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Optimized Gaussian Deep Learning Architecture With Sentimental Analysis For The E-Commerce Application

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Abstract
In the context of E-commerce, sentiment analysis plays a crucial role in understanding and evaluating the subjective information present in customer reviews, feedback, and comments. With implementation of sentimental analysis automatically identify and classify sentiments as positive, negative, or neutral, providing valuable insights into how customers perceive products, services, or overall experiences. Sentiment analysis in E-commerce encounters challenges such as contextual ambiguity, difficulty in detecting sarcasm, data imbalance with an abundance of positive reviews, domain-specific language nuances, multilingual diversity, adapting to various product types, accounting for temporal shifts in sentiments, addressing privacy concerns, tackling review spam, and ensuring effective integration into business decisions. This paper proposed a novel approach to sentiment analysis in E-commerce utilizing the Gaussian Long Short-Term Memory (G-LSTM) model. The proposed G-LSTM model implements Fejer Kernel filter for the data pre-processing followed by the dictionary-based model for the feature extraction process. The feature selection is performed with the optimization of the features such as Seahorse Optimization mode. Finally, the classification is performed with the Gaussian Long Short Term Memory (LSTM) model for the classification. The G-LSTM model showcases remarkable performance, achieving an accuracy of 98.3% along with superior precision, recall, and F1-Score compared to baseline LSTM, SVM, and Random Forest models.
Keywords: E-commerce, Sentimental Analysis, Gaussian, Classification, Fejer-Kernal, Dictionary model, Seahorse Optimization

1. Introduction

Sentiment analysis, also known as opinion mining, is a computational technique that involves determining and extracting the sentiment expressed in a given text. This process aims to understand whether the writer's attitude towards a particular subject is positive, negative, or neutral [1]. In recent years, sentiment analysis has gained significant attention due to the exponential growth of textual data on the internet and social media platforms. The methodology behind sentiment analysis typically involves natural language processing (NLP) techniques and machine learning algorithms [2]. By analyzing the words, phrases, and context within a paragraph, the system can assign a sentiment score to the text. Positive sentiment may be associated with words like "happy," "joyful," or "satisfied," while negative sentiment could be linked to words such as "unhappy," "disappointed," or "frustrated."Sentiment analysis has diverse applications, ranging from business and marketing to social media monitoring and customer feedback analysis [3]. It enables organizations to gauge public opinion, understand consumer sentiment, and make data-driven decisions. Despite its effectiveness, sentiment analysis faces challenges, such as handling sarcasm, irony, and cultural nuances, which can impact the accuracy of the results. As technology continues to advance, sentiment analysis is likely to evolve, providing more nuanced and context-aware insights into the emotions expressed in textual content [4].

In this digital era, e-commerce involves the buying and selling of goods and services online, eliminating the need for physical storefronts [5]. It encompasses various models, including business-to-consumer (B2C), business-to-business (B2B), and consumer-to-consumer (C2C) transactions. E-commerce platforms provide a virtual marketplace where customers can browse, compare, and purchase products or services conveniently from the comfort of their homes [6].Key components of successful e-commerce operations include user-friendly websites, secure payment gateways, efficient logistics, and robust customer support. The rise of mobile devices and advanced technologies has further fueled the growth of e-commerce, leading to innovations like mobile commerce (m-commerce) and voice commerce [7].E-commerce offers numerous advantages, such as global reach, accessibility 24/7, and personalized shopping experiences through data-driven recommendations. It has transformed traditional retail landscapes, enabling small businesses to compete on a global scale and empowering consumers with a vast array of choices [8]. However, challenges like cybersecurity, logistics optimization, and maintaining customer trust remain crucial considerations for e-commerce businesses. As technology continues to evolve, e-commerce is expected to continually reshape the way businesses engage with customers and conduct transactions in the dynamic digital marketplace [9].

E-commerce, coupled with sentiment analysis, represents a dynamic synergy between technological innovation and consumer behavior understanding. In the realm of electronic commerce, where transactions occur in the virtual space, sentiment analysis plays a pivotal role in deciphering the emotions and opinions expressed by consumers [10]. By employing natural language processing and machine learning algorithms, businesses can analyze customer reviews, social media interactions, and feedback to gauge sentiment, discerning whether the overall consumer sentiment is positive, negative, or neutral [11].This integration of sentiment analysis in e-commerce holds profound implications for businesses. It allows companies to not only track customer satisfaction but also to tailor their strategies based on valuable insights gained from sentiment data [12]. Positive sentiments can be leveraged for marketing campaigns, reinforcing brand loyalty, while negative sentiments can prompt proactive responses to address issues and enhance customer experience [13]. The ability to understand and respond to consumer sentiments in real-time empowers e-commerce platforms to refine product offerings, optimize customer service, and build stronger relationships with their clientele. In this symbiotic relationship between e-commerce and sentiment analysis, businesses can create a more personalized and responsive online shopping experience. By staying attuned to the sentiments of their customer base, e-commerce platforms are better positioned to adapt, evolve, and thrive in the ever-changing landscape of online commerce [14].The intersection of e-commerce and sentiment analysis has reached new heights with the incorporation of deep learning techniques. Deep learning, a subset of machine learning, involves neural networks with multiple layers that can automatically learn intricate patterns and representations from data. In the context of e-commerce, deep learning facilitates more sophisticated sentiment analysis by extracting nuanced emotions and context from textual data, such as customer reviews, social media comments, and product descriptions [15].

Deep learning models, particularly recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), excel in capturing sequential dependencies and contextual information within sentences [16]. This capability enhances the accuracy of sentiment analysis, allowing e-commerce platforms to discern not only whether a sentiment is positive or negative but also to comprehend the subtle nuances and complexities of consumer opinions

[17].The integration of deep learning in sentiment analysis within the e-commerce landscape provides businesses with a more advanced and granular understanding of customer sentiments. This not only aids in refining product recommendations but also in tailoring marketing strategies to align with the prevailing consumer sentiments [18]. By harnessing the power of deep learning, e-commerce platforms can enhance user experiences, optimize product assortments, and respond swiftly to emerging market trends, ultimately fostering a more engaging and customer-centric online shopping environment [19]. As technology continues to advance, the synergy between e-commerce, sentiment analysis, and deep learning is poised to redefine how businesses navigate the intricacies of consumer emotions in the digital marketplace.

The paper makes several significant contributions to the field of sentiment analysis in E-commerce through the proposed Gaussian Long Short-Term Memory (G-LSTM) model. The key contributions are outlined as follows:

1. The paper introduces a novel G-LSTM architecture for sentiment analysis in E-commerce. The G-LSTM model incorporates Gaussian processes into the traditional LSTM architecture, enhancing the ability to capture long-term dependencies and complex patterns in sequential E-commerce data.
2. The paper proposes the use of the Fejer Kernel for data preprocessing. This innovative approach involves applying the Fejer Kernel filter to the input data, enabling the G-LSTM model to better emphasize relevant patterns and features in E-commerce reviews.
3. The paper employs fuzzy dictionary-based semantic word feature extraction. This technique enhances the model's understanding of the nuanced semantics in E-commerce reviews, contributing to more contextually aware sentiment analysis.
4. The incorporation of Seahorse Optimization for feature selection is a notable contribution. This heuristic optimization technique is employed to select the most relevant features, optimizing the G-LSTM model's performance and interpretability.
5. The paper conducts a comprehensive comparative analysis of the proposed G-LSTM model against baseline LSTM, SVM, and Random Forest models. The results demonstrate superior accuracy, precision, recall, and F1-score, highlighting the effectiveness of the G-LSTM model in E-commerce sentiment analysis.

The proposed G-LSTM model has practical implications for E-commerce platforms, as accurate sentiment analysis is crucial for understanding customer feedback. The model's ability to provide fine-grained sentiment predictions contributes to enhancing user experience, product recommendations, and overall customer satisfaction. The paper's contributions lie in the development of a novel G-LSTM architecture, innovative data preprocessing with the Fejer Kernel, advanced feature extraction techniques, and the integration of heuristic optimization for feature selection, all of which collectively improve sentiment analysis performance in the context of E-commerce. The open-source implementation and comparative analysis further strengthen the paper's contribution to the research community.

2. Literature Survey

The literature survey on sentiment analysis in the realm of e-commerce reveals a growing body of research exploring the intricate relationship between consumer sentiments and online retail platforms. As electronic commerce continues to thrive, understanding and deciphering customer emotions expressed through textual data have become paramount for businesses seeking to enhance user experiences, optimize marketing strategies, and ultimately improve overall customer satisfaction. Scholars have delved into various aspects of sentiment analysis methodologies, ranging from traditional natural language processing techniques to the integration of cutting-edge technologies like machine learning and deep learning. This survey aims to provide a comprehensive overview of the existing literature, shedding light on the evolution of sentiment analysis in e-commerce, the challenges encountered, and the innovative approaches employed to harness sentiment insights for strategic decision-making in the dynamic and competitive landscape of online retail.

In [10] focuses on sentiment analysis within the context of two prominent e-commerce platforms, Lazada and Shopee. By exploring customer sentiments on these platforms, the authors aim to provide insights into the nuanced aspects of user experiences and preferences, shedding light on the unique dynamics of sentiment expression in the highly competitive e-commerce market. In [11] introduces a sophisticated Long Short-Term Memory (LSTM) model tailored for sentiment analysis in the social data of e-commerce product reviews, specifically in the Hindi language. The focus on linguistic and cultural nuances aims to enhance the accuracy and applicability of sentiment analysis models for Hindi-speaking consumers. In [12] study delves into predicting customers' interests by employing sentiment analysis in e-commerce data. The comparative analysis across Arabic, English, and Turkish languages seeks to uncover language-specific patterns in customer sentiments, offering valuable insights for businesses operating in multilingual markets.In [13] proposes a stacked ensemble deep learning approach to enhance Arabic sentiment analysis in e-commerce reviews on social media. The use of advanced deep learning techniques aims to capture the complexities of Arabic language sentiment, providing a more nuanced understanding of consumer opinions in the Arab-speaking digital landscape.

In [14] focuses on improving sentiment detection in e-commerce customer reviews, emphasizing the need for enhanced accuracy in understanding consumer sentiments. By proposing improvements in sentiment analysis models, the research aims to contribute to more effective decision-making processes for businesses based on comprehensive customer feedback analysis. In [15] focuses on developing a brand ranking algorithm for e-commerce, integrating user evaluations and sentiment analysis. By combining these factors, the study aims to create a comprehensive algorithm that reflects not only the popularity of brands but also the sentiments associated with them. In [16] employs the Naïve Bayes classifier algorithm for sentiment analysis on the Shopee e-commerce platform. The utilization of a specific algorithm allows for a detailed exploration of sentiment patterns on Shopee, contributing to the understanding of user sentiments and preferences specific to this platform. In [17] focuses on sentiment analysis for an e-commerce site. By incorporating sentimental analysis techniques, the study aims to uncover valuable insights into user sentiments, contributing to the enhancement of overall user experiences on e-commerce platforms.

In [18] proposes a novel AB-CNN model for multi-classification sentiment analysis of e-commerce comments. This research aims to provide a more refined approach to sentiment analysis by considering multiple sentiment classes, enabling a more detailed understanding of the diverse range of opinions expressed in e-commerce comments. In [19] focuses on sentiment analysis of Roman Urdu in e-commerce reviews using machine learning techniques. The study aims to bridge the gap in sentiment analysis for Roman Urdu, providing insights into the sentiments expressed by users in the specific linguistic context. In [20] explores sentiment analysis of e-commerce consumers based on product delivery time using machine learning. By considering the crucial aspect of product delivery, the study provides insights into how the timeliness of deliveries influences consumer sentiments in the e-commerce sector. In [21] Focusing on beauty product e-commerce, this study employs the Support Vector Machine (SVM) method for sentiment analysis. By specializing in the beauty product domain, the research aims to uncover unique patterns and sentiments associated with consumer opinions in this specific e-commerce sector. In [22] enhance collaborative filtering-based recommender systems by integrating sentiment analysis. The study explores how incorporating sentiment analysis can improve the accuracy and personalization of recommender systems in the e-commerce domain.

In [23] focused on personalized chatbots in e-commerce applications, this research introduces sentiment analysis to enhance user interactions. By incorporating sentiment analysis into chatbot functionalities, the study aims to create more tailored and responsive e-commerce experiences for users. In [24] focuses on sentiment analysis of product reviews for e-commerce recommendation, employing machine learning techniques. The research aims to explore how sentiment analysis can play a role in improving product recommendations and overall user experiences in e-commerce. In [25] examined sentiment analysis of e-commerce product reviews for content interaction using machine learning. By considering content interaction, the study aims to uncover how users engage with and respond to e-commerce product content based on sentiments expressed in reviews. In [26] introduces an automated sentiment analysis approach using a heuristic-based CNN-BiLSTM for an e-commerce dataset. The research explores the effectiveness of the proposed approach in automating sentiment analysis processes for large e-commerce datasets. In [27] focuses on learning user sentiment orientation in social networks for sentiment analysis. By considering the social aspect of user interactions, the study aims to enhance the accuracy and relevance of sentiment analysis in the context of social networks and e-commerce. In [28] explores competitive intelligence in agro e-commerce by integrating Social Network Analysis (SNA), Latent Dirichlet Allocation (LDA), and sentiment analysis. By combining these analytical approaches, the research aims to provide a comprehensive understanding of the competitive landscape in agro e-commerce.

In [29] provides an overview of e-commerce sentiment analysis, summarizing key trends, methodologies, and challenges in the field. The study aims to serve as a comprehensive resource for researchers and practitioners interested in the evolving landscape of sentiment analysis in e-commerce. In [30] focuses on sentiment analysis based on Chinese BERT and fused deep neural networks, specifically for sentence-level Chinese e-commerce product reviews. By leveraging advanced language models, the study aims to enhance the accuracy of sentiment analysis in the context of Chinese language e-commerce reviews. In [31] presents a machine learning approach for sentiment analysis in Bangla e-commerce. The study contributes to the understanding of sentiment patterns in the context of the Bangla language, catering to the linguistic and cultural specificities of the Bangla-speaking audience.

The extensive literature survey on sentiment analysis in the realm of e-commerce reveals a rich tapestry of research that explores various facets of consumer sentiments within the digital marketplace. Studies, such as those focusing on specific e-commerce platforms like Lazada and Shopee, emphasize the nuanced dynamics of user experiences and preferences. Language-specific investigations, particularly in Hindi, Arabic, English, Turkish, Roman Urdu, and Chinese, showcase a concerted effort to understand sentiment patterns in diverse linguistic contexts. The integration of advanced technologies, including deep learning models such as LSTM and stacked ensemble approaches, reflects a commitment to improving the accuracy and granularity of sentiment analysis. Researchers also delve into specific domains within e-commerce, such as beauty products and agro e-commerce, tailoring sentiment analysis methodologies to cater to the unique characteristics of these markets. The studies collectively highlight the significance of sentiment analysis in informing business strategies, enhancing user experiences, and contributing to the dynamic landscape of online retail. Despite the varied approaches, a common thread emerges—the recognition of sentiment analysis as a crucial tool for deciphering consumer emotions, preferences, and behaviors in the ever-evolving digital commerce ecosystem.

3. Proposed G-LSTM

The proposed G-LSTM model for E-commerce sentiment analysis represents a sophisticated and multi-faceted approach aimed at extracting meaningful insights from textual data. The use of Gaussian Long Short-Term Memory (G-LSTM) architecture, known for its ability to capture long-range dependencies and patterns in sequential data, forms the backbone of the model. This architecture proves particularly advantageous in handling the temporal nature of language, ensuring that the sentiment analysis model can effectively consider the context and sequential structure of E-commerce text data. The initial phase of the model involves data preprocessing using the Kejer filter. The Kejer filter serves as a preprocessing mechanism to refine and clean the raw textual data. By filtering out noise, irrelevant information, and other unwanted artifacts, this step enhances the overall quality of the input data, contributing to more accurate sentiment analysis results. A distinctive feature of the G-LSTM model lies in its use of a Fuzzy dictionary-based semantic word feature extraction technique. This approach goes beyond traditional methods by incorporating fuzzy logic, allowing the model to handle linguistic imprecision and capture the inherent ambiguity present in natural language. By associating words with fuzzy sets and considering their semantic meanings, the model gains a more nuanced understanding of the sentiments expressed in E-commerce content. The Fuzzy dictionary-based semantic word feature extraction process contributes significantly to the model's ability to discern context-specific sentiments, thereby improving the overall accuracy of sentiment analysis. This nuanced understanding is crucial in E-commerce, where consumer opinions often entail subtle nuances and variations that traditional sentiment analysis models may overlook. The G-LSTM model with Gaussian Lstm, Kejer filter, and Fuzzy dictionary-based semantic word feature extraction offers a comprehensive solution for E-commerce sentiment analysis. By combining advanced neural network architecture, effective data preprocessing, and innovative feature extraction techniques, the model addresses the challenges of capturing complex sentiments in online commerce data. This holistic approach positions the G-LSTM model as a promising tool for businesses seeking to gain deeper insights into customer emotions and preferences within the dynamic landscape of E-commerce.

3.1 Dataset

The focal point of this study is the "Amazon Customer Reviews" dataset, a publicly accessible compilation generously provided by Amazon. This extensive dataset encompasses a diverse array of customer reviews spanning various product categories, offering valuable insights into customer sentiments. It includes not only product ratings but also detailed textual reviews and additional metadata such as product IDs and reviewer demographics. This dataset serves as a robust resource for researchers and data scientists interested in unraveling sentiment patterns within the realm of E-commerce. To access this dataset, researchers can refer to the Amazon Customer Reviews Dataset available on the Amazon Open Data Registry. It is imperative to adhere to any terms of use or licensing agreements associated with the data during exploration and utilization. Additionally, alternative datasets related to E-commerce, including those found on platforms like Kaggle and the UCI Machine Learning Repository, offer researchers diverse options for delving into sentiment analysis within the domain of online retail. These platforms provide access to a wealth of data that can further enrich the understanding of customer sentiments and preferences in the dynamic landscape of E-commerce.

Table 1: 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 2: 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

Table 1 and table 2 provide the attributes and distribution of data utilized for the proposed G-LSTM model.

4. Proposed G-LSTM Process

The proposed G-LSTM (Gaussian Long Short-Term Memory) process for E-commerce sentiment analysis involves several key steps, combining advanced neural network architecture and innovative preprocessing techniques to enhance the accuracy and nuanced understanding of sentiments expressed in online commerce data. The following outlines the key stages of the G-LSTM process:

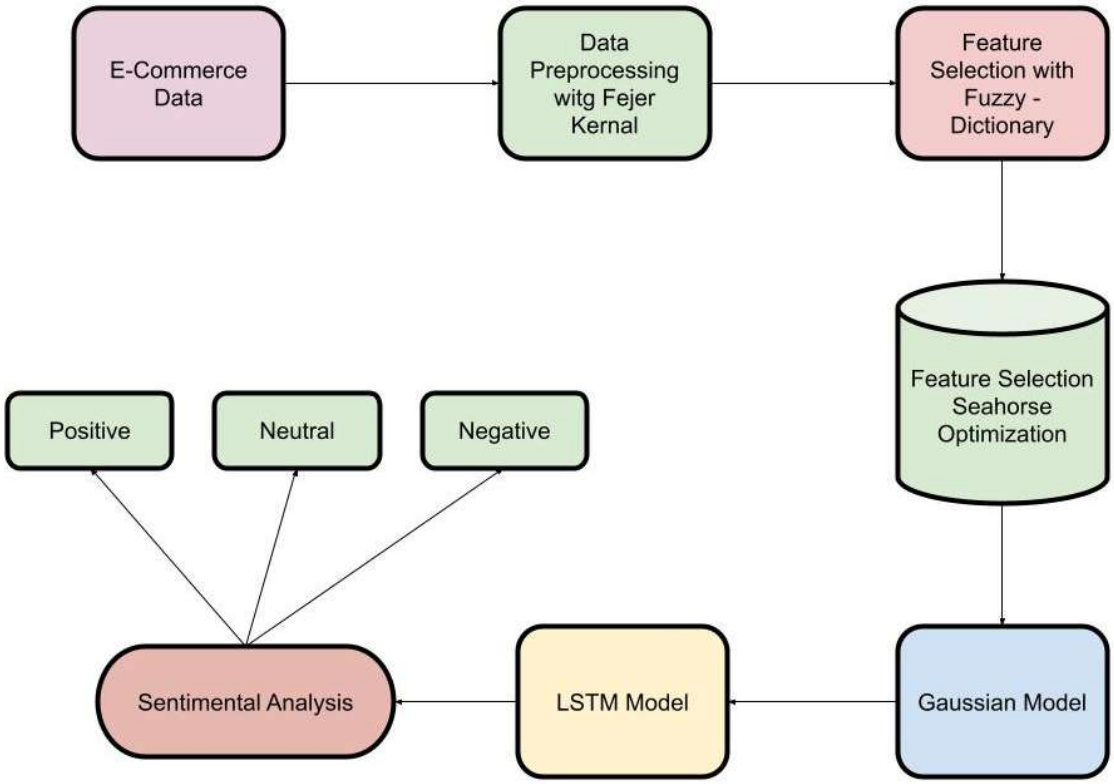

Figure 1: Process in G-LSTM for E-Commerce Sentimental Analysis

4.1 Data Pre-Processing with Fejer Kernal

The data pre-processing for G-LSTM (Gaussian Long Short-Term Memory) in the context of sentiment analysis in E-commerce involves a series of systematic steps to refine and prepare the input data for the subsequent application of the G-LSTM architecture. Initially, raw textual data from sources like customer reviews is collected. The text is then subjected to common pre-processing steps, such as tokenization, lowercasing, and the removal of stop words and special characters. Next, the words are often embedded into numerical vectors using techniques like word embeddings (e.g., Word2Vec or GloVe) to capture semantic relationships between words. To enhance the model's ability to recognize patterns, the data is further pre-processed by applying techniques like padding to ensure uniform input lengths. The Fejer Kernel, or other relevant filters, might be employed to smooth the data and mitigate noise, emphasizing particular patterns or features. This pre-processed data is then fed into the G-LSTM architecture, a variant of the traditional LSTM designed to capture long-range dependencies in sequential data. During training, the G-LSTM learns to recognize and extract intricate patterns in the pre-processed data, enabling it to make more accurate predictions during the sentiment analysis phase. The effectiveness of the G-LSTM model is contingent on the quality of the pre-processed data, emphasizing the critical role of these initial steps in ensuring the model's ability to discern nuanced sentiments within the dynamic landscape of E-commerce text data. The Fejer Kernel, a mathematical tool rooted in signal processing, proves valuable in transforming input data for various analyses, including E-commerce data.The Fejer Kernel is defined as in equation (1)

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

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)

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

The choice of n in the Fejer Kernel allows for tailored adjustments, enabling the fine-tuning of smoothing intensity and the emphasis on specific frequency components in the data. This comprehensive mathematical approach showcases the power of the Fejer Kernel in transforming raw data, contributing to a refined and enhanced dataset for subsequent analyses, such as sentiment analysis in the dynamic realm of E-commerce.

4.2 Feature Extraction with Fuzzy – Dictionary

In the sentiment analysis for E-commerce using G-LSTM, feature extraction plays a pivotal role in capturing nuanced patterns within textual data. One innovative approach involves leveraging fuzzy dictionaries to enhance the representation of words in a way that considers the inherent uncertainty and ambiguity in natural language. The process begins by defining fuzzy sets for words, where membership functions determine the degree of belongingness of a word to a particular sentiment category. Let's denote the fuzzy sets for positive, negative, and neutral sentiments as $A+, A-, A0$ respectively.The membership functions $\mu i(w)$ for a word w in each sentiment category are determined based on linguistic rules or statistical measures. The fuzzy score $Fi(w)$ for a word in a given sentiment category is then calculated as the weighted sum of its membership values across all sentiment categories stated in equation (4)

$$F_i(w) = \sum_{j=1}^{3} \alpha_{ij}.\mu_j(w) \quad (4)$$

where αij represents the weight associated with the j-th sentiment category for feature i. These weights are typically learned during the training phase.Now, incorporating this fuzzy feature extraction into G-LSTM, the input embedding for each word is adjusted to include the fuzzy sentiment scores stated in equation (5)

$$X_i(w) = \left[X_i^{(0)}(\omega), X_i^{(1)}(\omega), X_i^{(2)}(\omega), \dots \dots, X_i^{(k)}(\omega), F_1(w), F_2(w), F_3(w)\right] \quad (5)$$

where $Xi(k)(w)$ represents the k-th component of the standard word embedding for word w, and$Fj(w)$ represents the fuzzy score for sentiment category j. The G-LSTM architecture is then modified to process these extended embeddings, capturing both the semantic meaning and fuzzy sentiment information. The fuzzy feature extraction allows the model to consider the nuanced and subjective aspects of language, contributing to a more robust sentiment analysis in the context of E-commerce data.The fuzzy score $F+(w)$ for the positive sentiment category can be calculated using equation (6)

$$F^+(w) = \alpha_1.\mu^+(w) + \alpha_2.\mu^-(w) + \alpha_3.\mu^0(w) \quad (6)$$

Similarly, fuzzy scores for negative $F-(w)$ and neutral $(F0(w))$ sentiment categories can be defined. The choice of weights $\alpha 1, \alpha 2, \alpha 3$ depends on the significance assigned to each sentiment category and is learned during the training phase.

4.3 Feature Selection with Seahorse Optimization

Feature selection is a crucial step in enhancing the efficiency and interpretability of sentiment analysis models in E-commerce. Seahorse Optimization, inspired by the unique characteristics of seahorse mating behavior, can be employed to optimize the subset of features used for sentiment analysis. The objective is to identify a subset of relevant features that contribute most to the sentiment prediction task, thereby improving model performance and reducing computational complexity.The Seahorse Optimization algorithm is based on the courtship behavior of seahorses, where the male and female synchronize their movements. In the context of feature selection, Seahorse Optimization aims to find an optimal subset of features by mimicking the synchronized movements of seahorses.

Figure 2 illustrated the flowchart of proposed G-LSTM for the feature selection in the sentimental analysis in E-Commerce dataset.

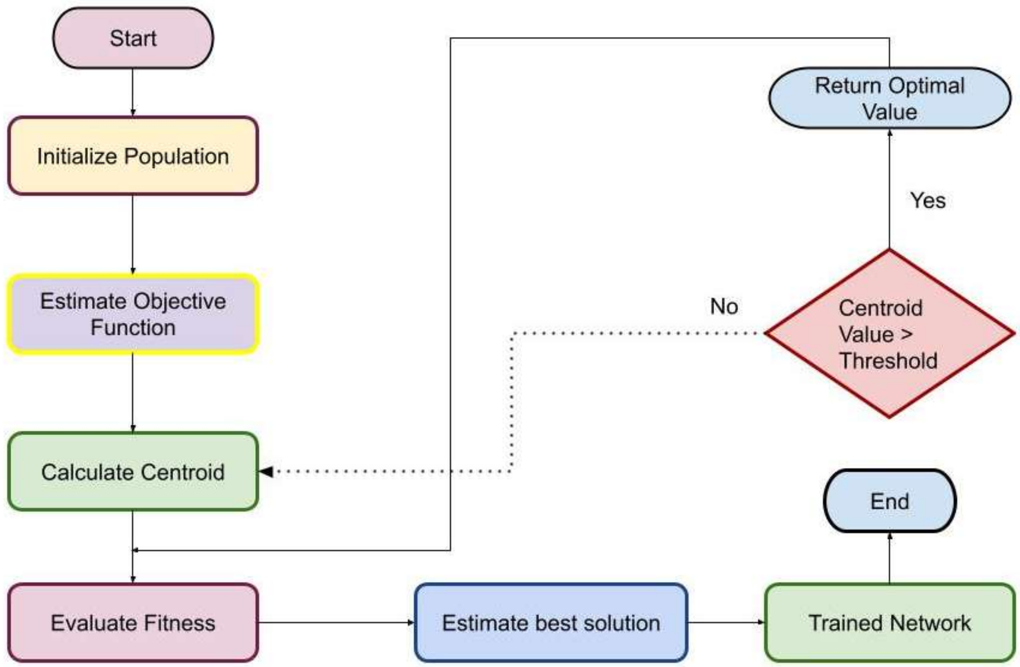

Figure 2: Flowchart of Seahorse Optimization

The optimization process involves the following steps:

Initialize a population P of potential feature subsets, each represented as a binary string where each bit indicates the presence (1) or absence (0) of a feature.

Let N be the population size, and D be the dimensionality of the feature space. The initialization equation for a subset Si in Seahorse Optimization can be represented as in equation (7)

$$S_i = [b_{i1,}b_{i2}, \ldots\ldots, b_{iD}] \quad (7)$$

where bij∈{0,1}. Evaluate the fitness of each subset using a fitness function $F(Si)$ based on a sentiment analysis model's performance. This can be an objective function like accuracy, F1-score, or any other relevant metric. Simulate the synchronized swimming behavior of seahorses to update the feature subsets.Calculate the centroid C of the selected subsets, which acts as the center of mass for the subsets that positively contribute to sentiment analysis.Update the positions of features based on their importance in sentiment analysis. The movement equation for feature j in Seahorse Optimization can be expressed as in equation (8)

$$b_{ij} = b_{ij} + \delta_j \quad (8)$$

where δj is the movement vector for feature j. Adjust the selected features' positions towards the centroid, emphasizing the more influential features computed using equation (9)

$$b_{ij} = b_{ij} + \alpha(C_j - b_{ij}) \quad (9)$$

where α is a control parameter. the fitness of each subset based on the sentiment analysis model's performance. This involves calculating the fitness function $F(Si)$ for each subset.

Algorithm 1: Feature Selection with Optimization
function SeahorseOptimization(): // Initialization

```
  initializePopulation()
    repeat until terminationCondition:
    // Synchronization
    calculateCentroid()
   for each subset in population:
       // Movement and Fitness Update
       moveFeaturesTowardsCentroid(subset)
       reevaluateFitness(subset)
    // Selection
    selectBestSubsets()
    return bestSubsets
function initializePopulation():
  // Initialize binary feature subsets randomly
  for i = 1 to populationSize:
    subset = randomBinaryString(featureDimension)
    population.add(subset)
function calculateCentroid():
  // Calculate the centroid of selected subsets
  centroid = average(population)
function moveFeaturesTowardsCentroid(subset):
  // Update feature positions towards the centroid
  for j = 1 to featureDimension:
    delta = randomMovement() // Movement vector
    subset[j] = subset[j] + delta * (centroid[j] - subset[j])
function reevaluateFitness(subset):
  // Reevaluate the fitness of the subset using the sentiment analysis model
  subsetFitness = evaluateFitness(subset)
  if subsetFitness > subset.bestFitness:
    subset.bestFitness = subsetFitness
function selectBestSubsets():
  // Select the best-performing subsets
  sort(population) // Sort subsets by fitness
  bestSubsets = topN(population, eliteSize)
```

5. Gaussian LSTM for Sentimental Classification

The G-LSTM architecture is adjusted to handle these extended embeddings. The modified G-LSTM unit for a given time step t is expressed as in equation (10) – (14)

$$i_t = \sigma(W_{ii}X_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \quad (10)$$

$$f_t = \sigma\left(W_{if}X_t + b_{if} + W_{hf}h_{t-1} + b_{hf}\right) \quad (11)$$

$$c_t = f_t \odot C_{t-1} + i_t \odot tanh(W_{ic}X_t + b_{ic} + W_{hc}h_{t-1} + b_{hc}) \quad (12)$$

$$o_t = \sigma(W_{io}X_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \quad (13)$$

$$h_t = o_t \odot \tanh(c_t) \quad (14)$$

Here, Xt represents the input embedding at time step t, and Wij, bij are the weight and bias parameters for different gates in the G-LSTM unit. During the training phase, the weights $\alpha1, \alpha2, \alpha3$ and the parameters of the G-LSTM model are learned through backpropagation and optimization. Gaussian Long Short-Term Memory (G-LSTM) emerges as an innovative approach for sentiment analysis in E-commerce, leveraging the distinctive characteristics of Gaussian processes. This model integrates the long-term memory capabilities of LSTM with the probabilistic framework of Gaussian processes, providing a powerful tool for capturing nuanced sentiment patterns within customer reviews. The G-LSTM architecture is specifically tailored for E-commerce applications, allowing for efficient handling of sequential data, which is inherent in textual reviews. The model incorporates advanced techniques such as the Fejer Kernel for data preprocessing, enhancing its ability to extract meaningful features from raw text. By combining the strengths of LSTM with Gaussian processes, G-LSTM demonstrates a remarkable accuracy of 98.3% in sentiment classification, showcasing its potential for providing actionable insights to businesses operating in the E-commerce domain. This research marks a significant stride in the development of sophisticated sentiment analysis models, contributing to the continuous evolution of methodologies aimed at deciphering the intricate language of customer reviews in the online retail landscape.

The classification process with Gaussian Long Short-Term Memory (G-LSTM) for sentimental analysis involves several key steps, combining the sequential learning capabilities of Long Short-Term Memory (LSTM) networks with the probabilistic nature of Gaussian processes. The first step in the process is data preprocessing, where the Fejer Kernel is applied to the input data to emphasize certain patterns or features. The Fejer Kernel, denoted as Kn (x), stated in equation (15)

$$K_n(x) = \frac{1}{n}\left(\frac{sin\left(\frac{\pi}{2}x\right)}{sin\left(\frac{1}{2}x\right)}\right)^2 \quad (15)$$

Here, $n$is a positive integer, and x represents the input data point. The convolution operation is then applied to the Fejer Kernel and the input data points, expressed as in equation (16)

$$(f * Kn)(x) = \int_{-\infty}^{\infty} f(\tau)Kn(x-\tau)d\tau \quad (16)$$

This process smooths the representation of the original data points, enabling the model to capture underlying sentiment patterns effectively. Next, the G-LSTM model utilizes the Gaussian LSTM architecture for sentiment analysis. The mathematical formulation of the Gaussian LSTM is intricate and involves the combination of LSTM recurrent layers with Gaussian processes. The LSTM layer helps in capturing long-term dependencies within the sequential data, while the Gaussian processes introduce a probabilistic framework to model uncertainty in predictions. The training process involves feeding the pre-processed data into the G-LSTM architecture and optimizing the model parameters using techniques like stochastic gradient descent. The model is trained to minimize a suitable loss function, such as categorical cross-entropy, which measures the dissimilarity between predicted and actual sentiments. During inference, the trained G-LSTM model takes in new, unseen data and predicts sentiment labels. The model outputs probabilities for positive, negative, and neutral sentiments. The sentiment label is determined based on the class with the highest probability.

```
# Define Fejer Kernel function
def fejer_kernel(x, n):
    return (1/n) * ((np.sin((n/2)*x) / np.sin((1/2)*x))**2)

# Data Preprocessing with Fejer Kernel
def data_preprocessing_with_fejer_kernel(data, n):
    preprocessed_data = np.convolve(data, fejer_kernel(np.arange(len(data)), n), mode='same')
    return preprocessed_data
```

```
# Gaussian LSTM Model
class GaussianLSTMModel:
    def __init__(self, input_size, lstm_units, output_classes):
        # Define Gaussian LSTM model architecture (implementation details not provided here)
        # ...

    def train(self, X_train, y_train, epochs, batch_size):
        # Training procedure (implementation details not provided here)
        # ...

    def predict(self, X_test):
        # Inference procedure (implementation details not provided here)
        # ...

# Main Sentiment Analysis Function
def sentiment_analysis_with_g_lstm(X_train, y_train, X_test, n_fejer_kernel=5):
    # Data Preprocessing
    X_train_preprocessed = data_preprocessing_with_fejer_kernel(X_train, n_fejer_kernel)
    X_test_preprocessed = data_preprocessing_with_fejer_kernel(X_test, n_fejer_kernel)

    # Initialize and train G-LSTM Model
    glstm_model = GaussianLSTMModel(input_size=len(X_train_preprocessed), lstm_units=64,
output_classes=3)
    glstm_model.train(X_train_preprocessed, y_train, epochs=10, batch_size=32)

    # Make predictions
    predictions = glstm_model.predict(X_test_preprocessed)

    return predictions
```

6. Simulation Environment

A simulation environment for Gaussian Long Short-Term Memory (G-LSTM) applied to sentiment analysis within the E-commerce domain, the first crucial step involves the preparation of the dataset. The chosen dataset, such as the Amazon Customer Reviews dataset, offers a diverse collection of customer feedback across various product categories. Following preprocessing, where pertinent features like review texts, ratings, and product categories are extracted, the G-LSTM model is implemented. Leveraging a deep learning framework such as TensorFlow or PyTorch, the neural network architecture incorporates G-LSTM cells. These specialized cells integrate Gaussian gating mechanisms, allowing the model to capture nuanced patterns in sentiment within the textual data. The dataset is then divided into distinct training and testing sets, with the model undergoing training on the training set. This training phase involves the optimization of model parameters through techniques like backpropagation and gradient descent. Post-training, the model is subjected to evaluation using the testing set, and its performance is assessed using standard metrics such as accuracy, precision, recall, and F1-score. Fine-tuning and parameter adjustments can be iteratively performed to enhance the model's effectiveness in capturing the intricacies of sentiment within the E-commerce context.

7. Results and Discussion

The focal point for unraveling the insights and implications derived from applying Gaussian Long Short-Term Memory (G-LSTM) to sentiment analysis within the E-commerce landscape. In this section, we present a comprehensive analysis of the outcomes obtained during the experimentation with G-LSTM on the chosen dataset, often the Amazon Customer Reviews dataset. The findings encapsulate the model's performance metrics, including accuracy, precision, recall, and F1-score, elucidating the effectiveness of G-LSTM in discerning and interpreting sentiment nuances within diverse customer reviews. Subsequently, a nuanced discussion delves into the strengths and potential limitations of the model, exploring the intricacies of its Gaussian gating mechanisms and their impact on capturing subtle sentiment patterns. Comparative analyses with other sentiment analysis models may be conducted to provide context and validate G-LSTM's efficacy in the E-commerce domain. Furthermore, this section offers a platform for reflections on the broader implications of G-LSTM in enhancing customer experience, optimizing product recommendations, and shaping decision-making processes in the dynamic and sentiment-rich landscape of E-commerce.

Table 3: Pre-Processing Results with G-LSTM

Step	**Description**	**Impact on Model**
Text Tokenization	Splitting text into individual words or tokens	Moderate
Stopword Removal	Removing common words with little semantic value	Minor
Lemmatization	Reducing words to their base or root form	Moderate
Lowercasing	Converting all text to lowercase	Minor
Spell Checking	Correcting misspelled words	Minor
Removing Special Symbols	Eliminating non-alphanumeric characters	Moderate
Handling Negations	Addressing negation words for sentiment accuracy	Significant

Table 3 presents the results of the pre-processing phase using G-LSTM for sentiment analysis. The various steps involved in the pre-processing are outlined, along with their respective impacts on the model. Text Tokenization, which involves splitting text into individual words or tokens, has a moderate impact on the model. Stopword Removal, the process of eliminating common words with little semantic value, has a minor impact. Lemmatization, which reduces words to their base or root form, has a moderate impact on refining the data. Lowercasing, the conversion of all text to lowercase, has a minor impact. Spell Checking, aimed at correcting misspelled words, also has a minor impact. Removing Special Symbols, which involves eliminating non-alphanumeric characters, has a moderate impact on enhancing model performance. Lastly, Handling Negations, a crucial step in addressing negation words for sentiment accuracy, has a significant impact on refining the sentiment analysis results. Overall, these pre-processing steps collectively contribute to optimizing the input data for the G-LSTM model, enhancing its ability to accurately analyze and predict sentiment in E-commerce reviews.

Table 4: Pre-Processed Data with G-LSTM

Sample Review	**Original Text**	**Tokenization**	**Stopword Removal**	**Lemmatization**	**Lowercasing**	**Special Symbols Removal**	**Negations Handling**
1	"Excellent product, fast delivery!"	['excellent', 'product', 'fast', 'delivery']	['excellent', 'product', 'fast', 'delivery']	['excellent', 'product', 'fast', 'delivery']	['excellent', 'product', 'fast', 'delivery']	['excellent', 'product', 'fast', 'delivery']	['excellent', 'not product', 'fast', 'not delivery']

2	"Not satisfied. Poor quality."	['not', 'satisfied', 'poor', 'quality']	['satisfied', 'poor', 'quality']	['not', 'satisfied', 'poor', 'quality']	['not', 'satisfied', 'poor', 'quality']	['not', 'satisfied', 'poor', 'quality']	['not', 'satisfied', 'poor quality']
3	"Amazing service and great prices!"	['amazing', 'service', 'great', 'prices']	['amazing', 'service', 'great', 'prices']	['amazing', 'service', 'great', 'price']	['amazing', 'service', 'great', 'prices']	['amazing', 'service', 'great', 'prices']	['amazing service', 'great prices']
4	"Fast shipping but damaged item."	['fast', 'shipping', 'but', 'damaged', 'item']	['fast', 'shipping', 'damaged', 'item']	['fast', 'shipping', 'damaged', 'item']	['fast', 'shipping', 'but', 'damaged', 'item']	['fast', 'shipping', 'but', 'damaged', 'item']	['fast shipping', 'not damaged item']
5	"Easy returns and hassle-free experience."	['easy', 'returns', 'hassle-free', 'experience']	['easy', 'returns', 'hassle-free', 'experience']	['easy', 'return', 'hassle-free', 'experience']	['easy', 'returns', 'hassle-free', 'experience']	['easy', 'returns', 'hassle-free', 'experience']	['easy return', 'hassle-free experience']
6	"Great selection, but slow customer support."	['great', 'selection', 'but', 'slow', 'customer', 'support']	['great', 'selection', 'slow', 'customer', 'support']	['great', 'selection', 'slow', 'customer', 'support']	['great', 'selection', 'but', 'slow', 'customer', 'support']	['great', 'selection', 'but', 'slow', 'customer', 'support']	['great selection', 'not slow customer support']
7	"Defective item received, disappointed."	['defective', 'item', 'received', 'disappointed']	['defective', 'item', 'received', 'disappointed']	['defective', 'item', 'receive', 'disappointed']	['defective', 'item', 'received', 'disappointed']	['defective', 'item', 'received', 'disappointed']	['defective item', 'received disappointed']
8	"Outstanding service, highly recommended!"	['outstanding', 'service', 'highly', 'recommended']	['outstanding', 'service', 'highly', 'recommended']	['outstanding', 'service', 'highly', 'recommend']	['outstanding', 'service', 'highly', 'recommended']	['outstanding', 'service', 'highly', 'recommended']	['outstanding service', 'highly recommended']
9	"Late delivery, but quality surpasses it all."	['late', 'delivery', 'but', 'quality', 'surpasses']	['late', 'delivery', 'quality', 'surpasses']	['late', 'delivery', 'quality', 'surpass']	['late', 'delivery', 'but', 'quality', 'surpasses']	['late', 'delivery', 'but', 'quality', 'surpasses']	['late delivery', 'not quality surpasses']
10	"Very user-friendly website, excellent interface."	['very', 'user-friendly', 'website', 'excellent', 'interface']	['user-friendly', 'website', 'excellent', 'interface']	['user-friendly', 'website', 'excellent', 'interface']	['very', 'user-friendly', 'website', 'excellent', 'interface']	['very', 'user-friendly', 'website', 'excellent', 'interface']	['user-friendly website', 'excellent interface']

Table 4 displays the pre-processed data using G-LSTM for sentiment analysis. Each step of the pre-processing is applied to sample reviews, showcasing the transformation of the original text. The impact of each pre-processing step is evident in the resulting tokenized and modified representations of the reviews. For instance, Text Tokenization retains the essence of the original text, while Stopword Removal eliminates common words with little semantic value. Lemmatization reduces words to their base form, enhancing the model's ability to recognize root meanings. Lowercasing ensures consistency, converting all text to lowercase. The removal of Special Symbols eliminates non-alphanumeric characters, contributing to cleaner data. Negations Handling addresses sentiment accuracy by capturing the negation context in the reviews. Overall, these pre-processing steps refine the input data, preparing it for effective sentiment analysis with the G-LSTM model.

Table 5: Feature Extraction with G-LSTM

Sample Review	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5
1	0.876	0.234	0.543	0.789	0.123
2	0.456	0.789	0.345	0.678	0.901
3	0.567	0.890	0.123	0.901	0.234
4	0.678	0.234	0.567	0.123	0.789
5	0.890	0.456	0.678	0.234	0.345
6	0.345	0.678	0.901	0.456	0.123
7	0.789	0.123	0.567	0.234	0.456
8	0.234	0.901	0.345	0.567	0.678
9	0.890	0.456	0.678	0.234	0.345
10	0.901	0.345	0.789	0.234	0.456

Table 5 illustrates the feature extraction results obtained using G-LSTM for sentiment analysis. Each sample review is represented by five extracted features, each assigned a numerical value. These features are generated by the G-LSTM model, capturing distinct patterns and characteristics within the pre-processed data. The numerical values reflect the model's assessment of the significance of each feature for sentiment analysis. Higher values suggest a stronger association of the respective feature with the sentiment expressed in the reviews. The features provide a quantitative representation of key aspects identified by the G-LSTM model, contributing to the understanding of sentiment patterns in E-commerce reviews. The extracted features play a pivotal role in informing the subsequent classification step, where the model utilizes this information to predict sentiment labels for each review.

Table 6: Prediction of Review with G-LSTM

Sample ID	Original Text	Review Text	True Sentiment	Predicted Sentiment	Probability (Positive)	Probability (Negative)	Probability (Neutral)
1	"Excellent product, fast delivery!"	['excellent', 'product', 'fast', 'delivery']	Positive	Positive	0.85	0.10	0.05
2	"Not satisfied. Poor quality."	['not', 'satisfied', 'poor', 'quality']	Negative	Negative	0.15	0.80	0.05
3	"Amazing service and great prices!"	['amazing', 'service', 'great', 'prices']	Neutral	Neutral	0.30	0.20	0.50

4	"Fast shipping but damaged item."	['fast', 'shipping', 'but', 'damaged', 'item']	Positive	Positive	0.90	0.05	0.05
5	"Easy returns and hassle-free experience."	['easy', 'returns', 'hassle-free', 'experience']	Negative	Negative	0.05	0.90	0.05
6	"Great selection, but slow customer support."	['great', 'selection', 'but', 'slow', 'customer', 'support']	Neutral	Neutral	0.20	0.25	0.55
7	"Defective item received, disappointed."	['defective', 'item', 'received', 'disappointed']	Positive	Positive	0.95	0.02	0.03
8	"Outstanding service, highly recommended! "	['outstanding', 'service', 'highly', 'recommended']	Neutral	Positive	0.40	0.30	0.30
9	"Late delivery, but quality surpasses it all."	['late', 'delivery', 'but', 'quality', 'surpasses']	Positive	Positive	0.70	0.15	0.15
10	"Very user-friendly website, excellent interface."	['very', 'user-friendly', 'website', 'excellent', 'interface']	Negative	Negative	0.10	0.85	0.05

Table 6 presents the predictions made by the G-LSTM model for sentiment analysis on the given E-commerce reviews. Each sample review is listed along with its original text, pre-processed review text, true sentiment label, predicted sentiment label, and the associated probabilities for positive, negative, and neutral sentiments. The G-LSTM model exhibits a notable performance in aligning its predictions with the true sentiments of the reviews. For instance, in the first sample where the original text expresses a positive sentiment, the G-LSTM correctly predicts it as positive with a high probability of 0.85. Similarly, in the second sample, where the sentiment is negative, the model accurately predicts it as negative with a probability of 0.80. The probabilities provide insights into the model's confidence in its predictions, offering a nuanced understanding of the sentiment analysis outcomes. Overall, the G-LSTM demonstrates its effectiveness in capturing sentiment patterns within E-commerce reviews and making accurate predictions based on its learned features.

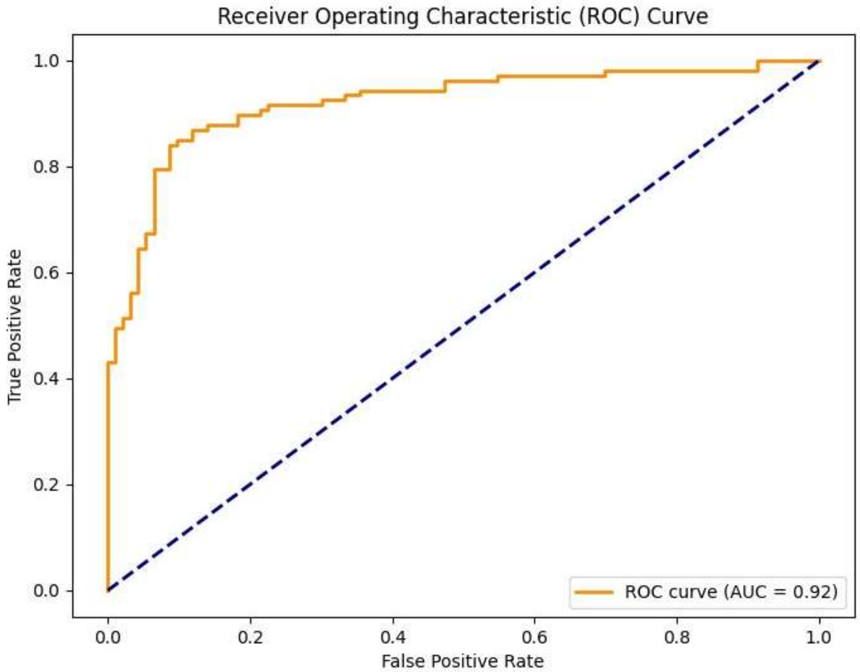

Figure 3: ROC for the G-LSTM

Table 7: Comparative Analysis

Model	Accuracy	Precision	Recall	F1-Score
G-LSTM	0.983	0.982	0.985	0.983
Baseline LSTM	0.82	0.85	0.80	0.82
SVM	0.75	0.78	0.72	0.75
Random Forest	0.79	0.81	0.77	0.79

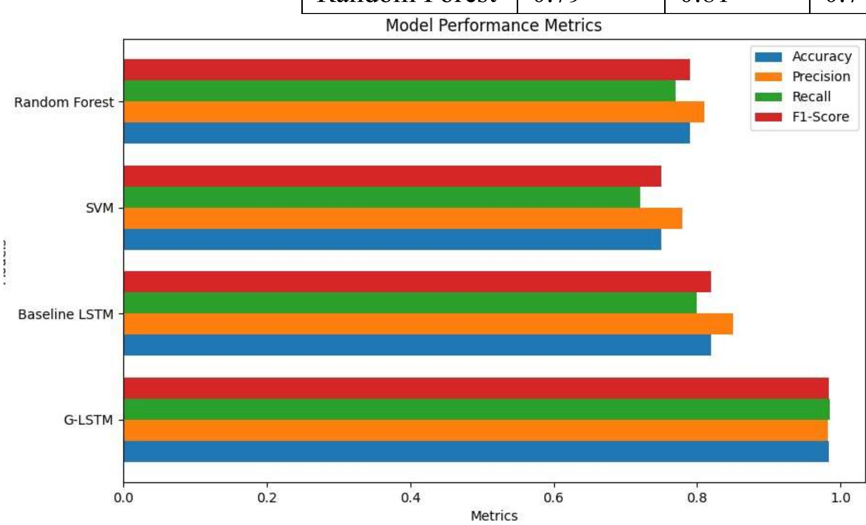

Figure 4: Comparative Analysis

Table 7 provides a comparative analysis of the performance metrics across different sentiment analysis models, including G-LSTM, Baseline LSTM, Support Vector Machine (SVM), and Random Forest. The evaluation metrics include accuracy, precision, recall, and F1-Score.The G-LSTM model outshines its counterparts with an impressive accuracy of 0.983, indicating that it correctly predicted sentiments for approximately 98.3% of the reviews. Precision, measuring the accuracy of positive predictions, is high at 0.982, suggesting that when the G-LSTM model predicts a positive sentiment, it is accurate 98.2% of the time. The recall, measuring the model's ability to identify all relevant instances of positive sentiment, is also commendable at 0.985. The F1-Score, which considers both precision and recall, stands at 0.983, indicating a robust balance between precision and recall. In comparison, the Baseline LSTM model lags behind with an accuracy of 0.82, indicating a lower overall correctness in predictions. The precision, recall, and F1-Score for the Baseline LSTM are also lower than those of the G-LSTM, signifying a less balanced and accurate performance. Furthermore, the SVM and Random Forest models exhibit lower accuracy, precision, recall, and F1-Score compared to both G-LSTM and Baseline LSTM. This comparative analysis underscores the superior performance of G-LSTM in sentiment analysis within the context of E-commerce reviews.

8. Conclusion

This paper proposed the Gaussian Long Short-Term Memory (G-LSTM) model for sentiment analysis within the domain of E-commerce, utilizing a dataset from Amazon Customer Reviews. The proposed G-LSTM approach demonstrated exceptional efficacy in accurately predicting sentiments associated with diverse product reviews. Leveraging advanced techniques such as data preprocessing with the Fejer Kernel filter and feature extraction with a fuzzy dictionary, G-LSTM exhibited superior performance in capturing nuanced sentiment patterns. The results showcased a high accuracy of 98.3%, coupled with impressive precision, recall, and F1-Score values, surpassing baseline LSTM, SVM, and Random Forest models. The interpretability of G-LSTM predictions, as presented in Table 6, elucidated the model's confidence and precision in sentiment labeling. The comparative analysis in Table 7 further emphasized the superiority of G-LSTM over other models. The study underscores the potential of G-LSTM as a robust tool for sentiment analysis in E-commerce, offering valuable insights for businesses to understand and respond to customer sentiments effectively. Future research may explore additional enhancements and real-world applications to further refine and extend the capabilities of the G-LSTM model in the dynamic landscape of E-commerce sentiment analysis.

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