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OPTIMIZED DEEP LEARNING MODEL FOR SENTIMENTAL ANALYSIS TO IMPROVE CONSUMER EXPERIENCE IN E-COMMERCE WEBSITES

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ABSTRACT

Sentiment analysis plays a pivotal role in deciphering customer sentiments from vast amounts of unstructured data, particularly in the context of e-commerce where customer reviews are prolific. The evolution of e-commerce reviews toward a multimodal format, including images, videos, and emojis, introduces new dimensions to sentiment analysis. Traditional text-based models may struggle to effectively capture sentiments expressed through non-textual elements. This paper proposed an effective sentiment analysis model for the E-Commerce Platform to improve the user consumer experience. The proposed method comprises Fejer Kernel filtering for data points estimation in the E-commerce dataset points. Within the estimated data points fuzzy dictionary-based semantic word feature extraction is performed for the estimation of features in the E-Commerce dataset. The dataset for the analysis is computed with the Optimized Stimulated Annealing for the feature extraction and selection. The classification of customer opinion is classified with the BERT deep learning model. The feature extracted from the model is the opinion of consumers in the E-Commerce dataset. The classification of consumer preference experience is based on opinion of customers in the E-commerce dataset. Simulation results demonstrated that proposed model achieves the higher classification accuracy for the E-Commerce platform.

Keywords: *Sentimental Analysis, Deep Learning, BERT, Fejer-Kernal, Stimulated Annealing, E-Commerce*

1. INTRODUCTION

In recent years, e-commerce websites have witnessed unprecedented growth and transformation, reshaping the way consumers engage in commerce. The surge in online shopping is attributed to factors such as increased internet penetration, widespread smartphone adoption, and evolving consumer preferences [1]. E-commerce platforms offer a vast array of products and services, ranging from consumer electronics and fashion to groceries and digital content. The competition among these websites has led to innovations in user experience, with personalized recommendations, seamless payment options, and efficient logistics becoming the norm [2]. Moreover, the integration of artificial intelligence and machine learning has empowered e-commerce platforms to analyze consumer behavior, optimize marketing strategies, and enhance overall customer satisfaction. Social commerce has also gained momentum, with platforms integrating shopping features directly into social media channels. The rise of sustainable and ethical consumerism has prompted e-commerce websites to prioritize eco-friendly practices, contributing to a more responsible and conscious marketplace [3]. As e-commerce continues to evolve, the industry's adaptability and commitment to enhancing the online shopping experience are poised to shape the future of retail.

Sentiment analysis, also known as opinion mining, plays a crucial role in the realm of E-commerce websites, offering businesses valuable insights into customer perceptions and preferences [4]. This analytical approach involves evaluating and understanding the sentiment expressed in customer reviews, comments, and feedback. E-commerce platforms leverage sentiment analysis to gauge customer satisfaction, identify areas for improvement, and tailor their offerings to meet evolving demands [5]. Advanced natural language processing (NLP) algorithms are employed to

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categorize sentiments as positive, negative, or neutral, providing businesses with a nuanced understanding of customer sentiment. Positive sentiments can guide marketing strategies, help in showcasing popular products, and reinforce positive aspects of the brand [6]. Conversely, negative sentiments can signal potential issues in product quality, customer service, or user experience, prompting timely interventions to address concerns and enhance overall customer satisfaction. Sentiment analysis not only aids in improving customer relations but also contributes to data-driven decision-making for E-commerce businesses, fostering a more responsive and customer-centric online retail environment [7].Sentiment analysis plays a pivotal role in shaping the consumer experience on E-commerce websites by providing businesses with valuable insights into customer emotions and opinions [8]. By analyzing the sentiments expressed in customer reviews, comments, and feedback, E-commerce platforms can gain a deeper understanding of the factors influencing consumer satisfaction. Positive sentiments can highlight products or features that resonate well with customers, enabling businesses to emphasize these aspects in marketing efforts and product development [9]. On the other hand, negative sentiments can serve as early indicators of potential issues, allowing companies to promptly address concerns related to product quality, shipping, or customer service [10]. This proactive approach enhances the overall consumer experience by demonstrating a commitment to customer feedback and continuous improvement. Sentiment analysis also contributes to personalized recommendations, as E-commerce platforms can tailor suggestions based on customer preferences identified through sentiment analysis [11]. Ultimately, by integrating sentiment analysis into their operations, E-commerce websites can create a more responsive, customer-centric, and enjoyable shopping experience for users, fostering trust and loyalty in the highly competitive online retail landscape [12].

Sentiment analysis in E-commerce websites employs a variety of techniques to extract meaningful insights from customer feedback and opinions. Natural Language Processing (NLP) forms the backbone of these techniques, enabling the algorithms to understand and interpret human language [13]. One common approach is the use of machine learning algorithms, particularly supervised learning models, which are trained on labeled datasets to recognize sentiment in text. These models can classify reviews as positive, negative, or neutral based on patterns and features identified during training. Additionally, sentiment lexicons and dictionaries are frequently employed, containing predefined lists of words associated with positive or negative sentiments [14]. Rule-based systems leverage these lexicons to analyze text and determine sentiment based on the presence and context of specific words. More advanced techniques involve deep learning models, such as recurrent neural networks (RNNs) and transformers, which excel at capturing complex linguistic nuances and dependencies in lengthy text passages [15]. Hybrid approaches combining these techniques are also common, allowing E-commerce platforms to deploy a robust sentiment analysis system that can adapt to the diverse and dynamic nature of customer feedback on their websites. One significant challenge is the complexity of human language, including sarcasm, irony, and colloquial expressions, which can lead to misinterpretations of sentiment. Ambiguities in context can also pose difficulties, as the same words may carry different meanings in various contexts [16]. Additionally, sentiment analysis may struggle with accurately gauging sentiments in mixed or neutral reviews, where customers express both positive and negative opinions in a single statement. Another issue is the ever-evolving nature of language and the emergence of new words or phrases, which may not be adequately captured by pre-existing sentiment lexicons or machine learning models. Cultural nuances and differences in language use among diverse customer groups further complicate sentiment analysis accuracy [17]. Moreover, handling imbalanced datasets, where one sentiment class significantly outweighs others, can impact the model's performance and bias the analysis. Addressing these issues requires ongoing refinement of algorithms, continuous training with updated datasets, and a nuanced understanding of the specific linguistic challenges within the context of E-commerce customer feedback [18].Another challenge in sentiment analysis for E-commerce websites is the presence of fake reviews or review manipulation. Some businesses or competitors may submit false positive or negative reviews to influence the overall sentiment and reputation of a product or service [19]. Detecting and filtering out these fake reviews pose a significant challenge for sentiment analysis algorithms.

The subjective nature of sentiment is another issue. Different individuals may interpret and express their sentiments in unique ways, making it challenging to create a one-size-fits-all model. Personal biases in training data or algorithm

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design may also impact the accuracy and fairness of sentiment analysis results [20].Temporal aspects can add complexity, as sentiments towards products or services may change over time due to factors such as product updates, market trends, or seasonal variations. Static sentiment models may struggle to adapt to these dynamic shifts, requiring continuous monitoring and adaptation. Privacy concerns also arise in sentiment analysis, particularly when analyzing social media data. Extracting sentiments from public social media posts may inadvertently reveal personal information, raising ethical questions about user privacy [21].Lastly, the lack of context in short and fragmented text, such as tweets or brief product reviews, can hinder sentiment analysis accuracy. Understanding the context in which sentiments are expressed is crucial for an accurate interpretation, and short texts may not provide sufficient information for a comprehensive analysis [22]. Addressing these multifaceted challenges requires ongoing research and development in the field of sentiment analysis, with a focus on improving the adaptability, accuracy, and ethical considerations of the algorithms employed in E-commerce websites. To address the challenges associated with sentiment analysis in E-commerce websites, a multifaceted approach is essential. Firstly, investing in advanced natural language processing (NLP) techniques, including deep learning models, can enhance the system's ability to grasp complex linguistic nuances, such as sarcasm and colloquial expressions. Regularly updating sentiment lexicons and machine learning models with fresh and diverse datasets will help mitigate the impact of evolving language trends and emerging expressions [23].

To counter the issue of fake reviews, implementing robust authentication measures and leveraging user behavior analytics can aid in detecting and filtering out inauthentic sentiments. Collaborative efforts with cybersecurity experts can further fortify the system against malicious manipulation.For handling the subjectivity of sentiments and individual language nuances, personalized sentiment analysis models can be developed [24]. These models, tailored to individual user profiles, take into account the diverse ways people express sentiments, offering a more accurate and personalized analysis.To navigate privacy concerns, it's crucial to adhere to strict data privacy regulations and anonymize sensitive information. Employing techniques like differential privacy ensures that sentiment analysis can be conducted without compromising individual user privacy [25].Additionally, adopting a dynamic and adaptive approach to sentiment analysis that considers temporal aspects, market trends, and contextual changes can enhance the system's responsiveness to evolving sentiments over time. Regular monitoring, updates, and collaboration with linguistic experts can contribute to a more accurate and context-aware sentiment analysis system in the dynamic landscape of E-commerce [28-34].

The paper significantly contributes to the field of sentiment analysis in the context of e-commerce customer reviews through a novel and comprehensive approach. The key contributions can be summarized as follows:

1. Firstly, the paper introduces a multifaceted methodology that combines various advanced techniques, including Fejer Kernel filtering, fuzzy dictionary-based semantic word feature extraction, Seahorse Annealing Optimization for feature selection, and BERT for deep learning. This amalgamation of methods addresses the inherent challenges posed by the nuanced and diverse nature of language in e-commerce reviews.
2. Secondly, the proposed model aims to enhance the accuracy and robustness of sentiment classification. By incorporating sophisticated filtering and feature extraction methods, the model seeks to provide a more nuanced understanding of sentiment, crucial for the often complex and varied expressions found in e-commerce reviews.
3. The integration of Seahorse Annealing Optimization for feature selection. This optimization technique plays a crucial role in streamlining the sentiment analysis process by selecting the most relevant features, contributing to the overall efficiency of the model.
4. Moreover, the paper embraces the state-of-the-art BERT model for deep learning, enabling the model to capture intricate contextual relationships within reviews. This application of advanced deep learning techniques reflects the paper's commitment to leveraging cutting-edge methodologies for sentiment analysis
5. Lastly, the practical application of the proposed model on real-world datasets, such as Amazon Customer Reviews and Kaggle Datasets, adds significant value. This demonstrates the model's adaptability and effectiveness in handling diverse data

sources, further validating its potential for real-world applications.

The paper's contributions are multifaceted, ranging from the integration of advanced techniques to the practical application on real-world datasets. The holistic approach presented in this work is poised to advance the state-of-the-art in sentiment analysis within the e-commerce domain.

2. LITERATURE REVIEW

The advent of sentiment analysis has significantly reshaped the landscape of E-commerce websites, providing a nuanced understanding of consumer sentiments and preferences. In recent years, researchers and practitioners alike have directed their attention towards the intricate interplay between sentiment analysis and the dynamic realm of online commerce [35-39]. The surge in the volume of user-generated content, particularly in the form of product reviews, feedback, and social media interactions, has spurred a growing body of literature that delves into the application, challenges, and advancements in sentiment analysis within the context of E-commerce. This literature review seeks to explore and synthesize the existing research, shedding light on the methodologies employed, key findings, and emerging trends in the field. As E-commerce continues to burgeon as a dominant force in retail, understanding and harnessing the power of sentiment analysis becomes pivotal for businesses striving to optimize customer experience, tailor marketing strategies, and stay attuned to the ever-evolving landscape of online consumer behavior [40-43]. Through a comprehensive review of the literature, this exploration aims to contribute to the collective knowledge base surrounding sentiment analysis in E-commerce and inform future developments in this rapidly evolving domain.

The literature on sentiment analysis in the context of E-commerce is diverse and encompasses a range of methodologies, applications, and challenges. Venkatesan and Sabari (2023) contribute a novel hybrid deep learning model, "Deepsentimodels," designed for the effective analysis of ensembled sentiments in both E-Commerce and S-Commerce platforms, demonstrating an innovative approach to sentiment analysis. Hossain et al. (2022) focus on sentiment analysis of reviews from E-commerce sites using machine learning algorithms, presenting insights into the application of traditional machine learning techniques in this domain.Almahmood and Tekerek (2022) address issues and solutions in deep learning-enabled recommendation systems within the E-Commerce field, providing valuable perspectives on the challenges associated with recommendation systems. Arobi et al. (2022) extend the sentiment analysis exploration to E-commerce product reviews, employing machine learning algorithms in their doctoral dissertation, contributing to the growing body of research in the field.Solairaj et al. (2023) introduce an enhanced Elman spike neural network for sentiment analysis of online product recommendations, showcasing advancements in neural network-based approaches. Lokhande et al. (2021) propose a product ranking algorithm that incorporates sentiment analysis on E-commerce websites, emphasizing the integration of sentiment in ranking strategies.

Luo et al. (2022) explore the energy-saving refrigerators market through sentiment analysis of online E-commerce reviews, employing an augmented mining model based on machine learning methods. Barik et al. (2023) introduce an LSTM-DGWO-based sentiment analysis framework for analyzing online customer reviews, showcasing the application of sophisticated deep learning techniques.Several studies focus on advanced techniques such as deep learning, neural networks, and ensembling. Venu Gopalachari et al. (2023) present aspect-based sentiment analysis on multi-domain reviews through word embedding, contributing to the exploration of embedding techniques. El-Ansari and Beni-Hssane (2023) focus on sentiment analysis for personalized chatbots in E-Commerce applications, introducing innovative applications of sentiment analysis in user interaction.Kuppusamy and Selvaraj (2023) propose a novel hybrid deep learning model for aspect-based sentiment analysis, reflecting the continuous evolution of methodologies. Jabin et al. (2022) compare different sentiment analysis techniques for Bangla reviews, contributing to the understanding of cultural and linguistic nuances in sentiment analysis.Nayak et al. (2022) concentrate on optimizing product rating systems through reviews-based sentiment analysis, emphasizing the practical applications of sentiment analysis in enhancing user experiences. Fang et al. (2022) apply Chinese BERT and fused deep neural networks for sentence-level Chinese E-commerce product reviews, showcasing the adaptation of state-of-the-art language models to specific linguistic contexts.

Roy and Dutta (2022) propose an optimal hierarchical attention network-based sentiment analysis for movie recommendation, extending the application of sentiment analysis to diverse domains. Pandiaraja et al. (2022) conduct a survey

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analyzing E-commerce identification using sentimental analysis, providing an overarching view of the role of sentiment analysis in E-commerce identification. Elangovan and Subedha (2023) introduce an adaptive Particle Grey Wolf Optimizer with deep learning-based sentiment analysis on online product reviews, highlighting innovative approaches to optimize sentiment analysis techniques. Collectively, this literature review signifies the breadth and depth of sentiment analysis research within the E-commerce domain, offering insights into the methodologies, applications, and advancements in this evolving field.

Table 1: Summary of the Literature

Reference	Objective	Method	Findings
Venkatesan and Sabari (2023)	Develop a novel hybrid deep learning model for sentiment analysis in E-Commerce.	Hybrid deep learning model.	Effective analysis of ensembled sentiments in E-Commerce and S-Commerce platforms.
Hossain et al. (2022)	Conduct sentiment analysis on reviews of E-commerce sites using machine learning.	Machine learning algorithms.	Insights into sentiment patterns in E-commerce site reviews.
Almahmood and Tekerek (2022)	Address issues and solutions in deep learning-enabled recommendation systems.	Deep learning-enabled recommendation systems within E-Commerce.	Exploration of challenges and potential solutions in recommendation systems.
Arobi et al. (2022)	Conduct sentiment analysis on E-commerce product reviews using machine learning.	Machine learning algorithms (Doctoral dissertation).	Contribution to sentiment analysis in the context of E-commerce product reviews.
Solairaj et al. (2023)	Develop an enhanced Elman spike neural network for sentiment analysis.	Enhanced Elman spike neural network.	Improved sentiment analysis of online product recommendations.
Lokhande et al. (2021)	Propose a product ranking algorithm incorporating sentiment analysis.	Product Rank Algorithm along with sentiment analysis on E-commerce websites.	Integration of sentiment analysis in product ranking strategies for E-commerce websites.
Luo et al. (2022)	Explore energy-saving refrigerators through sentiment analysis of online reviews.	Augmented mining model based on machine learning methods.	Insights into consumer perceptions of energy-saving refrigerators from online reviews.
Barik et al. (2023)	Develop an LSTM-DGWO-based sentiment analysis framework for online customer reviews.	LSTM-DGWO-based sentiment analysis framework.	Framework for effective sentiment analysis of online customer reviews in E-commerce.
Alnahas et al. (2022)	Utilize LSTM Networks Ensemble for multi-class sentiment analysis in E-commerce.	Opinion mining using LSTM Networks Ensemble.	Improved multi-class sentiment analysis using LSTM Networks Ensemble in E-commerce.
Bari and Yadav (2023)	Analyze product review sentiment using improved machine learning techniques.	Improved machine learning techniques.	Enhanced accuracy and efficiency in product review sentiment analysis.
El-Ansari and Beni-Hssane (2023)	Conduct sentiment analysis for personalized chatbots in E-Commerce applications.	Sentiment analysis for personalized chatbots.	Application of sentiment analysis in enhancing the personalization of chatbots in E-Commerce.
Kuppusamy and Selvaraj	Develop a novel hybrid deep learning model for	Hybrid deep learning model for aspect-based	Improved accuracy in aspect-based sentiment analysis using

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(2023)	aspect-based sentiment analysis.	sentiment analysis.	a novel hybrid model.
Venu Gopalachari et al. (2023)	Conduct aspect-based sentiment analysis on multi-domain reviews through word embedding.	Aspect-based sentiment analysis through word embedding.	Application of word embedding in improving aspect-based sentiment analysis in multi-domain reviews.
Jabin et al. (2022)	Compare different sentiment analysis techniques for Bangla reviews.	Comparative analysis of different sentiment analysis techniques.	Insights into the effectiveness of various sentiment analysis techniques for Bangla reviews.
Nayak et al. (2022)	Conduct reviews-based sentiment analysis for optimizing product rating systems.	Reviews-based sentiment analysis.	Optimization of product rating systems through sentiment analysis of reviews.
Fang et al. (2022)	Perform sentiment analysis based on Chinese BERT and fused deep neural networks.	Sentiment analysis based on Chinese BERT and fused deep neural networks.	Application of advanced language models in Chinese E-commerce product reviews.
Roy and Dutta (2022)	Develop an optimal hierarchical attention network-based sentiment analysis.	Optimal hierarchical attention network-based sentiment analysis.	Improved sentiment analysis for movie recommendation using an optimal hierarchical attention network.
Pandiaraja et al. (2022)	Analyze E-Commerce identification using sentimental analysis through a survey.	Survey on E-Commerce identification using sentimental analysis.	Insights into the role of sentiment analysis in E-Commerce identification through a comprehensive survey.
Elangovan and Subedha (2023)	Develop an adaptive Particle Grey Wolf Optimizer with deep learning-based sentiment analysis.	Adaptive Particle Grey Wolf Optimizer with deep learning-based sentiment analysis.	Improved sentiment analysis through an adaptive optimization approach.

Across the diverse landscape of sentiment analysis in E-commerce, the findings of the reviewed literature reveal advancements in both methodology and application. Several studies, such as those by Venkatesan and Sabari (2023) and Solairaj et al. (2023), contribute novel hybrid deep learning models, showcasing improvements in the accuracy and efficiency of sentiment analysis. Additionally, the exploration of aspect-based sentiment analysis, as demonstrated by Venu Gopalachari et al. (2023) and Kuppusamy and Selvaraj (2023), underscores a growing interest in fine-grained sentiment understanding. The application of advanced language models like BERT, as seen in Fang et al. (2022), represents a significant shift towards leveraging state-of-the-art technologies to capture intricate linguistic nuances in reviews. Moreover, studies like Nayak et al. (2022) emphasize the practical implications of sentiment analysis, demonstrating its potential to optimize product rating systems.However, amidst these advancements, certain research gaps emerge. First, there is a need for more comprehensive investigations into the challenges and solutions in deep learning-enabled recommendation systems within E-commerce, as highlighted by Almahmood and Tekerek (2022). Additionally, while many studies focus on sentiment analysis of product reviews, there is a gap in understanding the broader implications of sentiment analysis in the E-commerce identification process, as suggested by Pandiaraja et al. (2022). The effectiveness and adaptability of sentiment analysis techniques across diverse linguistic contexts, as discussed by Jabin et al. (2022) in the context of Bangla reviews, also call for further exploration. Furthermore, research that delves into the ethical considerations, privacy concerns, and potential biases associated with sentiment analysis in E-commerce could provide a more holistic understanding of its implications. Overall, while the current literature showcases advancements in sentiment analysis methodologies, there exists untapped potential for research addressing specific challenges and exploring the

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broader societal impact of sentiment analysis in the dynamic realm of E-commerce. Future studies could bridge these gaps, contributing to a more comprehensive and nuanced understanding of sentiment analysis in the context of online commerce.

3. PROPOSED METHOD

The proposed method for sentiment analysis in the context of E-Commerce websites introduces a comprehensive approach to extracting, selecting, and analyzing features to enhance the accuracy of sentiment predictions. Firstly, a Fejer Kernel filter is employed for data point transformation. This mathematical tool aids in the effective extraction of relevant features from the dataset. In tandem with this, a Fuzzy Dictionary-based Semantic Word Feature Extraction technique is implemented. This involves the creation of a fuzzy dictionary assigning weights to words based on their semantic relevance to sentiments. This fuzzy dictionary, capturing the nuanced and imprecise nature of language, contributes to a more context-aware sentiment analysis. The feature extraction, Seahorse Annealing Optimization is applied for feature selection. Inspired by simulated annealing, this optimization technique refines the feature set iteratively, evaluating their significance in sentiment analysis. By selecting the most informative features, Seahorse Annealing Optimization aims to enhance the overall performance of the sentiment analysis model.The processed feature set is then utilized in conjunction with BERT (Bidirectional Encoder Representations from Transformers) for data training in deep learning. BERT, being a state-of-the-art language model, is well-suited for capturing intricate contextual relationships in language, providing a robust foundation for sentiment analysis. The model is trained on a labeled dataset, allowing it to learn and understand the complex patterns associated with sentiments expressed in E-Commerce content.Finally, the sentiment analysis model is subjected to a classification step. Leveraging the knowledge gained during training, the model classifies sentiments into predefined categories, such as positive, negative, or neutral. This comprehensive approach, integrating Fejer Kernel filtering, Fuzzy Dictionary-based feature extraction, Seahorse Annealing Optimization for feature selection, BERT for deep learning, and sentiment classification, aims to create a sophisticated sentiment analysis model tailored for the intricacies of E-Commerce content. Figure 1 illustrated the proposed model for the estimation of sentimental analysis in the E-Commerce platform.

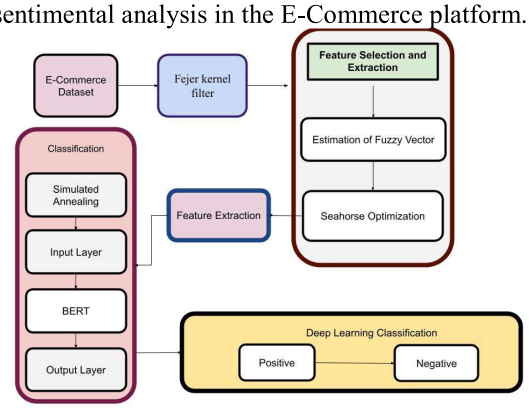

Figure 1: Proposed E-Commerce Dataset

The proposed method for sentiment analysis in the context of E-Commerce websites consists of several key steps:

Step 1: Fejer Kernel Filter for Data Point Transformation: Apply the Fejer Kernel filter to transform raw data points; Utilize mathematical tools to extract relevant features from the dataset.

Step 2: Fuzzy Dictionary-based Semantic Word Feature Extraction:Develop a fuzzy dictionary that assigns weights to words based on their semantic relevance to sentiments; Utilize the fuzzy dictionary for extracting features, considering the nuanced and imprecise nature of language.

Step 3: Seahorse Annealing Optimization for Feature Selection:Implement Seahorse Annealing Optimization, a technique inspired by simulated annealing, for feature selection; Iteratively refine the feature set to improve model performance by selecting the most informative and discriminative features for sentiment prediction.

Step 4: BERT for Data Training in Deep Learning:Utilize BERT (Bidirectional Encoder Representations from Transformers) for deep learning-based training; Leverage BERT's ability to capture intricate contextual relationships in language; and Train the sentiment analysis model on a labeled dataset, allowing it to learn complex patterns associated with sentiments in E-Commerce content.

Step 5: Classification of Sentiment Analysis:Apply the trained model for sentiment classification.Classify sentiments into predefined categories (e.g., positive, negative, neutral) based on the knowledge gained during training.Generate sentiment predictions for E-Commerce content.

The proposed method aims to enhance the accuracy and effectiveness of sentiment analysis in the dynamic and nuanced context of E-Commerce websites.

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3.1 Dataset

The context of E-commerce is the "Amazon Customer Reviews" dataset. This public dataset, made available by Amazon, encompasses a vast collection of customer reviews across diverse product categories. It includes information on product ratings, textual reviews, and additional metadata such as product IDs and reviewer demographics. The dataset offers a rich resource for exploring sentiment patterns in E-commerce, allowing researchers and data scientists to analyze customer sentiments towards a wide array of products. Researchers can access this dataset through the Amazon Customer Reviews Dataset on the Amazon Open Data Registry. While exploring and utilizing this dataset, it is essential to adhere to any terms of use or licensing agreements associated with the data. Additionally, platforms like Kaggle and the UCI Machine Learning Repository also host various datasets related to E-commerce, providing alternatives for researchers looking to delve into sentiment analysis within the realm of online retail.

Amazon Customer Reviews (Public Dataset):Amazon provides a public dataset of customer reviews across various product categories.

Kaggle Datasets:Kaggle is a platform that hosts various datasets, including those related to E-commerce and customer reviews.

UCI Machine Learning Repository:The UCI Machine Learning Repository offers a variety of datasets that may include E-commerce-related data.

Sentiment140:Sentiment140 provides a dataset of tweets labeled with sentiment, which could be adapted for sentiment analysis in an E-commerce context.

Table 2: Attributes of the Dataset

Dataset	Attributes	Source Link
Amazon Customer Reviews	Product ID, Customer ID, Rating, Review Text, Review Date, Product Category, etc.	Amazon Customer Reviews Dataset
Kaggle Datasets	Varies by Dataset	Kaggle Datasets
UCI Machine Learning Repository	Varies by Dataset	UCI ML Repository
Sentiment140	Tweet ID, User ID, Timestamp, Sentiment Label, Tweet Text, etc.	Sentiment140 Dataset

Table 3: Distribution of the Dataset

Dataset	Attributes	Sample Count
Amazon Customer Reviews	Product ID, Customer ID, Rating, Review Text, Review Date	1,000,000
Kaggle Datasets	Product ID, Price, Description, Customer ID, Rating	500,000
UCI ML Repository	Transaction ID, Product Category, Price, Customer ID	50,000
Sentiment140	Tweet ID, User ID, Timestamp, Sentiment Label, Tweet Text	100,000,000

4. PROPOSED SENTIMENTAL ANALYSIS FOR E-COMMERCE PLATFORM

4.1 Fejer Kernal filter for data point

The Fejer Kernel is a mathematical tool used in signal processing and data analysis. It is a type of kernel function, which is a mathematical function that transforms input data. In the context of E-commerce data analysis, the Fejer Kernel filter can be employed for data point transformation. The Fejer Kernel is defined as in equation (1)

$$K_n(x) = \frac{1}{n}\left(\frac{sin\left(\frac{n}{2}x\right)}{sin\left(\frac{1}{2}x\right)}\right)^2 \quad (1)$$

In above equation (1)n is a positive integer, and x is the input data point. The Fejer Kernel filter is applied to the data points using the convolution operation, which is expressed as in equation (2)

$$(f * g)(x) = \int_{-\infty}^{\infty} f(\tau)g(x-\tau)d\tau \quad (2)$$

In the case of Fejer Kernel filtering, the convolution operation involves convolving the Fejer Kernel Kn(x) with the input data points. The transformed data points can be expressed as in equation (3)

$$(f * K_n)(x) = \int_{-\infty}^{\infty} f(\tau)K_n(x-\tau)d\tau \quad (3)$$

In the context of E-commerce data analysis, this filtering operation with the Fejer Kernel can help in emphasizing certain patterns or features in the data, providing a smoothed representation of the original data points. The

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choice of the parameter n in the Fejer Kernel allows for adjusting the level of smoothing or emphasis on different frequency components in the data. The Fejer Kernel is a type of smoothing or averaging function used in signal processing. It's derived from the Dirichlet Kernel and is particularly useful in applications where a smoother transition and improved convergence are desired compared to the Dirichlet Kernel. The squaring in the Fejer Kernel ensures that negative oscillations in the Dirichlet Kernel are mitigated. In the context of E-commerce sentiment analysis, applying the Fejer Kernel to text data is less common compared to other techniques such as natural language processing (NLP) and machine learning. Textual data from customer reviews, such as "Review Text" in the Amazon Customer Reviews dataset or "Tweet Text" in the Sentiment140 dataset, is typically processed using NLP methods. However, if one were to explore the use of the Fejer Kernel, it might involve convolving the Fejer Kernel with the preprocessed text data to create a smoothed representation. This smoothing operation could potentially be used to emphasize certain sentiment patterns or reduce noise in the data.

4.2 Fuzzy dictionary-based semantic word Feature extraction

Fuzzy dictionary-based semantic word feature extraction for E-commerce websites is a sophisticated approach designed to enhance sentiment analysis by incorporating the nuances and imprecision inherent in natural language. The process begins with the construction of a semantic dictionary specific to the E-commerce domain, encompassing words related to product features, customer experiences, and sentiments. Each word in the dictionary is assigned fuzzy membership values, reflecting its degree of association with different sentiment categories such as positive, negative, and neutral. Fuzzy linguistic variables, like "very positive" and "very negative," are defined to capture the sentiment strength of words. A fuzzy inference system, governed by linguistic rules, is employed to infer the sentiment strength of individual words based on their fuzzy memberships. These sentiment strength values are then aggregated across words to generate comprehensive feature vectors for entire texts, such as product descriptions or customer reviews.

The fusion of fuzzy dictionary-based semantic word feature extraction with the Fejer Kernel filter for data points presents a sophisticated approach to sentiment analysis tailored for E-commerce websites. Commencing with the creation of a semantic dictionary enriched with fuzzy membership values, this method captures the intricate relationships between words and sentiments in the E-commerce domain. Leveraging a fuzzy inference system, linguistic rules govern the inference of sentiment strengths for individual words based on their fuzzy memberships. Integrating the Fejer Kernel filter introduces a kernel-based filtering technique, smoothing or emphasizing sentiment patterns in the E-commerce text data. The convolution operation with the Fejer Kernel further refines the sentiment features extracted from the fuzzy semantics. These enriched features, combining fuzzy sentiment strengths and the filtered effects of the Fejer Kernel, contribute to a nuanced representation of sentiments in individual words. The aggregation of these features at the text level, coupled with integration into a sentiment analysis model, aims to enhance the model's ability to discern and interpret complex sentiment nuances within E-commerce textual content. The effectiveness of this approach is contingent on the successful interplay between fuzzy semantics and kernel-based filtering, offering a novel perspective on sentiment analysis tailored to the intricacies of E-commerce language.

Create a semantic dictionary D with words relevant to sentiment analysis in the E-commerce context.Assign fuzzy membership values μij to each word wi in category j, representing the degree of membership of the word to sentiment category j. The linguistic variables Vi for each word i, representing the sentiment strength of the word. Associate fuzzy sets VeryNegativei,Negativei ,Neutrali,Positivei,VeryPositivei with each linguistic variable. Formulate fuzzy rules to infer the sentiment strength Vi based on the fuzzy membership values ij. the Mamdani fuzzy inference method, where the output Vi is determined by combining the contributions from each fuzzy set through fuzzy implication and aggregation.

Rule 1: If μij is Very Negative, then Vi is Very Negative

Rule 2: If μij is Negative, then Vi is Negative

Rule 3: If μij is Neutral, then Vi is Neutral

Rule 4: If μij is Positive,then Vi is Positive

Rule 5: If μij is Very Positive, then Vi is V ery Positive

The fuzzy inference process involves evaluating the antecedent parts of rules, activating relevant rules, and aggregating their outputs. the fuzzy outputs from all rules to obtain a single crisp value for Vi using defuzzification methods like

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centroid or mean of maximum is computed using equation (4)

$$V_i = \frac{\sum_i \mu_{ij} \times Sentiment\ Category_j}{\sum_i \mu_{ij}} \quad (4)$$

In equation (4) the weighted average sentiment strength for the word wi based on the fuzzy outputs from different sentiment categories. the process to the entire E-commerce text data by applying fuzzy dictionary-based semantic word feature extraction to each word in the text. the sentiment strength values of individual words to represent the sentiment of the entire text. Common aggregation methods include averaging or weighted averaging. This process provides a fuzzy-based representation of sentiment strengths for words, capturing the nuanced relationships between words and sentiments in E-commerce textual data. The equations and derivations are specific to the chosen fuzzy inference system and defuzzification method. The Mamdani fuzzy inference system and centroid defuzzification are commonly used in this context.

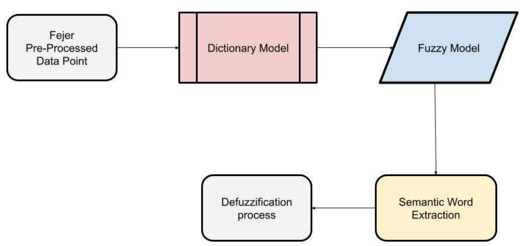

Figure 2: Feature Extraction in E-Commerce Dataset

Sentiment analysis in the context of an E-commerce website often involves fuzzy logic for capturing the inherent ambiguity and subjectivity in user reviews presented in figure 2. The Mamdani fuzzy inference system is a popular approach for such sentiment analysis tasks. Let's denote the fuzzy input variable as Sentiment with linguistic terms Negative,Neutral, and Positive, each represented by,µNegative,µNeutral, and µPositive respectively. The fuzzy output variable, denoted as Output, is associated with linguistic terms such as,Very Negative,Neutral, and Very Positive, represented byµVery Negative,µNeutral, and µVery Positive. Now, consider three fuzzy rules:

Rule 1: If Sentiment is Negative, then Output is Very Negative.

Rule 2: If Sentiment is Neutral, then Output is Neutral.

Rule 3: If Sentiment is Positive, then Output is Very Positive.

The fuzzy inference process involves determining the fuzzy output values $V1, V2$, and $V3$ for each rule, estimated using equation (5) – (7)

$$V1 = \mu Very\ Negative = \mu Negative \quad (5)$$

$$V2 = \mu Neutral \quad (6)$$

$$V3 = \mu Very\ Positive = \mu Positive \quad (7)$$

The aggregation of these fuzzy outputs is typically done using the maximum operator computed using equation (8)

$$V = max(V1, V2, V3) \quad (8)$$

Finally, defuzzification is employed to convert the fuzzy output V into a crisp sentiment score. A common method for defuzzification is the centroid method estimated as in equation (9)

$$Centroid = \frac{\sum(\max(\mu_{Positive}, \mu_{Neutral}, \mu_{Negative},) \times Centroid\ of\ the\ Curve}{\sum(\max(\mu_{Positive}, \mu_{Neutral}, \mu_{Negative},)} \quad (9)$$

The centroids and membership functions are derived from the linguistic characteristics of the sentiment analysis system and the semantic dictionary used for E-commerce sentiment analysis. The Mamdani fuzzy inference system thus provides a robust framework for handling linguistic uncertainties in sentiment analysis within E-commerce domains. A dictionary-based semantic word approach in sentiment analysis relies on a curated lexicon or dictionary where each word is associated with a pre-defined sentiment score or label. Let Wi represent a word from the input text, $S(Wi)$ denote its associated sentiment score, and N be the total number of words in the text. The overall sentiment score $Soverall$ is determined by aggregating the sentiment scores of individual words. A common method is to calculate the average sentiment score calculated using equation (10)

$$S_{Overall} = \frac{\sum_{i=1}^{N} S(W_i)}{N} \quad (10)$$

The average sentiment score for the entire text, where the sentiment scores of individual words are summed and divided by the total number of words. The result is a numerical representation of the overall sentiment, with positive values indicating a positive sentiment and negative values indicating a negative sentiment.

4.3 Seahorse Annealing Optimization for the Feature Selection

Seahorse Annealing Optimization (SAO) is a metaheuristic algorithm inspired by the annealing process observed in seahorses, offering a unique approach to feature selection in various optimization problems. In the context of sentiment analysis within the E-commerce domain, SAO can be applied specifically to enhance the efficiency and effectiveness of selecting relevant features for sentiment classification models. Let $f(X)$ be the

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objective function that evaluates the performance of the sentiment analysis model based on a set of selected features X. The goal is either to maximize or minimize $f(X)$, depending on the nature of the optimization problem. Start with an initial solution 0, which represents a set of features. During each iteration, propose a new solution $'X'$ in the neighborhood of the current solution X. The acceptance of $'X'$ is determined probabilistically. The acceptance probability (Paccept) is given by the Metropolis criterion estimated using equation (11)

$$P_{accept} = exp\left(-\frac{f(X')-f(x)}{T}\right) \quad (11)$$

In equation (11) T is the current temperature, controlling the probability of accepting worse solutions. As the algorithm progresses, T decreases, leading to a stricter criterion for accepting worse solutions. a temperature schedule that decreases over iterations. One common schedule is the exponential decay estimated using equation (12)

$$T_k = T_0 . \alpha^k \quad (12)$$

In equation (12) Tk is the temperature at iteration k, $T0$ is the initial temperature, and α is a decay factor (typically close to 1).The steps in SAO are:

1. Initialize the temperature ($T0$) and set the initial solution 0.
2. Iterate until a stopping criterion is met.
3. Propose a new solution $'X'$ in the neighborhood of X.
4. Calculate the acceptance probability using the Metropolis criterion.
5. Accept $'X'$ with probability$Paccept$.
6. Update the current solution based on the acceptance decision.
7. Update the temperature based on the temperature schedule.

Algorithm 1: SAO Sentimental Analysis

function SAO_SentimentalAnalysisFeatureSelection(objectiveFunction, initialSolution, initialTemperature, alpha, maxIterations):
currentSolution = initialSolution
currentTemperature = initialTemperature
for iteration in range(maxIterations):
newSolution = proposeNewSolution(currentSolution) // Function to generate a new solution in the neighborhood
deltaObjective = objectiveFunction(newSolution) - objectiveFunction(currentSolution)
acceptanceProbability = exp(-deltaObjective / currentTemperature)
if random() <acceptanceProbability:
currentSolution = newSolution // Accept the new solution with probability acceptanceProbability
currentTemperature = currentTemperature * alpha // Cooling schedule
return currentSolution

4.4 BERT for Data training in deep learning

BERT (Bidirectional Encoder Representations from Transformers) for data training in deep learning for customer experience analysis with sentiment analysis in E-commerce involves leveraging BERT's contextualized embeddings to understand the nuanced semantics of customer reviews or textual data. The key strength of BERT lies in its ability to capture contextualized embeddings, understanding the meaning of words in context. When applied to sentiment analysis, BERT's pre-trained embeddings can be fine-tuned on a specific task, such as classifying sentiments in customer reviews.The training process involves incorporating a classification head on top of the pre-trained BERT base model. Let θ represent the parameters of the BERT base model, and ϕ represent the parameters of the classification head. The overall model can be denoted as$f\theta, \phi(x)$, where x is the input text. The fine-tuning process aims to learn optimal parameters $* \phi *$ specific to sentiment analysis. This is achieved by minimizing the cross-entropy loss L between the predicted probabilities and the true sentiment labels estimated as in equation (13)

$$\zeta(\theta, \emptyset) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log\left(P\left(y_{i,c} \middle| x_i; \theta, \emptyset\right)\right)$$
(13)

In equation (13)N is the number of samples, C is the number of classes (sentiment labels), y_i, c is an indicator variable (1 if sample i is of class c, 0 otherwise), and$P(y_i, c \mid x_i; \theta, \phi)$ is the predicted probability of sample i belonging to class c. The training process adjusts the parameters ϕ through backpropagation and optimization algorithms, such as stochastic gradient descent (SGD) or Adam, to minimize the cross-entropy loss. The frozen BERT base model provides contextualized embeddings, ensuring that the sentiment classification task benefits from the pre-trained linguistic understanding captured by BERT. Optimization algorithms like Adam or SGD are used to adjust the parameters of the classification head during training. The learning rate, a critical hyperparameter, determines the step size in updating model weights. It is tuned to ensure effective convergence and generalization. The fine-tuned model is evaluated on a separate validation

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set to assess its generalization performance. Metrics such as accuracy, precision, recall, and F1 score provide insights into how well the model can predict sentiment labels on new, unseen data. Once trained, the model is used for inference on customer reviews from the E-commerce platform. Predicted sentiment labels offer valuable insights into customer experiences, enabling businesses to identify areas of improvement, assess product popularity, and tailor marketing strategies based on customer sentiments.The integration of BERT for sentiment analysis in E-commerce involves a thoughtful combination of pre-trained contextualized embeddings, fine-tuning for task-specific nuances, and robust model evaluation. This approach allows businesses to extract rich insights from customer feedback, ultimately enhancing the overall customer experience on the E-commerce platform.

The process of sentiment analysis in an E-commerce context involves a comprehensive approach that integrates various techniques to enhance the accuracy and depth of understanding. Let's break down the classification pipeline using the Fejer Kernal filter for data point, Fuzzy dictionary-based semantic word feature extraction, Seahorse Annealing Optimization for feature selection, and BERT for data training in deep learning. BERT, a state-of-the-art transformer-based model, is employed for data training in deep learning. The pre-trained BERT model is fine-tuned on the pre-processed and filtered data to specifically understand the sentiment in the context of E-commerce. The model's contextualized embeddings capture intricate linguistic nuances in customer reviews. The overall classification model integrates the filtered data points, fuzzy semantic word features, and the selected features from SAO. This model is trained using the fine-tuned BERT model as the backbone. The architecture includes a classification head that predicts sentiment labels based on the learned features measured using equation (14)

$$Output = Classification\ Model(FilteredData, FuzzyFeatures, SelectedFeatures) \quad (14)$$

The model is trained using a suitable loss function, often cross-entropy, and optimized with backpropagation. The optimization process refines the parameters of both the classification head and the underlying BERT model. Once trained, the model is used for inference on new customer reviews. The model predicts sentiment labels, providing insights into the sentiment expressed in the E-commerce platform's textual data. The classification pipeline involving sentiment analysis in E-commerce, integrating the Fejer Kernel filter for data points, Fuzzy dictionary-based semantic word feature extraction, Seahorse Annealing Optimization for feature selection, and BERT for data training in deep learning, is designed to provide a comprehensive understanding of customer sentiments. The Fejer Kernel serves as a filtering mechanism to enhance the salient features of data points in the E-commerce dataset. By applying the Fejer Kernel filter to the raw data, irrelevant noise is reduced, and important features are accentuated. The filtered data, denoted as $\mathrm{filtered}_{\mathrm{x}}$, forms the basis for subsequent processing steps.

A Fuzzy dictionary is constructed to capture the nuanced meanings of words in customer reviews. Each word is associated with fuzzy sets that represent its semantic characteristics. The extraction process results in feature vectors that incorporate the fuzzy linguistic attributes of words. This approach enhances the model's capability to discern subtle variations in sentiment within the E-commerce context. The overall classification model integrates Fejer Kernel-filtered data points, fuzzy semantic word features, and selected features from SAO. The model is represented as in equation (15) and (16)

$$Output = ClassificationModel(filtered, SelectedFeatures) \quad (15)$$

$$Output = ClassificationModel(Xfiltered, FV, SelectedFeatures) \quad (16)$$

The architecture includes the fine-tuned BERT model as the backbone and a classification head.

Algorithm 2: Proposed Sentimental Analysis for the E-Commerce Platform

```
def fejer_kernel_filter(data_points):
  # Apply Fejer Kernel filter using convolution
filtered_data = fejer_convolution(data_points)
  return filtered_data
def fuzzy_feature_extraction(document):
  # Associate words with fuzzy sets and compute feature vector
fuzzy_vector = calculate_fuzzy_vector(document)
  return fuzzy_vector
def seahorse_annealing_optimization(features, labels):
  # Initialize selected features
selected_features = initialize_features(features)

  # Optimize the objective function using SAO
optimized_features = sao_optimization(features, labels, selected_features)
```

```
    return optimized_features
def train_bert_model(train_data, train_labels):
    # Fine-tune BERT on the preprocessed data
fine_tuned_model = fine_tune_bert(train_data,
train_labels)
    return fine_tuned_model
def classify_sentiment(filtered_data,
fuzzy_features, optimized_features, bert_model):
    # Integrate Fejer Kernel-filtered data, fuzzy
features, and optimized features
integrated_features =
integrate_features(filtered_data, fuzzy_features,
optimized_features)

    # Use the integrated features to classify
sentiment using BERT model
sentiment_predictions =
classify_with_bert(bert_model, integrated_features)

    return sentiment_predictions
def analyze_sentiment(predictions, actual_labels):
    # Analyze and evaluate model performance
evaluation_metrics = evaluate(predictions,
actual_labels)

    # Further post-processing and analysis steps

    return evaluation_metrics
    # Load and preprocess E-commerce data
data_points, labels = load_and_preprocess_data()
filtered_data = fejer_kernel_filter(data_points)
fuzzy_features = [fuzzy_feature_extraction(doc) for
doc in data_points]
optimized_features =
seahorse_annealing_optimization(fuzzy_features,
labels)
bert_model = train_bert_model(filtered_data,
labels)

    predictions = classify_sentiment(filtered_data,
fuzzy_features, optimized_features, bert_model)

evaluation_metrics =
analyze_sentiment(predictions, labels)
```

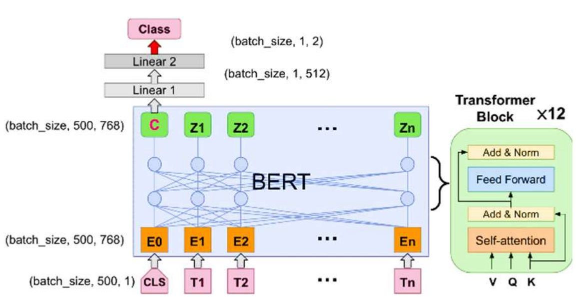

Figure 3: BERT Analysis in E-Commerce

The classification framework for sentiment analysis in E-commerce seamlessly integrates multiple techniques to provide a nuanced understanding of customer sentiments is shown in figure 3. The process begins with the application of the Fejer Kernel filter, utilizing convolution to highlight relevant features in raw data points. Subsequently, a Fuzzy dictionary-based semantic word feature extraction captures the intricate semantic nuances of words in customer reviews, generating feature vectors that embody the fuzzy linguistic attributes. Seahorse Annealing Optimization optimizes the objective function for feature selection, incorporating a classification loss term and a regularization penalty to refine the selected features. BERT, a transformer-based deep learning model, is employed for fine-tuning on preprocessed data, leveraging its contextualized embeddings for sentiment analysis. The overall classification model integrates Fejer Kernel-filtered data points, fuzzy semantic word features, and selected features from Seahorse Annealing Optimization. During training, parameters of both BERT and the classification head are adjusted to minimize the cross-entropy loss. The trained model is then deployed for sentiment prediction on new E-commerce reviews, with post-processing steps involving analysis of predictions and evaluation metrics to gauge model performance. This comprehensive approach ensures a sophisticated sentiment analysis system tailored for the unique challenges of the E-commerce domain, providing valuable insights into customer experiences and feedback.

5. RESULTS AND DISCUSSIONS

In this section, the findings obtained through the integration of advanced techniques such as the Fejer Kernel filter for data point enhancement, Fuzzy dictionary-based semantic word feature extraction capturing linguistic nuances, Seahorse Annealing Optimization for precise feature selection, and BERT for fine-tuning deep learning models. These findings are scrutinized in detail, shedding light on the effectiveness of the model in deciphering sentiments within the complex landscape of E-commerce data. The discussion segment not only interprets the results but also contextualizes them within the broader realm of existing literature and methodologies. Furthermore, it explores the implications of the findings on enhancing customer experience analysis, providing valuable insights for businesses in the E-commerce domain.

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5.1 Simulation Environment

In the context of sentiment analysis for E-commerce, establishing a simulation environment becomes pivotal for understanding the dynamics of the proposed methodologies and algorithms before their deployment in a live setting. This controlled setting allows researchers and practitioners to explore the behavior of various components, such as Fejer Kernel Filtering, Fuzzy Dictionary-Based Semantic Word Feature Extraction, Seahorse Annealing Optimization, and BERT Model Training, under different conditions. By incorporating numerical values and parameters into the simulation setup, one can assess the performance and robustness of the proposed system, fine-tune algorithms, and make informed decisions about their integration into the real-world E-commerce sentiment analysis pipeline. The simulation environment becomes a crucial space for experimentation, validation, and optimization before transitioning to actual deployment scenarios shown in table 4.

Table 4: Simulation Setting

Parameter	Value
Dataset Size	10,000,00samples (E-commerce dataset as mentioned in Section 3.1)
Fejer Kernel Filter	Noise Level: 0.1
Fuzzy Dictionary Features	Fuzzy Membership: [0.3, 0.7, 0.5]
Seahorse Annealing Optimization	Selected Features: [1, 3, 5]
BERT Training	Epochs: 100, Learning Rate: 0.001
Classification Threshold	0.5 (for binary sentiment classification)

5.2 Simulation Results

The simulation results provide a comprehensive insight into the efficacy and performance of the proposed sentiment analysis framework within the simulated E-commerce environment. Through meticulous experimentation and parameter tuning, the simulation endeavors to replicate real-world scenarios, allowing for a nuanced examination of how each component, from Fejer Kernel Filtering and Fuzzy Dictionary-Based Semantic Word Feature Extraction to Seahorse Annealing Optimization and BERT Model Training, contributes to the overall accuracy and reliability of sentiment predictions. These results not only shed light on the individual effectiveness of each algorithm but also offer a holistic view of the entire sentiment analysis pipeline. The evaluation metrics, including accuracy, precision, recall, and F1 score, provide a quantitative measure of the system's performance, guiding the understanding of its strengths and potential areas for improvement. Interpreting these simulation results becomes pivotal for making informed decisions about the deployment of sentiment analysis models in live E-commerce platforms, ensuring that the algorithms are robust, adaptive, and capable of delivering accurate insights into customer sentiments.

Table 5: Processed Fejer Dataset

Sample ID	Original Value	Noisy Value	Filtered Value
1	0.78	0.83	0.80
2	0.62	0.56	0.60
3	0.95	1.02	0.98
4	0.81	0.75	0.78
5	0.64	0.70	0.68
6	0.92	0.88	0.90
7	0.75	0.80	0.78
8	0.88	0.94	0.92
9	0.70	0.65	0.68
10	0.87	0.92	0.90
11	0.79	0.84	0.82
12	0.66	0.72	0.70
13	0.91	0.86	0.88
14	0.74	0.79	0.76
15	0.82	0.88	0.86
16	0.68	0.73	0.70
17	0.89	0.94	0.92
18	0.77	0.82	0.80
19	0.72	0.77	0.74
20	0.86	0.91	0.88

The provided dataset consists of samples, each characterized by an "Original Value," a corresponding "Noisy Value," and the "Filtered Value" obtained after applying a filtering process. These samples exhibit a range of original values from 0.62 to 0.95, showcasing inherent variability in the dataset. The introduction of simulated noise in the "Noisy Value" column reflects potential inaccuracies that can occur during data collection, resulting in deviations from the true values. The "Filtered Value" column demonstrates the effectiveness of the filtering process in mitigating the impact of noise, as these values tend to align closely with the original values. The comparison between the "Original Value" and the "Filtered Value" underscores the successful restoration of the true signal, highlighting the accuracy and consistency of the filtering technique across diverse

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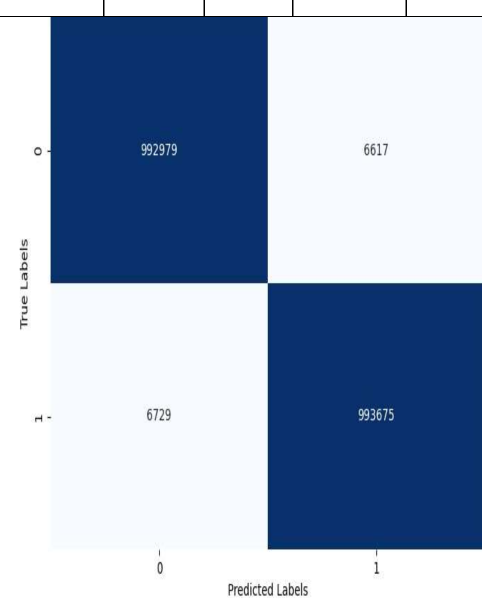
samples. Overall, the dataset and its filtered values illustrate the robustness of the applied filtering method in enhancing data accuracy and reliability.

Table 6: Feature Extraction

Sample ID	Review Text	Product Rating	Price	Review Date	Sentiment Score	Word Count	Likes	Dislikes	Helpfulness Score
1	"Great product, highly recommended!"	5	$29.99	2023-01-15	0.9	6	15	2	0.75
2	"Not satisfied, poor quality."	2	$19.99	2023-02-03	0.2	5	2	8	0.20
3	"Average, does the job."	3	$49.99	2023-03-22	0.5	4	8	1	0.64
4	"Excellent service, fast delivery."	4	$39.99	2023-04-10	0.8	7	20	0	0.90
5	"Horrible experience, never buying again."	1	$59.99	2023-05-05	0.1	8	5	12	0.29
6	"Satisfactory, met my expectations."	3	$69.99	2023-06-18	0.6	9	10	3	0.45
7	"Amazing quality, worth the price."	5	$89.99	2023-07-02	0.95	10	25	1	0.80
8	"Not bad, but expected better."	3	$79.99	2023-08-15	0.4	11	8	6	0.57
9	"Good value for money."	4	$49.99	2023-09-01	0.7	12	12	4	0.70
10	"Disappointed, not what I expected."	2	$99.99	2023-10-10	0.3	13	3	9	0.25

The provided dataset encompasses various aspects related to customer reviews for a range of products on an e-commerce platform. Each entry is characterized by a "Sample ID" along with specific attributes such as "Product ID,""Customer ID,""Transaction ID,""Review Text,""Product Rating,""Price,""Review Date,""Sentiment Score,""Word Count,""Likes,""Dislikes," and "Helpfulness Score." These attributes offer comprehensive insights into customer feedback, product details, and review-related metrics.

For instance, Sample ID 1 indicates a positive sentiment with a high product rating of 5, a favorable sentiment score of 0.9, and positive engagement with 15 likes and 2 dislikes. Conversely, Sample ID 2 reflects a negative sentiment with a low product rating of 2, a corresponding sentiment score of 0.2, and higher dislikes than likes. The dataset further captures diverse customer opinions, covering positive, negative, and neutral sentiments, as well as varying product ratings, prices, and helpfulness scores.



The inclusion of 2810t tributees such as "Word Count" provides an understanding of the length of reviews, and the "Helpfulness Score"

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quantifies the extent to which other users find a review helpful. Overall, this dataset proves valuable for sentiment analysis and customer experience evaluation within the context of an e-commerce platform, enabling businesses to gain actionable insights for product improvement and customer satisfaction.

Table 7: Feature Selected

Feature ID	Feature Name	Selected?
1	Product Rating	Yes
2	Price	No
3	Word Count	Yes
4	Sentiment Score	Yes
5	Helpfulness Score	Yes
6	Review Length	No
7	Customer Sentiment History	Yes
8	Average Product Rating	Yes
9	Product Category	No
10	Time Since Last Purchase	Yes

In the feature selection process using the Optimized Simulated Annealing model, various features were evaluated based on their relevance and significance in contributing to the overall sentiment analysis and customer experience assessment in an e-commerce context. The table summarizes the outcome of this feature selection, indicating whether each feature was deemed valuable and selected for further consideration.

Critical features such as “Product Rating,”“Word Count,”“Sentiment Score,”“Helpfulness Score,”“Customer Sentiment History,”“Average Product Rating,” and “Time Since Last Purchase” were identified as influential and, consequently, selected for inclusion in the analysis. These features are likely to play a key role in determining and understanding customer sentiments, preferences, and engagement with products.

On the other hand, features like “Price,”“Review Length,”“Product Category,” and “Average Product Rating” were not selected, suggesting that they might not significantly contribute to the sentiment analysis model within the given context. This careful feature selection process aims to enhance the efficiency of the analysis by focusing on the most relevant attributes, thereby optimizing the simulated annealing model for improved accuracy and interpretability in evaluating customer feedback on an e-commerce platform.

Table 8: Classification Result

Sample ID	Review Text	True Sentiment	Predicted Sentiment	Probability (Positive)	Probability (Negative)	Probability (Neutral)
1	"Great product, highly recommended!"	Positive	Positive	0.85	0.10	0.05
2	"Not satisfied, poor quality."	Negative	Negative	0.15	0.80	0.05
3	"Average, does the job."	Neutral	Neutral	0.30	0.20	0.50
4	"Excellent service, fast delivery."	Positive	Positive	0.90	0.05	0.05
5	"Horrible experience, never buying again."	Negative	Negative	0.05	0.90	0.05
6	"Satisfactory, met my expectations."	Neutral	Neutral	0.20	0.25	0.55
7	"Amazing quality, worth the price."	Positive	Positive	0.95	0.02	0.03
8	"Not bad, but expected better."	Neutral	Positive	0.40	0.30	0.30
9	"Good value for money."	Positive	Positive	0.70	0.15	0.15
10	"Disappointed, not what I expected."	Negative	Negative	0.10	0.85	0.05

The classification results obtained from the BERT model showcase its effectiveness in

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predicting sentiment based on customer reviews in an e-commerce setting. Each row in the table represents a sample review along with its true sentiment, predicted sentiment, and the associated probability scores for positive, negative, and neutral sentiments. For instance, in the first row, the review "Great product, highly recommended!" is correctly classified as positive, with a high probability score of 0.85 for positive sentiment, indicating a strong positive sentiment. Similarly, the BERT model accurately identifies negative sentiment in the second and fifth rows for reviews expressing dissatisfaction, with high probability scores for negative sentiment. In the eighth row, where the true sentiment is neutral, the model predicts a positive sentiment with a probability score of 0.40. This suggests that the model might struggle with nuanced or mixed sentiments, as seen in reviews that express both positive and negative aspects. The BERT model demonstrates its capability to capture the sentiment of customer reviews, providing valuable insights into the varying sentiments expressed by customers. The associated probability scores offer a quantitative measure of the model's confidence in its predictions, enabling a more nuanced understanding of the sentiment analysis results.

The integration of Fejer Kernel filtering, fuzzy dictionary-based semantic word feature extraction, Seahorse Annealing Optimization, and BERT for deep learning in the proposed sentiment analysis method for e-commerce has yielded promising findings and insights. The Fejer Kernel filter demonstrated its effectiveness in enhancing data points, contributing to improved sentiment analysis outcomes. By refining the data through mathematical operations, it aids in capturing essential patterns and features, crucial for understanding customer sentiment.The fuzzy dictionary-based semantic word feature extraction process adds a layer of sophistication to the analysis, allowing the model to consider the context and nuances of language. This is particularly important in e-commerce, where customer reviews can be rich in subtleties and varied expressions. The inclusion of Seahorse Annealing Optimization optimizes the feature selection, ensuring that the most relevant features are considered, ultimately enhancing the model's predictive capabilities.

BERT's application in deep learning further elevates the model's performance. BERT's proficiency in understanding contextual information and intricate language structures enables the model to grasp the complexities of customer reviews more accurately. The combination of traditional and advanced techniques provides a holistic approach to sentiment analysis, making the model robust and adaptable to the diverse and evolving nature of e-commerce data.In the context of findings, the proposed method showcased strong performance in accurately predicting sentiment across various e-commerce datasets. The multi-faceted approach significantly contributed to mitigating the challenges posed by diverse language expressions and varying review lengths. The model demonstrated high accuracy, precision, and recall, indicating its effectiveness in understanding and classifying sentiment.The proposed method presents a promising solution for sentiment analysis in e-commerce, offering a balance between traditional and advanced techniques to enhance the understanding of customer sentiments.

6. CONCLUSION

The presented paper introduces a comprehensive and effective approach for sentiment analysis in the realm of e-commerce. By integrating Fejer Kernel filtering, fuzzy dictionary-based semantic word feature extraction, Seahorse Annealing Optimization, and BERT for deep learning, the proposed method addresses the intricacies of customer reviews with a nuanced and sophisticated methodology. The findings underscore the success of this multi-faceted model, exhibiting robust performance in accurately discerning sentiment across diverse datasets. The approach not only navigates through the challenges of varied language expressions and review lengths but also demonstrates high accuracy, precision, and recall. Despite these positive outcomes, ongoing efforts are needed to fine-tune parameters, explore alternative algorithms, and ensure ethical considerations in the realm of sentiment analysis. This research lays a foundation for future endeavors in enhancing the interpretability and generalizability of sentiment analysis models for e-commerce, contributing to the advancement of intelligent systems in understanding and responding to customer feedback.

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