024)	Sentiment analysis for MSME decision-making	LSTM model achieved 94% accuracy, proving its advantage for product development	Focused on only Indonesian e-commerce reviews during the pandemic
Ma, X., Li, Y., & Asif, M. (2024)	BERT-LSTNet-Softmax model for sentiment analysis	Successful in forecasting time-series sentiment trends and providing insights into consumer behavior	Limited to time-series sentiment analysis
Wu, Y., et al. (2024)	BERT architecture and optimization for sentiment analysis	Fine-tuned BERT models show improved performance in sentiment analysis tasks	Does not explore all possible BERT optimizations
Wan, B., et al. (2024)	Emotion-Cognitive Reasoning integrated BERT (ECR-BERT)	ECR-BERT outperformed traditional BERT with improved sentiment derivation and reasoning	Not evaluated across a wide range of sentiment analysis tasks
Yi, G., et al. (2024)	Disentanglement Translation Network (DTN) with Slack Reconstruction	DTN model improved sentiment analysis accuracy by disentangling modality-specific and common features	Limited testing on multimodal sentiment analysis
Li, X., Li, Q., & Kim, J. (2023)	CNN-TRI model for review helpfulness prediction	Outperformed other models in reducing information overload and enhancing decision-making	Limited to review helpfulness prediction on Amazon
Li, H., et al. (2023)	BiLSTM-CNN model with Attention mechanism	Enhanced sentiment classification performance using a three-class sentiment approach and weighted attention	Focused on Chinese e-commerce sentiment analysis
Mahmud, F. A. M., et al. (2023)	Sentiment analysis of women's clothing reviews	Achieved 96.51% accuracy with Random Forest classifier, correlating product aspects with customer attitudes	Limited to women's clothing review analysis
Alzahrani, M. E., et al. (2022)	Fraudulent review detection with CNN-LSTM and LSTM models	Models achieved 94% and 91% accuracy across Amazon product categories	Limited to fraudulent review detection
Fang, L., et al. (2022)	Sense-aware BERT (SenBERT) for multimodal sentiment analysis	Outperformed baselines on CMU-MOSI and CMU-MOSEI datasets with balanced modality attention	Limited to multimodal sentiment analysis
Ye, J., et al. (2022)	SMP framework for multimodal sentiment analysis	Captured sentiment signals effectively with cross-modal contrastive learning	Focused on multimodal sentiment analysis with sentiment-specific objectives
Zou, W., et al. (2022)	BERT intermediate layers for multimodal fusion	Hierarchical Fusion Model improved sentiment analysis performance on CMU-MOSI and CMU-MOSEI datasets	Limited to BERT-based multimodal fusion
Yang, B., et al. (2022)	Two-Phase Multi-task Sentiment Analysis (TPMSA)	Optimized pre-trained models for multimodal sentiment analysis, achieving strong performance	Limited to CMU-MOSI and CMU-MOSEI datasets

Wang, D., et al. (2022)	Cross-modal Enhancement Network (CENet)	Achieved high performance on multimodal sentiment analysis by enhancing text representations with visual and acoustic cues	Limited to dealing with differences in modality distribution

Research gaps Discussion

Despite the significant advancements in sentiment analysis through various hybrid models and deep learning techniques, several research gaps remain. Many of the existing models, while effective in their specific contexts, have limitations in terms of generalizability across diverse datasets and domains. For instance, models like RoBERTa-1D-CNN-BiLSTM and ECR-BERT excel in cross-domain sentiment analysis but may struggle with the complexities of unstructured, short, and emotive reviews. Additionally, the use of deep learning models such as LSTM and BERT has shown promising results in specific applications like MSME decision-making and e-commerce, yet the models often lack flexibility when dealing with multimodal data that spans different types of inputs such as text, visual, and acoustic signals. Moreover, the focus on specific languages, product categories, or regions, such as the analysis of Chinese e-commerce reviews or Indonesian MSME decisions, limits the applicability of these models on a global scale. A significant gap also exists in addressing the trade-offs between model complexity and interpretability, as many of the proposed models, though accurate, often lack transparency in sentiment derivation and decision-making processes. Finally, there is a need for more robust evaluation across diverse and real-world datasets to ensure these models perform well under varying conditions, such as different modalities, noisy data, or adversarial scenarios.

IV. CONCLUSION

In this review paper, we have examined the evolving landscape of sentiment analysis in e-commerce, with a particular emphasis on the application of machine learning and deep learning techniques. As the e-commerce industry continues to expand, the volume of user-generated content, such as product reviews and social media feedback, has provided businesses with a valuable resource for understanding customer sentiments. Traditional sentiment analysis methods, such as Naïve Bayes and Support Vector Machines, have laid the foundation for sentiment classification; however, the advent of deep learning approaches has significantly enhanced the accuracy, scalability, and contextual understanding of sentiment analysis.

Key advancements, particularly through the use of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based models like BERT and GPT, have transformed the field by enabling models to capture nuanced emotional tones, detect sarcasm, and perform context-aware sentiment analysis. Furthermore, the integration of multimodal data (text, images, and social media signals) has opened new doors for more sophisticated sentiment analysis techniques that offer a richer understanding of customer behavior and preferences.

Despite these significant advancements, challenges remain in the application of sentiment analysis in e-commerce, including handling domain-specific jargon, processing large-scale datasets, and ensuring model interpretability. As businesses strive for deeper insights into customer satisfaction, the need for explainable AI and privacy-preserving techniques, such as federated learning, will continue to grow. These emerging areas offer promising opportunities for future research and development.

The review provides a comprehensive overview of current methodologies, challenges, and applications in sentiment analysis, guiding researchers and industry professionals in building more effective solutions for the e-commerce sector. Moving forward, continued innovation in machine learning and deep learning techniques, alongside collaborative efforts across disciplines, will be essential to meet the increasing demand for personalized, data-driven customer experiences in the e-commerce space.

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