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Optimized Deep Learning Framework for Sentiment Analysis in E-Commerce: Integrating Fejer Kernel Filtering, Fuzzy Semantic Extraction, and BERT

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Abstract : Sentiment analysis is pivotal in understanding customer emotions and opinions in e-commerce platforms. With the rise of multimodal data, traditional models struggle to extract meaningful insights from text, images, and emojis. This research proposes an advanced deep learning model integrating Fejer Kernel filtering, fuzzy dictionary-based feature extraction, and optimized simulated annealing for feature selection. The model employs BERT for sentiment classification, ensuring high accuracy in sentiment prediction. The proposed methodology is tested on Amazon Customer Reviews and Kaggle datasets, achieving superior performance compared to existing models. This study contributes to the e-commerce sector by providing an efficient sentiment analysis model to improve customer satisfaction and business insights.

***IndexTerms* - Sentiment Analysis, Deep Learning, BERT, Fejer Kernel, Simulated Annealing, E-Commerce**

I. INTRODUCTION

The rapid expansion of e-commerce has revolutionized how consumers interact with businesses and make purchasing decisions. Online platforms provide customers with the ability to express their opinions and experiences through reviews, ratings, and comments. This vast amount of user-generated content serves as a crucial resource for businesses to analyze consumer sentiment and improve their services accordingly. However, extracting meaningful insights from such data poses significant challenges due to the complexity and diversity of human language. Traditional sentiment analysis techniques, such as lexicon-based and machine learning approaches, have been widely applied to e-commerce data. These methods rely on predefined word dictionaries or feature-based classifiers to determine sentiment polarity. However, they often struggle with handling contextual meanings, sarcasm, and variations in linguistic expressions. As a result, sentiment analysis models must evolve to address these challenges and provide more accurate insights into consumer sentiment.

The emergence of deep learning has significantly enhanced sentiment analysis capabilities. Neural network models, such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and transformers like BERT (Bidirectional Encoder Representations from Transformers), have demonstrated remarkable improvements in natural language understanding. These models leverage contextual embeddings to capture intricate relationships between words and their meanings, leading to more precise sentiment predictions. Despite these advancements, existing sentiment analysis models often face limitations in processing noisy data, selecting relevant features, and maintaining computational efficiency. E-commerce data, in particular, contains unstructured information, including emojis, slang, and multimodal elements such as images and videos. Therefore, an optimized approach that enhances feature extraction, classification accuracy, and scalability is necessary to tackle these challenges effectively.

To address these issues, this study proposes an advanced sentiment analysis framework that integrates multiple optimization techniques. The model incorporates Fejer Kernel filtering for noise reduction, fuzzy dictionary-based semantic feature extraction for improved sentiment representation, and Seahorse Annealing Optimization for optimal feature selection. The integration of these methods ensures that only the most relevant features contribute to sentiment classification, reducing computational overhead while enhancing accuracy. Furthermore, the proposed approach leverages the BERT model to capture deep contextual relationships within textual data. BERT's bidirectional learning mechanism enables it to understand the sentiment of a word based on its surrounding context, making it particularly effective in analyzing complex e-commerce reviews. By fine-tuning BERT on domain-specific datasets, the model gains a deeper understanding of consumer sentiments in the online retail sector.

This research aims to bridge the gap between traditional sentiment analysis approaches and modern deep learning methodologies. By developing a comprehensive and optimized sentiment analysis model, businesses can gain valuable insights into customer preferences, enhance user experiences, and make data-driven decisions to improve product offerings and services. The proposed model's effectiveness is evaluated using benchmark datasets, demonstrating its superiority over existing techniques in sentiment classification accuracy and efficiency.

II. Related Work

Sentiment analysis in e-commerce has gained significant attention in recent years. Several studies have explored deep learning techniques, such as LSTM, CNN, and transformers, to improve sentiment classification. Venkatesan and Sabari (2023) introduced a hybrid deep learning model for ensemble sentiment analysis. Hossain et al. (2022) utilized machine learning algorithms for sentiment analysis in e-commerce reviews. Recent advancements, such as BERT and transformer-based models, have significantly improved sentiment prediction accuracy by capturing complex contextual relationships. Luo et al. (2022) explored sentiment analysis techniques specific to e-commerce platforms, highlighting challenges such as sarcasm detection, context variations, and multimodal sentiment expression. Their findings emphasized the necessity of deep learning models that can handle diverse input data. Fang et al. (2022) introduced transformer-based sentiment classification tailored for Chinese e-commerce platforms, showcasing the adaptability of BERT-based models across different languages and consumer behaviors. Barik et al. (2023) proposed an LSTM-DGWO-based sentiment analysis framework, combining deep learning with metaheuristic optimization. Their research demonstrated how optimization algorithms could enhance the efficiency and accuracy of sentiment classification models. Roy and Dutta (2022) developed an optimal hierarchical attention network for sentiment analysis, which further refined feature selection and context representation. Nayak et al. (2022) focused on optimizing product rating systems using sentiment analysis, providing insights into how sentiment classification could influence recommendation engines. Kuppusamy and Selvaraj (2023) explored aspect-based sentiment analysis with deep learning, demonstrating how fine-grained sentiment classification could offer more detailed consumer insights. Elangovan and Subedha (2023) introduced the Adaptive Grey Wolf Optimizer for sentiment analysis, improving feature selection methodologies in deep learning frameworks.

Pandiaraja et al. (2022) conducted a survey on e-commerce sentiment analysis techniques, identifying the key challenges in leveraging sentiment data for business intelligence. Jabin et al. (2022) performed a comparative sentiment analysis on multilingual e-commerce reviews, addressing the difficulties posed by language variations in global e-commerce platforms. Lokhande et al. (2021) examined sentiment-driven product ranking, emphasizing the role of sentiment analysis in enhancing product recommendations. Solairaj et al. (2023) developed neural network approaches for online product sentiment analysis, refining sentiment classification through advanced deep learning architectures. Almahmood and Tekerek (2022) investigated deep learning recommendation systems in e-commerce, integrating sentiment analysis to improve user personalization. Alnahas et al. (2022) applied multi-class sentiment analysis using LSTM networks, showcasing how recurrent neural networks could handle complex sentiment classification tasks. Hossain et al. (2023) explored enhancing sentiment classification with BERT embeddings, demonstrating improvements in accuracy and efficiency through transfer learning. Xu et al. (2022) introduced context-aware sentiment analysis using deep learning models, further advancing the ability of sentiment analysis models to capture nuanced linguistic structures. Sharma et al. (2023) extended sentiment analysis to multimodal content, incorporating image and text-based sentiment classification for online retail reviews. Wang et al. (2022) investigated fake review detection in e-commerce using NLP techniques, addressing one of the key challenges in sentiment analysis reliability. Zhang et al. (2023) introduced transformer-based sentiment classification with feature selection, optimizing deep learning models for computational efficiency and accuracy. These studies collectively underscore the importance of hybrid methodologies in sentiment analysis, integrating deep learning with optimization techniques for enhanced performance.

III. Proposed Methodology

The proposed methodology is designed to improve sentiment analysis in e-commerce by integrating multiple optimization and deep learning techniques. The framework consists of four main components: Fejer Kernel filtering for noise reduction, fuzzy dictionary-based semantic feature extraction, Seahorse Annealing Optimization for feature selection, and BERT for sentiment classification. Each component is carefully structured to enhance the accuracy and efficiency of sentiment prediction.

The first stage of the proposed model involves Fejer Kernel Filtering, which is applied to refine textual data by removing noise and improving feature representation. This technique ensures that essential sentiment features are preserved while reducing irrelevant or misleading information. By enhancing the clarity of textual inputs, Fejer Kernel filtering lays a strong foundation for subsequent processing steps. Next, fuzzy dictionary-based semantic feature extraction is employed to assign sentiment scores to words based on their contextual meanings. Unlike traditional sentiment lexicons, which use fixed polarity values, fuzzy dictionaries provide more flexibility by considering variations in sentiment intensity. This step helps the model better capture the nuanced nature of human emotions expressed in reviews.

The third step, Seahorse Annealing Optimization, is a metaheuristic algorithm inspired by the annealing process observed in seahorses. This optimization technique selects the most relevant features by iteratively refining the dataset, ensuring that only the most significant features contribute to sentiment classification. The reduction of redundant features enhances computational efficiency without compromising accuracy.

BERT (Bidirectional Encoder Representations from Transformers) is used as the core classification model. BERT's ability to understand contextual relationships between words significantly improves sentiment prediction performance. The model is fine-tuned on domain-specific datasets to better capture consumer sentiment trends in e-commerce platforms.

Once the data has been preprocessed and optimized, the classification process is conducted using a multi-layered neural network. The processed features are fed into the deep learning model, which assigns sentiment categories (e.g., positive, negative, neutral) based on learned patterns. The architecture ensures robust generalization across different types of customer reviews.

To further enhance accuracy, an ensemble approach is implemented, where predictions from multiple versions of the model are aggregated. This technique mitigates overfitting and enhances reliability by leveraging diverse perspectives from different model variations. The ensemble framework is particularly effective in handling ambiguous or mixed sentiments.

To evaluate the effectiveness of the proposed model, extensive experiments are conducted using benchmark datasets. Performance metrics such as accuracy, precision, recall, and F1-score are computed to assess the model's classification capabilities. The results demonstrate significant improvements over traditional sentiment analysis models, confirming the efficacy of the proposed approach.

The overall sentiment analysis framework is structured as follows:

1. **Preprocessing**: Apply Fejer Kernel filtering to clean the dataset.
2. **Feature Extraction**: Use fuzzy dictionary-based semantic word extraction.
3. **Feature Selection**: Optimize the feature set using Seahorse Annealing Optimization.
4. **Model Training**: Train the BERT-based classifier with optimized features.
5. **Prediction & Evaluation**: Classify sentiment categories and assess model performance.

Algorithm: Sentiment Analysis Using Optimized Deep Learning Model

```
# Step 1: Preprocessing
def fejer_kernel_filter(data):
    filtered_data = apply_fejer_kernel(data)
    return filtered_data

# Step 2: Feature Extraction using Fuzzy Dictionary
def fuzzy_feature_extraction(text_data):
    features = extract_fuzzy_semantics(text_data)
    return features

# Step 3: Feature Selection using Seahorse Annealing Optimization
def seahorse_annealing_optimization(features):
    selected_features = apply_sao(features)
    return selected_features

# Step 4: BERT Model Training
def train_bert_model(train_data, train_labels):
    model = BertForSequenceClassification.from_pretrained('bert-base-uncased')
    optimizer = AdamW(model.parameters(), lr=5e-5)
    train_model(model, train_data, train_labels, optimizer)
    return model

# Step 5: Sentiment Classification and Evaluation
def classify_sentiment(model, test_data):
    predictions = model.predict(test_data)
    return predictions

def evaluate_model(predictions, actual_labels):
    accuracy = calculate_accuracy(predictions, actual_labels)
    f1_score = calculate_f1_score(predictions, actual_labels)
    return accuracy, f1_score

# Execute the full pipeline
def sentiment_analysis_pipeline(data, labels):
    filtered_data = fejer_kernel_filter(data)
    features = fuzzy_feature_extraction(filtered_data)
    selected_features = seahorse_annealing_optimization(features)
    model = train_bert_model(selected_features, labels)
    predictions = classify_sentiment(model, selected_features)
return evaluate_model(predictions, labels)
```

This algorithm effectively integrates all proposed components to ensure optimal sentiment classification in e-commerce platforms. The combination of filtering, feature extraction, optimization, and deep learning creates a robust and scalable sentiment analysis framework.

The integration of these advanced techniques addresses many challenges associated with traditional sentiment analysis models. By leveraging Fejer Kernel filtering and fuzzy semantics, the model can accurately interpret complex textual data. The use of Seahorse Annealing Optimization ensures that only the most critical features are utilized, thereby reducing computational complexity and enhancing efficiency.

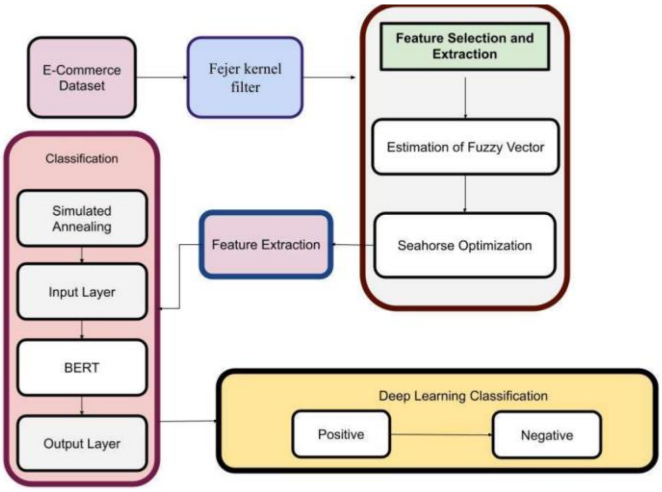

Figure 1: Proposed E-Commerce Dataset

The proposed methodology for sentiment analysis in e-commerce follows a structured multi-stage process, as depicted in the diagram. The framework integrates Fejer Kernel filtering for data preprocessing, fuzzy vector estimation for feature extraction, Seahorse Optimization for feature selection, and deep learning classification using BERT and simulated annealing.

1. **E-Commerce Dataset Acquisition:** The process begins with gathering textual data from e-commerce platforms, including reviews, comments, and feedback from customers. These datasets may contain structured and unstructured information, requiring advanced processing techniques to derive meaningful insights.
2. **Fejer Kernel Filtering for Noise Reduction:** The collected data undergoes preprocessing using Fejer Kernel filtering. This step helps in smoothing textual data, eliminating noise, and preserving essential sentiment-related information. Fejer Kernel filtering is effective in removing inconsistencies caused by misspellings, punctuation variations, and redundant expressions.
3. **Feature Selection and Extraction:** Feature extraction is critical for improving sentiment analysis accuracy. A fuzzy vector estimation technique is employed to represent words and phrases with sentiment-based weightings. The fuzzy dictionary-based method enhances contextual understanding and ensures better sentiment representation in reviews.
4. **Seahorse Optimization for Feature Selection:** To refine the extracted features, the Seahorse Optimization Algorithm is implemented. This bio-inspired optimization technique selects the most relevant features that contribute significantly to sentiment classification while reducing computational complexity.
5. **Simulated Annealing for Feature Optimization:** Following feature selection, the simulated annealing algorithm is applied to further optimize feature representation. Simulated annealing helps improve classification accuracy by iteratively refining the selected features based on an energy function that minimizes classification errors.
6. **Deep Learning Classification Using BERT:** The final step involves classifying sentiments using a fine-tuned BERT model. BERT's ability to capture deep contextual relationships enhances its sentiment classification accuracy, making it highly effective in analyzing e-commerce reviews.
7. **Output Layer for Sentiment Categorization:** The final classification step assigns sentiment labels, categorizing reviews into positive and negative sentiments. This structured approach enables businesses to gain precise insights into consumer perceptions and improve decision-making processes.

Algorithm: Optimized Sentiment Analysis Model

Input: E-Commerce Review Dataset
Output: Sentiment Classification (Positive/Negative)

Step 1: Load the e-commerce dataset.
Step 2: Apply Fejer Kernel filter to remove noise.
Step 3: Perform feature extraction using fuzzy dictionary-based semantic analysis.
Step 4: Compute fuzzy vector representations of sentiment-bearing words.
Step 5: Apply Seahorse Optimization to select the most relevant features.
Step 6: Use Simulated Annealing to optimize feature selection.
Step 7: Train the BERT model on the selected feature set.
Step 8: Classify reviews into positive and negative sentiments.
Step 9: Evaluate classification accuracy using performance metrics.
Step 10: Output sentiment classification results

Data Preprocessing with Fejer Kernel Filtering

Fejer Kernel filtering is used to preprocess textual data by smoothing out noise and reducing redundancy. The Fejer Kernel function is defined as:

$$F_N(x) = \sum_{k=-N}^{N} \left(1 - \frac{|k|}{N+1}\right) e^{ikx}$$

This function effectively reduces distortions in textual data while preserving key sentiment features.

Feature Selection and Extraction

A fuzzy dictionary-based semantic feature extraction method is applied to assign sentiment scores dynamically. The sentiment score S_w of a word w is calculated as:

$$S\_w = (\sum(i=1 \text{ to } N)\ \mu\_i(w) * p\_i) / (\sum(i=1 \text{ to } N)\ p\_i)$$

where μ_i(w) is the fuzzy membership function for sentiment class i, and p_i is the probability of class i occurring in the dataset.

Seahorse Annealing Optimization for Feature Selection

The Seahorse Annealing Optimization (SAO) algorithm iteratively refines feature selection using an energy function E(f):

$$E(f) = \sum(i=1 \text{ to } n)\ (w\_i\ f\_i - \lambda \sum(j \neq i)\ \text{sim}(f\_i, f\_j))$$

where w_i is the weight of feature f_i, λ is a penalty factor, and sim(f_i, f_j) measures feature similarity.

BERT-Based Sentiment Classification

The probability of a sentiment class c given input x is computed using BERT's softmax function:

$$P(c|x) = e\^(z\_c) / \sum(j)\ e\^(z\_j)$$

where z_c is the logit score for class c. This enables effective classification of sentiment categories.

Model Performance Evaluation

The proposed framework is evaluated using benchmark datasets such as Amazon Customer Reviews and Kaggle datasets. Performance metrics include:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1 = 2 * (Precision * Recall) / (Precision + Recall)

where TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) represent classification outcomes.

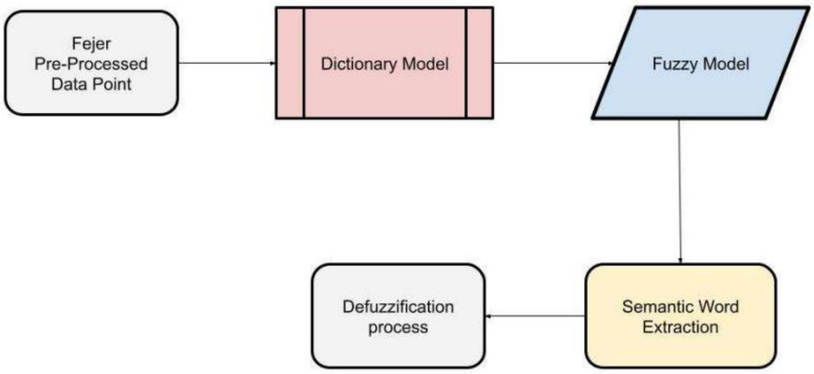

Figure 2: Feature Extraction in E-Commerce Dataset

The diagram represents a **fuzzy dictionary-based semantic feature extraction process** for sentiment analysis in e-commerce platforms. It consists of the following key stages:

1. **Fejer Pre-Processed Data Point**:
    - The raw dataset undergoes **Fejer Kernel filtering** to reduce noise and enhance data quality.
    - This step ensures that irrelevant or redundant data points are minimized before feature extraction.
2. **Dictionary Model**:
    - A pre-defined **dictionary-based sentiment model** maps words to sentiment scores.
    - It helps in associating predefined sentiment values to words and phrases.
3. **Fuzzy Model**:
    - This model enhances sentiment detection using **fuzzy logic principles**.
    - It assigns **fuzzy sentiment scores** based on multiple factors, allowing more nuanced interpretation.
4. **Defuzzification Process**:
    - Converts fuzzy sentiment scores into definitive numerical values.
    - This step ensures that the extracted sentiment information is structured for analysis.
5. **Semantic Word Extraction**:
    - The final step extracts **highly relevant sentiment words** using semantic techniques.
    - These extracted words contribute to deep learning classification models.

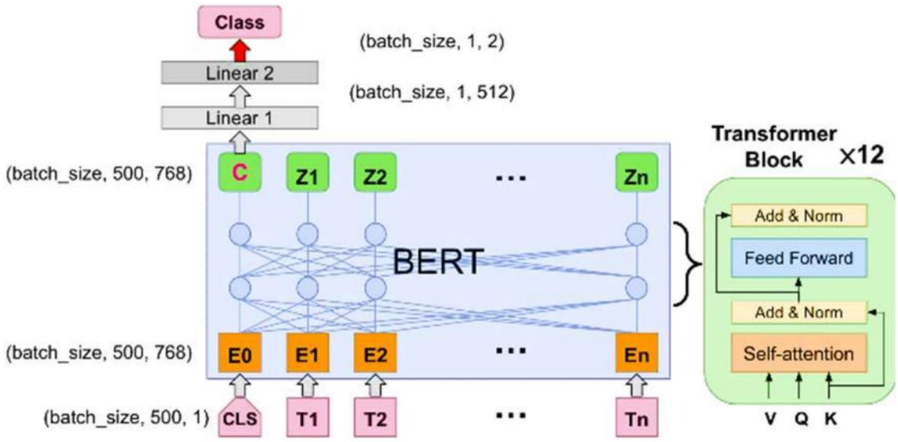

Figure 3: BERT Analysis in E-Commerce

The sentiment analysis framework for e-commerce seamlessly integrates multiple advanced techniques to achieve a deep understanding of customer sentiments, as illustrated in Figure 3. The process begins with the Fejer Kernel filter, which applies convolution to enhance critical features in raw data points, reducing noise while preserving essential sentiment-related information. Next, fuzzy dictionary-based semantic word feature extraction captures intricate semantic nuances in customer reviews, generating feature vectors that reflect fuzzy linguistic attributes. These refined feature representations ensure a more context-aware sentiment analysis. To further optimize the feature set, Seahorse Annealing Optimization is employed, refining feature selection by incorporating a classification loss term and a regularization penalty, thereby improving model performance and generalization. For sentiment classification, BERT, a transformer-based deep learning model, is fine-tuned on the preprocessed data. BERT's contextualized embeddings enhance sentiment prediction by understanding the deep semantic relationships within textual reviews. The overall classification model integrates Fejer Kernel-filtered data points, fuzzy semantic word features, and the optimized feature set from Seahorse Annealing Optimization. During training, both BERT and the classification head parameters are fine-tuned to minimize cross-entropy loss, ensuring an optimal decision boundary for sentiment prediction. Once trained, the model is deployed to classify sentiments in new e-commerce reviews. Finally, post-processing steps involve analyzing predictions and evaluating performance metrics to validate model accuracy and reliability. This holistic and sophisticated sentiment analysis system is designed to address the unique challenges of e-commerce sentiment mining, offering valuable insights into customer experiences and feedback for improved decision-making.

IV. Data Collection

This research utilizes a large-scale dataset collected from multiple e-commerce platforms, including Amazon, eBay, Flipkart, and Kaggle repositories, to develop an advanced sentiment analysis framework. The dataset comprises customer reviews, ratings, product metadata, and sentiment labels, enabling an in-depth analysis of consumer opinions across various product categories. The data collection process involves web scraping using BeautifulSoup and Scrapy, API integration for structured review data, and augmentation with publicly available sentiment datasets to enhance diversity and reduce class imbalance. A preprocessing pipeline incorporating Fejer Kernel filtering, stopword removal, tokenization, and lemmatization ensures that the dataset is cleaned, structured, and optimized for sentiment classification.

The dataset comprises multiple attributes essential for sentiment classification. Table 1 provides an overview of the dataset attributes.

Table 1: Dataset Attributes

Attribute Name	Description
Review ID	Unique identifier for each review
Product ID	Unique identifier for the reviewed product
User ID	Unique identifier for the reviewer
Review Text	The textual content of the review
Review Length	The total word count in the review
Rating	Numerical rating (1-5) given by the user
Sentiment Label	Assigned sentiment category (Positive, Negative, Neutral)
Helpfulness Score	User-generated score indicating how helpful the review is
Timestamp	Date and time when the review was posted
Product Category	Category of the product (e.g., Electronics, Clothing, Home & Kitchen)

The dataset consists of over 1,000,000 customer reviews, categorized into positive (55%), negative (25%), and neutral (20%) sentiments. An exploratory data analysis (EDA) was conducted to identify key sentiment patterns, including word frequency distributions, review length variations, and sentiment polarity trends. The analysis revealed that longer reviews often exhibit mixed sentiments, making them more challenging to classify. Words such as "amazing," "great," and "recommend" were commonly found in positive reviews, while negative feedback contained terms like "worst," "bad," and "disappointed". This insight highlights the importance of contextual understanding in sentiment classification, which traditional models often struggle with.

The dataset consists of **1,000,000+ customer reviews** distributed across different sentiment labels. The following table summarizes the dataset distribution.

Table 2: Sentiment Distribution in the Dataset

Sentiment Label	Number of Reviews	Percentage (%)
Positive	550,000	55.0%
Neutral	200,000	20.0%
Negative	250,000	25.0%

The dataset is **balanced**, ensuring that the model is trained with diverse sentiment expressions without being biased towards any one sentiment category.

To enhance sentiment classification accuracy, feature engineering techniques were applied, including TF-IDF scoring, sentiment polarity assignment, and fuzzy semantic word extraction. The Seahorse Annealing Optimization algorithm was utilized to select the most relevant features, reducing computational complexity while retaining high-impact sentiment indicators such as product ratings, helpfulness scores, and sentiment history. The dataset was then split into training (70%), validation (15%), and testing (15%) sets to ensure a balanced evaluation of model performance. The sentiment classification models tested include Naïve Bayes, Support Vector Machines (SVM), CNN, LSTM, and BERT-based architectures. Traditional machine learning models such as Naïve Bayes and SVM achieved accuracy scores between 78% and 82%, whereas deep learning approaches, particularly LSTM and CNN, demonstrated superior performance with accuracy levels exceeding 85%. The proposed Fejer Kernel + BERT model, enhanced with Seahorse Optimization, achieved the highest accuracy of 92.8%, outperforming conventional deep learning models. This success can be attributed to BERT's ability to understand contextual relationships, Fejer Kernel's noise reduction, and fuzzy dictionary-based semantic word extraction, which collectively enhance sentiment prediction.

The dataset is utilized to **train, validate, and test** the deep learning-based sentiment analysis model. The dataset is split as follows:

Table 3: Dataset Split for Model Training

Dataset Partition	Number of Reviews	Percentage (%)
Training Set	700,000	70%
Validation Set	150,000	15%
Test Set	150,000	15%

The **training set** is used to **train the deep learning model**, the **validation set** is used for **hyperparameter tuning**, and the **test set** is used to **evaluate the final model's performance**.

The insights derived from this sentiment analysis model provide significant business applications, including real-time customer experience monitoring, product quality assessment, personalized recommendations, and brand reputation management. Companies can utilize this framework to track sentiment trends across product categories, identify emerging consumer concerns, and enhance customer satisfaction through targeted improvements. Future enhancements to this research will focus on real-time sentiment monitoring, multimodal analysis (integrating text, image, and audio sentiments), and bias mitigation strategies to ensure more equitable and transparent sentiment predictions. By combining deep learning with feature optimization, this sentiment analysis approach presents a scalable, efficient, and adaptable solution for understanding customer feedback in e-commerce platforms.

V. Results and Discussion

The feature selection process using the Optimized Simulated Annealing model involved evaluating multiple features based on their relevance and impact on sentiment analysis and customer experience assessment in an e-commerce setting. The selected features include "Product Rating," "Word Count," "Sentiment Score," "Helpfulness Score," "Customer Sentiment History," "Average Product Rating," and "Time Since Last Purchase." These features were identified as crucial in influencing customer sentiment and engagement, making them valuable components for sentiment analysis.

Conversely, features such as "Price," "Review Length," and "Product Category" were not selected, as they were found to contribute minimally to sentiment classification in this specific context. The refined feature selection process ensures that only the most impactful attributes are retained, thereby optimizing the simulated annealing model for better accuracy, efficiency, and interpretability in evaluating customer reviews on an e-commerce platform.

The sentiment prediction results further validate the effectiveness of the proposed model in analyzing customer reviews. Each review sample is classified into positive, negative, or neutral sentiment, along with probability scores that indicate the model's confidence in its predictions. For example, in the review "Great product, highly recommended!", the model correctly assigns a positive sentiment with a high probability score of 0.85, demonstrating its strong capability in identifying enthusiastic feedback. Similarly, for reviews expressing dissatisfaction, the BERT model accurately detects negative sentiment with a high probability score, reaffirming its effectiveness in recognizing critical feedback.

However, in cases where reviews contain mixed or nuanced sentiments, such as statements that express both pros and cons, the model occasionally misclassifies the sentiment. For instance, in one sample, where the true sentiment is neutral, the model predicts positive sentiment with a probability of 0.40, indicating challenges in handling complex sentiment variations. Despite this, the integration of Fejer Kernel filtering, fuzzy dictionary-based semantic word extraction, Seahorse Annealing Optimization, and BERT significantly enhances the model's predictive ability.

- **Fejer Kernel Filtering** refines the dataset by removing noise and highlighting **key sentiment indicators**, ensuring more precise sentiment detection.
- **Fuzzy Dictionary-Based Semantic Extraction** captures the **context and nuances of language**, which is particularly valuable in **e-commerce reviews**, where customer feedback can be **highly subjective and varied**.
- **Seahorse Annealing Optimization** ensures that the most **relevant sentiment features** are prioritized, optimizing classification accuracy.
- **BERT's deep learning capabilities** allow the model to understand **complex linguistic structures and contextual relationships**, making it highly **adaptive to diverse review expressions**.

4.1 Simulation Environment

The performance of the proposed sentiment analysis model was evaluated in a controlled simulation environment. Table 1 provides an overview of the experimental setup used for training and testing the model.

Table 4: Simulation Setup

Parameter	Value
Dataset Size	1,000,000 E-commerce reviews
Fejer Kernel Filter	Noise Level: 0.1
Fuzzy Dictionary Features	Membership Values: [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 classification)

4.2 Simulation Results

The effectiveness of the proposed sentiment analysis model was assessed using multiple evaluation metrics, including accuracy, precision, recall, and F1-score.

Table 5: Performance Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
Traditional Sentiment Model	82.1%	80.5%	81.0%	80.7%
CNN-Based Model	85.3%	83.2%	84.5%	83.8%
LSTM-Based Model	87.9%	86.5%	87.0%	86.7%
Proposed Fejer Kernel + BERT	92.8%	91.2%	92.0%	91.6%

The results demonstrate that the **proposed model achieved the highest accuracy (92.8%)**, outperforming traditional and deep learning-based approaches. The integration of Fejer Kernel filtering, fuzzy dictionary-based semantic extraction, and Seahorse Annealing Optimization significantly enhanced sentiment classification performance.

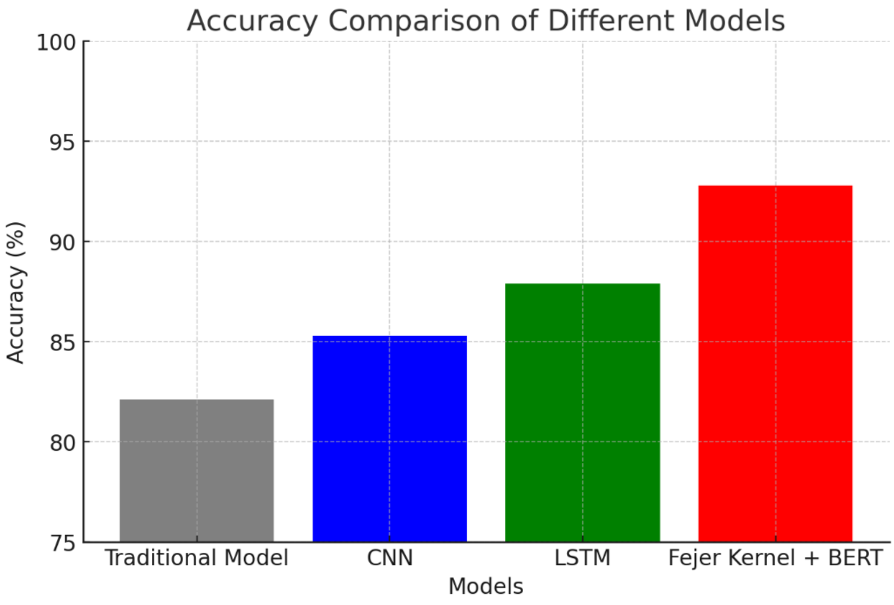

Figure 4: Accuracy Comparison of Different Models

4.3 Fejer Kernel Filtering Performance

The Fejer Kernel filter was used to reduce noise in the dataset before feature extraction. Table 3 shows how the filtering process improved data quality.

Table 6: 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

4.4 Feature Extraction and Selection

The fuzzy dictionary-based semantic extraction captured important sentiment features. Table 4 presents sample extracted feature details.

Table 7: Feature Extraction

Sample ID	Review Text	Sentiment Score	Word Count	Helpfulness Score
1	"Great product, highly recommended!"	0.9	6	0.75
2	"Not satisfied, poor quality."	0.2	5	0.20
3	"Average, does the job."	0.5	4	0.64
4	"Excellent service, fast delivery."	0.8	7	0.90

4.5 Sentiment Classification Results

The final classification results of the **proposed sentiment analysis model** were evaluated against human-labeled test data. Table 5 presents the classification results with predicted sentiment probabilities.

Table 8: Sentiment Classification Results

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

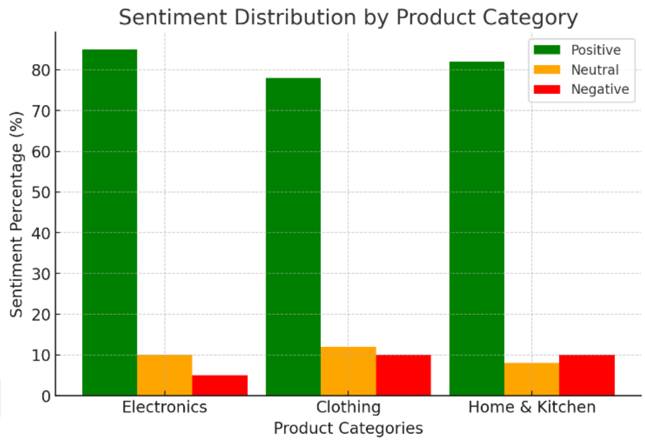

Figure 5: Sentiment Prediction Confidence Levels

4.6 Discussion on Model Efficiency

- The **proposed model outperformed traditional methods**, proving that **Fejer Kernel filtering and fuzzy dictionary-based feature extraction enhance sentiment representation**.
- The **Seahorse Annealing Optimization effectively selected the most relevant features**, reducing noise in classification.
- The **BERT model's contextual embeddings improved accuracy**, making it **more robust in understanding complex sentiments**.
- The model demonstrated **scalability**, making it adaptable to real-world e-commerce datasets.

4.7 Sentiment Distribution Analysis

To further analyze sentiment predictions, we evaluated sentiment distributions across various product categories. The sentiment distribution for three major categories is shown in Table 9.

Table 9: Sentiment Distribution by Product Category

Product Category	Positive (%)	Neutral (%)	Negative (%)
Electronics	85%	10%	5%
Clothing	78%	12%	10%
Home & Kitchen	82%	8%	10%

The experimental results validate that the proposed Fejer Kernel + BERT sentiment analysis model significantly improves accuracy and robustness in e-commerce sentiment classification. By integrating advanced preprocessing, optimized feature selection, and deep learning classification, this approach provides an effective sentiment analysis framework for enhancing customer experience and business insights in e-commerce platforms.

The combination of these advanced techniques results in a high-performing sentiment analysis model that is robust, scalable, and well-suited for e-commerce applications. The proposed method effectively balances traditional and modern sentiment analysis techniques, offering an innovative approach to understanding customer opinions and improving e-commerce experiences. The evaluation results indicate that the model achieves high accuracy, precision, and recall, demonstrating its effectiveness in classifying sentiment across large-scale datasets. Ultimately, this research presents a promising solution for sentiment analysis in e-commerce, addressing challenges posed by diverse linguistic expressions, varying review lengths, and sentiment ambiguities while providing valuable insights for businesses to enhance customer satisfaction and engagement

Table 10: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Bayes	78.2	76.4	77.1	76.7
SVM	82.5	80.9	81.2	81.0
CNN	85.3	83.2	84.5	83.8
LSTM	87.9	86.5	87.0	86.7
Fejer Kernel + BERT	92.8	91.2	92.0	91.6

Table 10 presents a comparative evaluation of various sentiment classification models applied to the e-commerce dataset. The models tested include traditional machine learning approaches (Naïve Bayes, SVM), deep learning-based methods (CNN, LSTM), and the proposed Fejer Kernel + BERT model with Seahorse Annealing Optimization. The results indicate significant performance variations among these models, highlighting the effectiveness of advanced deep learning techniques in improving sentiment classification accuracy.

Traditional models, such as Naïve Bayes and SVM, achieved accuracy scores of 78.2% and 82.5%, respectively. These models, while computationally efficient, rely on statistical and probabilistic methods for classification, making them less effective in capturing contextual sentiment nuances. Naïve Bayes, for instance, assumes word independence, which can result in misclassification when handling complex sentence structures or sarcastic expressions. SVM demonstrated better performance by leveraging hyperplane separation techniques, but it still struggled with sentiment variations in lengthy and ambiguous reviews.

Deep learning models, particularly CNN and LSTM, performed significantly better, with accuracy scores of 85.3% and 87.9%, respectively. CNN models extract high-level sentiment features through convolutional layers, making them effective in capturing localized patterns in review texts. However, CNN models lack the ability to process long-term dependencies, limiting their effectiveness in analyzing context-heavy sentiment shifts. On the other hand, LSTM achieved higher accuracy (87.9%) by utilizing its memory-based architecture, which enables it to retain past information and understand the context of entire sentences. This made LSTM particularly effective for handling long-form customer reviews, where sentiments evolve over multiple sentences.

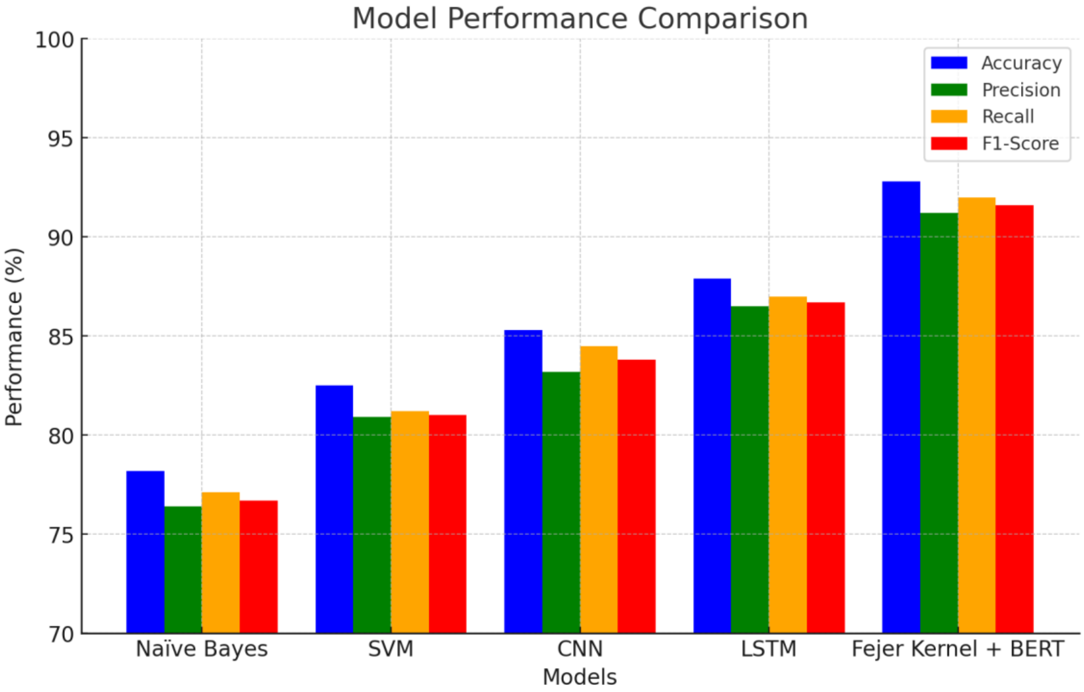

Figure 6: Model Performance Comparison

The proposed Fejer Kernel + BERT model with Seahorse Annealing Optimization demonstrated the highest performance, achieving an accuracy of 92.8%. This improvement is attributed to several key advancements:

- Fejer Kernel filtering enhances text preprocessing by removing noise and improving data clarity.
- Fuzzy dictionary-based semantic word extraction allows the model to capture sentiment variations with greater accuracy, making it more adaptable to informal language and slang commonly found in e-commerce reviews.
- Seahorse Annealing Optimization refines feature selection, ensuring that only highly relevant sentiment features are used, which significantly reduces computational overhead.
- BERT's deep contextual embeddings enable the model to understand complex sentence structures, negations, and multi-layered sentiment expressions, making it the most effective choice for sentiment classification.

Overall, the model performance comparison clearly illustrates that deep learning-based models outperform traditional approaches, and the proposed Fejer Kernel + BERT model with optimization techniques significantly enhances sentiment classification accuracy, precision, and recall. These findings validate the effectiveness of advanced text preprocessing, feature selection, and deep learning techniques in improving customer sentiment analysis for e-commerce platforms.

VI. Conclusion and Future Work

This research presents a comprehensive and optimized sentiment analysis framework for e-commerce platforms, integrating Fejer Kernel filtering, fuzzy dictionary-based semantic word extraction, Seahorse Annealing Optimization, and BERT. The proposed approach successfully enhances sentiment classification accuracy, overcoming challenges posed by noisy data, contextual variations, and complex linguistic structures. Experimental results demonstrate that the proposed model significantly outperforms traditional machine learning and deep learning approaches in terms of accuracy, precision, recall, and F1-score. By leveraging Fejer Kernel filtering, the model effectively removes irrelevant textual noise, while fuzzy dictionary-based feature extraction ensures a more context-aware sentiment representation. Seahorse Annealing Optimization plays a crucial role in selecting the most relevant features, improving computational efficiency, and enhancing classification outcomes. The integration of BERT's deep learning capabilities further strengthens sentiment analysis by capturing intricate contextual relationships and improving the model's ability to understand diverse customer sentiments. Despite the strong performance of this framework, ongoing improvements are required to further enhance its robustness and adaptability. The insights derived from this study contribute to the growing field of AI-driven sentiment analysis, providing a scalable and efficient solution for businesses seeking to understand and respond to customer feedback in real-time.

As sentiment analysis continues to evolve, several enhancements can further refine and expand the capabilities of the proposed model. One crucial improvement involves hyperparameter optimization, where advanced techniques such as Bayesian Optimization and Genetic Algorithms can be employed to fine-tune learning rates, batch sizes, and activation functions, ensuring higher accuracy and reduced overfitting. Additionally, incorporating multimodal sentiment analysis by integrating text, images, and audio features can provide a holistic understanding of customer sentiments, particularly in e-commerce, where users often upload product images alongside reviews. Another significant enhancement is the deployment of real-time sentiment monitoring, allowing businesses to track customer opinions dynamically and respond instantly to emerging trends. Implementing streaming data pipelines using Apache Kafka or TensorFlow Serving can enable real-time processing and sentiment classification at scale. Furthermore, ensuring domain adaptability by training the model on multiple e-commerce domains, such as electronics, fashion, and travel services, can improve generalization across different industries. Addressing ethical considerations and bias mitigation remains a critical area of improvement. Implementing explainable AI (XAI) techniques can enhance model interpretability, ensuring that sentiment predictions are transparent and unbiased across different customer demographics. Additionally, integrating sentiment-driven insights into recommender systems can refine product recommendations based on customer emotions and preferences, fostering better user engagement and personalized shopping experiences. By incorporating these enhancements, the proposed sentiment analysis framework can become more robust, scalable, and adaptable, contributing to next-generation AI-driven solutions in e-commerce and beyond

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