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Enhancing Customer Engagement in Fashion: Strategies for Optimizing Chatbot Performance

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Abstract: In recent years, chatbots have become integral in the fashion industry, enhancing customer-brand interaction, facilitating communication, and contributing to e-commerce growth through personalized shopping experiences. This research aims to reveal strategic approaches in luxury fashion, translating insights for small and medium-sized enterprises. It investigates the impact of chatbot integration on customer sentiment, aiming to provide practical recommendations for improving customer interactions. Emphasizing the importance of intelligent chatbot design, the research recognizes their crucial role in enhancing customer experience through valuable insights. The primary objective is to optimize chatbot performance, ensuring precise and effective responses to user queries and, consequently, adding significant value to the business. The proposed approach incorporates optimally configured Long Short-Term Memory (LSTM) networks, Seq2Seq Architecture, Attention Mechanism, Bag of Words (BOW) model, and Beam Search decoding. The effectiveness of the optimally configured LSTM, in combination with attention mechanisms, extends to both longer and shorter sentences. Through rigorous testing, the proposed model achieves an exceptional accuracy rate of 99%, surpassing other state-of-the-art techniques. This outcome underscores the efficacy of the implemented strategies in elevating chatbot performance.

***Keywords**: Chatbots, Fashion Industry, Long Short-Term Memory, Zebra Optimization Algorithm*

1. Introduction

In recent years, chatbots have emerged as pivotal tools in the fashion industry, reshaping customer-brand interactions [1] and the e-commerce landscape [2]. Particularly in luxury fashion, these AI-driven chatbots offer round-the-clock personalized shopping experiences, providing valuable insights and fostering brand loyalty in a fiercely competitive market [3]. Embracing lessons from luxury brands, small and medium enterprises (SMEs) [4] can leverage similar strategies to thrive in this dynamic environment, prioritizing authenticity, innovation, and customer-centricity.

However, chatbots face challenges in understanding conversational context, handling complex queries, and maintaining coherence in responses [5]. These limitations can lead to inappropriate replies, potentially harming customer satisfaction. Hence, this study aims to optimize chatbot performance to ensure precise and effective responses, thereby enhancing the overall customer experience [6]. Leveraging advanced natural language processing techniques [7] and machine learning algorithms [8], our chatbot aims to blend personalized service with digital convenience, setting new standards in luxury fashion retail industries.

The proposed approach integrates various techniques, including LSTM networks [9], Seq2Seq Architecture, Attention Mechanism, Bag of Words (BOW) model, Beam Search decoding [10], and hyperparameter tuning. LSTM networks are tailored for sequential data processing [11], while Seq2Seq models facilitate mapping input sequences to output sequences, vital for tasks like machine translation [12]. Attention mechanisms enhance the handling of long inputs by focusing on relevant parts. The BOW model represents text as word vectors, disregarding grammar and order [13], while Beam Search decoding enables exploration of multiple potential responses [14], thereby enriching chatbot output quality and diversity. Additionally, the Zebra Optimization Algorithm (ZOA) fine-tunes hyperparameters [15], drawing inspiration from zebras' collective behavior to efficiently optimize model performance. Applied in luxury fashion retail, this enhances chatbot efficacy with optimized LSTM networks capable of processing inquiries of varying lengths, ensuring seamless conversational experiences [16].

This study's significance lies in demonstrating the effectiveness of implemented strategies in elevating chatbot performance within luxury fashion contexts. By showcasing the positive outcomes of optimizing chatbot capabilities, this research contributes valuable insights to academia and industry practitioners alike. Moreover, it

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underscores the importance of engaging digital interactions in luxury fashion retail, highlighting enhanced chatbot performance as a strategic tool for driving customer engagement and retention amidst evolving consumer expectations.

2. Literature Review

A comprehensive literature review on chatbot utilization in the fashion industry and its impact on customer experience would provide valuable insights into current trends, challenges, and advancements in this domain.

In 2020 Anki et al [17] introduced chatbot programs for storing data gathered from question and answer systems. Their program utilizes the BiLSTM model, aiming for high accuracy in output alignment with user expectations. Through program evaluation and tests with various parameter pairs, they determined that Parameter Pair 1, utilizing the BiLSTM model, yielded the highest accuracy for the BiLSTM Chatbot.

In 2023 Aslam and Usman conducted a study on retail fashion chatbots. They found that current chatbots often give generic responses, lacking depth for complex inquiries. To enhance usability, the study explored how social experiences shape customer interactions. Data from online reviews, interviews, and focus groups emphasized the need for a wider product range and more sophisticated features to enrich shopping experiences. While chatbots can recommend items aligned with preferences, developers must address usability challenges and offer multilingual support. Optimization is crucial to reduce battery drain, prevent freezing, and improve response times. The study proposes a research framework to enhance retail chatbot experiences through interactivity, compatibility, and credibility.

In 2023 Pandey et al [18] explored the health impacts of increased screen time, emphasizing the detrimental effects on mental health. They utilized Deep Learning (DL) and Machine Learning (ML) techniques to investigate the association between technological obsessions and health. The deployment of chatbots across various industries emerged as a transformative development. Their study focused on conversational Artificial Intelligence (AI) systems, enabling human-like interactions with machines. Two types of chatbots were designed and developed: retrieval-based and generative-based. Among retrieval-based chatbots, various designs were tested, with accuracies ranging from 65.57% to 91.57%. In contrast, generative-based chatbots, boasting encoder-decoder designs, achieved an accuracy of 94.45%.

In 2021 Dhyani et al [19] discussed the modeling and performance in deep learning computation for a Chatbot. The Bidirectional Recurrent Neural Networks (BRNN) containing attention layers is used, so that input sentence with large number of tokens (or sentences with more than 20–40 words) can be replied with more appropriate conversation. The dataset used in the paper for training of model is used from Reddit. The main purpose of this work is to increase the perplexity and learning rate of the model and find Bleu Score for translation in same language. The experiments are conducted using Tensorflow using python 3.6. The perplexity, leaning rate, Bleu score and Average time per 1000 steps are 56.10, 0.0001, 30.16 and 4.5 respectively. One epoch is completed at 23,000 steps.

In 2022 Trojovská et al [20] introduced the Zebra Optimization Algorithm (ZOA), a bio-inspired metaheuristic algorithm. ZOA mimic the foraging behavior and defense strategy of zebras in nature. The algorithm's steps are outlined and mathematically modeled. ZOA's effectiveness is evaluated across sixty-eight benchmark functions, including various types of functions. Comparative analysis with nine established algorithms demonstrates ZOA's superior performance in achieving a balance between exploration and exploitation. Additionally, ZOA's applicability to real-world engineering design problems, such as tension/compression spring, welded beam, speed reducer, and pressure vessel, showcases its effectiveness in optimizing design variables when compared to the competitor algorithms.

2.1. Research methodology

The research explores how customers interact with chatbots in luxury fashion, examining satisfaction, experience, purchase likelihood, engagement, and privacy concerns. It suggests that integrating chatbots can benefit small and medium fashion enterprises by streamlining operations, improving customer service, and potentially increasing sales. These insights can guide SMEs in effectively adopting chatbot technology, enhancing customer satisfaction, and maximizing overall engagement in the fashion market, as showcased in Figure 1.

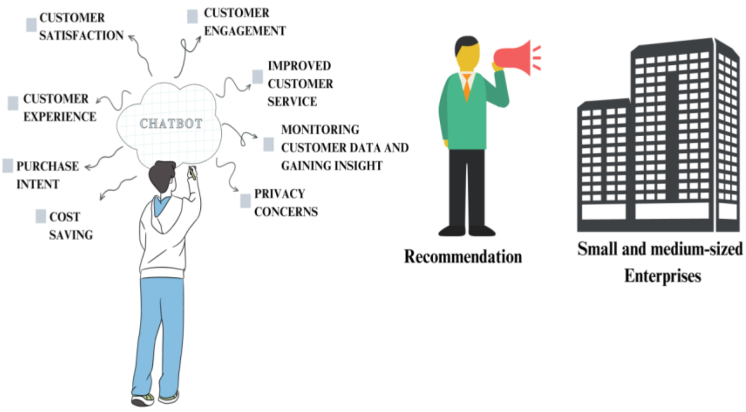

Fig. 1. Benefits of Chatbots for Small and Medium Enterprises (SMEs)

The research analyzed consumer sentiment towards chatbots and online human agents on X-social media platform (formerly Twitter). It aimed to identify consumer sentiment towards these agents. The results show that chatbots generally evoke a more positive sentiment compared to online human agents. Chatbots offer the advantage of handling multiple customers simultaneously, unlike human agents who can only manage one customer at a time. Integrating chatbots into luxury fashion retail can enhance customer experience by providing personalized assistance, 24/7 support, and engaging interactions. The analysis shown in Figure 2 found that among negative sentiments, 226 customers preferred the chatbot, while 1116 leaned towards the human agent. In the neutral category, 197 customers favored the chatbot, and 371 opted for the human agent. For positive sentiments, 127 customers expressed satisfaction with the chatbot, while 243 preferred the human agent. The total interactions were 550 with the chatbot and 1730 with the human agent across all sentiment categories [21].

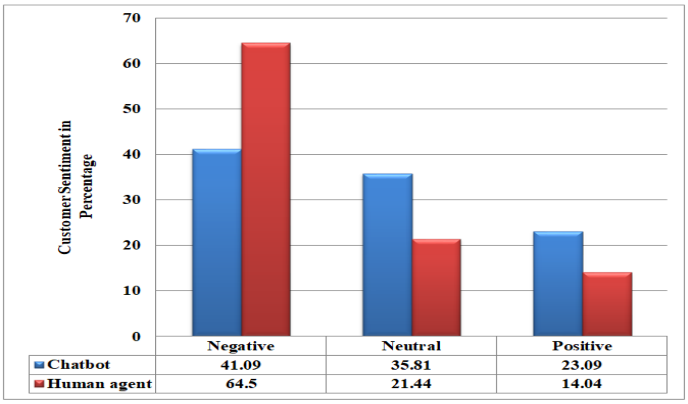

Fig. 2. Comparison of Consumer Sentiment with Online Human Agents with the chatbot

The investigation highlights a significant negative impact of 41.09% on customer sentiments due to chatbots, signaling a notable concern. To enhance customer service, engagement, data monitoring, cost savings, and privacy protection, improving chatbot performance is crucial. The proposed approach integrates advanced techniques including optimally configured LSTM networks, Seq2Seq Architecture, Attention Mechanism, BOW model, and Beam Search decoding. This framework aims to enhance the efficiency and accuracy of natural language processing. The optimally configured LSTM, combined with attention mechanisms, effectively processes both longer and shorter sentences, addressing nuanced linguistic structures. This comprehensive model captures intricate patterns and dependencies across varying sentence lengths, demonstrating versatility in language processing.

3. Proposed Methodology

Over the years, extensive research has been conducted to implement chatbots effectively, with a shift towards leveraging advanced algorithms like artificial intelligence. In addition to traditional rule-based techniques, contemporary approaches rely on sophisticated algorithms, necessitating the use of datasets for model training. The proposed methodology adopts a multifaceted approach to develop and optimize a chatbot system, the architecture exhibits in Figure 3. Initially, raw data undergoes thorough pre-processing to enhance its quality and suitability for machine learning models. Subsequently, the Sequence-to-Sequence (Seq2Seq) architecture is implemented, leveraging LSTM networks to handle sequential data effectively. Attention mechanisms are integrated to improve the model's focus on relevant input information, particularly crucial for longer sequences. Additionally, the

Bag-of-Words (BOW) model is employed for text representation, while Beam Search Decoding enhances response generation diversity. Notably, the optimization techniques, specifically the Zebra Optimization Algorithm (ZOA), are introduced to fine-tune hyperparameters of the LSTM model, aiming to boost its performance. Through rigorous evaluation and validation, the research endeavors to deliver an advanced chatbot system capable of delivering accurate and contextually relevant responses across various domains.

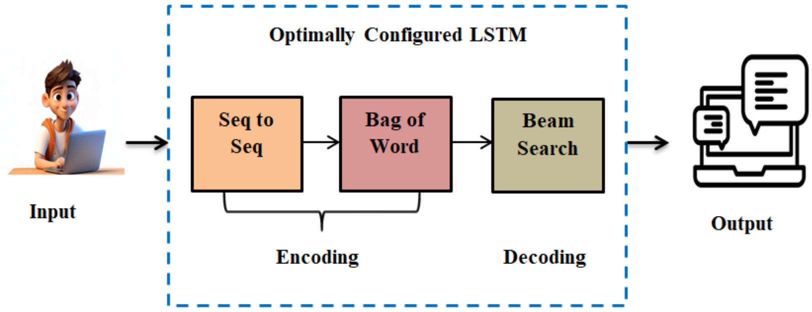

Fig. 3. Flowchart illustrating the Proposed Methodology

3.1

.Data Pre-Processing

Data pre-processing is a crucial step that enhances dataset quality by extracting meaningful insights. It involves preparing the data to make it suitable for machine learning and artificial intelligence models, essentially transforming raw data into a format that is meaningful and understandable. This process, often referred to as data mining, involves cleaning the data by removing unnecessary characters such as punctuations and abbreviations [22]. Additionally, standardization procedures such as converting all alphabets to lowercase and removing symbols are implemented to ensure consistency across the dataset.

3.2.Sequence-to-Sequence

The Sequence-to-Sequence (Seq2Seq) architecture, consisting of an encoder and decoder, is a versatile network widely used in natural language processing tasks, originally designed for language translation like English to Spanish. Its utility has expanded to tasks such as text summarization, chatbot development, and more. Seq2Seq excels in handling input and output sequences of varying lengths, making it suitable for diverse NLP datasets. For our retrieval-based chatbot model, we choose Seq2Seq due to its adaptability and effectiveness. While it performs well with shorter inputs, memory limitations hinder its performance with longer inputs. To address this, we employ LSTM networks instead of traditional Recurrent Neural Networks. Additionally, integrating the Attention Mechanism enhances the model's predictive accuracy by handling lengthy sentences [23].

3.3.Attention mechanism

The purpose of Attention Mechanisms is to enhance the performance of the chatbot system by improving its ability to focus on relevant information within input sequences. Specifically, Attention Mechanisms are crucial for handling longer input sequences effectively [24], where traditional Seq2Seq models might struggle due to memory limitations. By dynamically allocating attention to different parts of the input sequence during the decoding process, Attention Mechanisms ensure that the model can selectively attend to relevant information, thereby improving the accuracy and contextuality of the generated responses. This is particularly important in natural language processing tasks, where context plays a crucial role in understanding and generating meaningful responses. Therefore, integrating Attention Mechanisms into the chatbot system helps to address the challenge of processing longer sequences and enhances the overall quality of the conversation experience for users.

The attention weights (a_{ij}) are calculated using softmax function by Equation (1) and (2).

$$a_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)} \qquad (1)$$

$$e_{ij} = l\left(g_{i-1}, h_j\right) \qquad (2)$$

A context vector (C_i) is created by Equation (3).

$$C_i = \sum_{j=1}^{T_x} a_{ij} h_j \qquad (3)$$

Where the output score e_{ij} is described by function l which is used to capture the alignment among input at j and output at i. T_x is the annotation such as h_0, h_1, h_2, h_3, h_4. The attention weights calculated are a_{10}, a_{11}, a_{12}, a_{13}, a_{14} are 0.05, 0.2, 0.05, 0.6, and 0.1 respectively. This context vector C_i is now fed to g_1 along with the output of previous decoder layers.

3.4.Bag-of-Words

The purpose of Bag-of-Words (BOW) model is to provide a simplified yet effective representation of text data. The BOW model serves as a baseline technique for encoding input text, where each word in the vocabulary is represented as a unique feature[25]. By disregarding the order and grammar of the words in the text, the BOW model focuses solely on the presence or absence of words within the document. This approach enables efficient processing of text data and facilitates subsequent analysis and modeling tasks. In the context of the chatbot system, the BOW model helps in encoding user queries and responses, enabling the model to understand the basic content and context of the input text. While simplistic, the BOW model serves as a valuable starting point for text representation, laying the foundation for more sophisticated techniques used in the chatbot system.

3.5.Beam Search Decoding

The purpose of Beam Search Decoding is to enhance the quality and diversity of the responses generated by the chatbot system. Beam search decoding is a search algorithm used during the generation of output sequences, particularly in natural language processing tasks like language translation or dialogue generation. The primary aim of Beam Search Decoding is to explore multiple potential response candidates and select the most likely ones based on a scoring criterion. By considering a predetermined number of candidate sequences (referred to as the "beam width"), Beam Search Decoding allows the model to generate a range of plausible responses[26]. This approach helps to mitigate the issue of the model producing overly deterministic or repetitive responses, leading to more diverse and contextually appropriate outputs. In the context of the chatbot system, Beam Search Decoding enables the generation of varied and nuanced responses to user queries, improving the overall conversational experience. By considering multiple potential responses simultaneously, the chatbot system can offer more engaging and contextually relevant interactions, ultimately enhancing user satisfaction and usability.

3.6.Long Short-Term Memory

In our chatbot system, LSTM networks are employed to generate responses when customers ask questions. LSTM networks are a type of recurrent neural network designed to handle sequential data, such as natural language sentences. These networks are particularly effective in capturing long-term dependencies in the input sequence, allowing the chatbot to understand the context of the question and provide appropriate responses. By leveraging LSTM networks, our chatbot aims to deliver accurate and coherent answers, enhancing the overall customer experience.Hyperparameters tuning is essential in LSTM networks because it directly impacts the performance and effectiveness of the model. LSTM networks are powerful tools for processing sequential data, such as text or time series data, but their performance heavily depends on the values of various hyperparameters.The hyperparameter tuning is essential in LSTM networks to maximize performance, prevent overfitting, stabilize training, adapt to dataset characteristics, and enhance generalization, ultimately leading to more effective and reliable models for various sequential data processing tasks. The research involves utilizing the ZOA to identify the optimal hyperparameters for the LSTM.

3.7.Zebra Optimization Algorithm

Zebra’s social interactions mainly focus on finding food and protecting themselves from predators. In the foraging process, a leading zebra within the herd guides others to grazing areas across open plains. In times of danger from predators, zebras often resort to a zigzagging escape pattern, although they may also gather together to disorient or intimidate the threat. The ZOA is a metaheuristic optimization algorithm inspired by the collective behavior of zebras. It mimics the social behaviors observed in zebras, such as herding, foraging, and defense strategies against predators.To iteratively search for optimal solutions to optimization problems, ZOA employs mechanisms like communication, cooperation, and competition among solution candidates, aiming to efficiently explore the search space and converge towards promising solutions. This algorithm has been applied to various optimization tasks in fields such as engineering, computer science, and operations research, showcasing its effectiveness in finding high-quality solutions across diverse problem domains [21].The flow chart of ZOA shown in Figure 4 is used to configure the LSTM for performance enhancement.

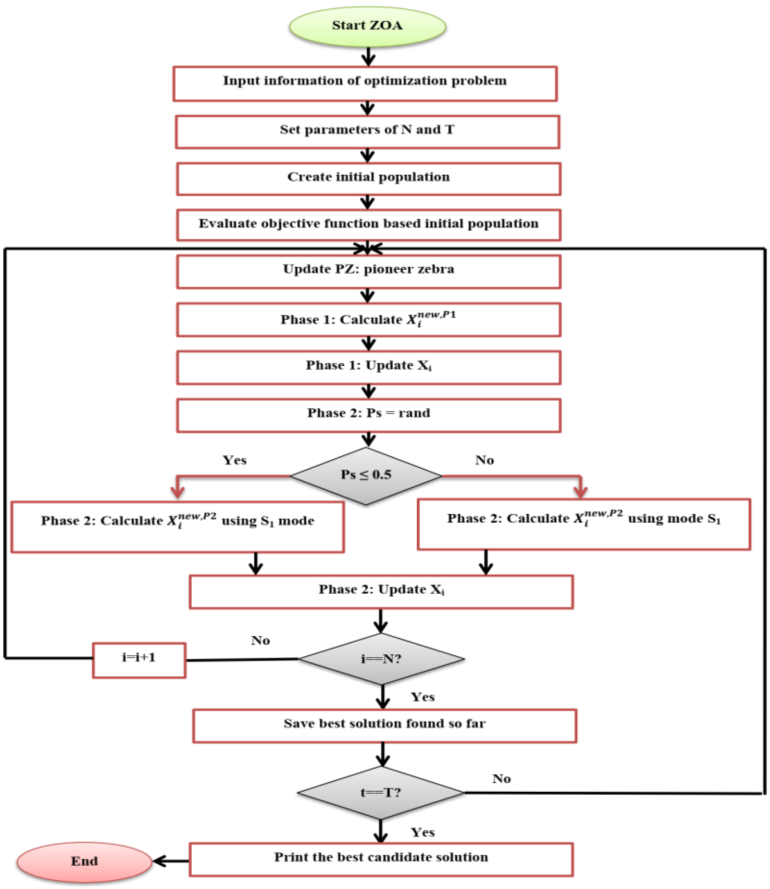

Fig. 4. Flow Chart of Zebra Optimization Algorithm

4. Results and Discussion

The research demonstrates that our optimally configured LSTM with ZOA-based chatbot system excels across various evaluation metrics, showcasing high Accuracy, Precision, F1-Score, Bilingual Evaluation Understudy (BLEU) Score and Recall-Oriented Understudy for Gisting Evaluation (ROUGE). The response quality of our proposed approach, integrated with the fashion industry chatbot, is marked by its ability to offer precise, relevant, and insightful responce to user queries pertaining to fashion products, trends, and services. Our chatbot uses advanced natural language processing to enhance user experience, boost satisfaction, increase purchase likelihood, foster engagement, and address privacy concerns, bolstering the brand's competitiveness in the fashion industry.

4.1.Performance Evaluation Metrics

In the assessment of a fashion industry chatbot response, several performance evaluation metrics such as Accuracy, Precision, F1-Score, BLEU Score and ROUGE can be utilized to measure its effectiveness and quality.

Accuracy is the proportion of correctly classified responses out of the total responses evaluated provides an overall measure of correctness, as shown in Equation (4).

$$Accuracy = \frac{Number\ of\ TP + Number\ of\ TN}{Number\ of\ TP + Number\ of\ TN + Number\ of\ FP + Number\ of\ FN}$$

(4)

In evaluating performance metrics across classifiers, notable findings emerge. Optimally configured LSTM models with ZOA and Gravitational Optimization Algorithm (GOA) demonstrated outstanding accuracy, with ZOA leading at 99% and GOA closely following at 98% shown in Figure 5. This underscores the efficacy of optimization algorithms in fine-tuning LSTM architectures for superior performance. The LSTM model with Seq-Seq architecture also achieved high accuracy at 98%, showcasing its effectiveness in capturing underlying patterns. Ensemble learning techniques like Random Forest and AdaBoost performed well with accuracies of 97.82% and 97.42% respectively, highlighting the strength of combining multiple models. Decision Tree and KNN classifiers achieved respectable accuracies of 97.26% and 96.13% respectively, though slightly trailing LSTM-based models and ensemble methods. Conversely, the Bidirectional LSTM (Bi-LSTM) model exhibited lower accuracy at 87%, suggesting potential limitations in capturing long-term dependencies.

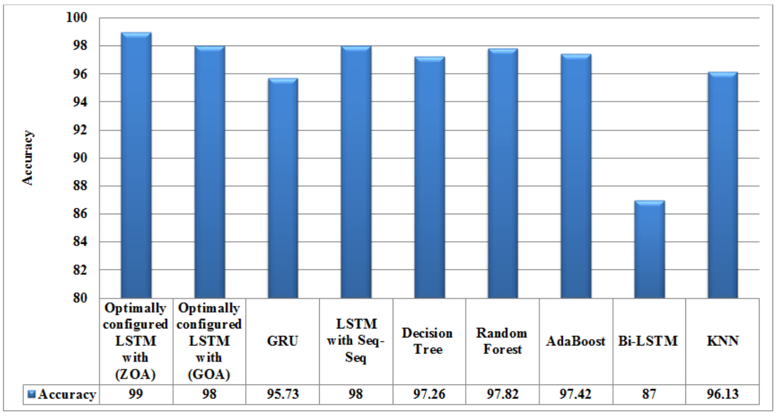

Fig. 5. Accuracy to evaluate the performance of chatbot's response

Precision is the proportion of correctly identified relevant responses out of all responses identified as relevant by the chatbot. It measures the accuracy of relevant response identification, as shown in Equation (5).

$$\Pr ecision = \frac{TP}{TP + FP} \quad (5)$$

The precision results offer valuable insights into each classifier's effectiveness in identifying relevant responses for fashion industry chatbots. The optimally configured LSTM with ZOA demonstrated in Figure 6 shows the highest precision at 98.5%, indicating the majority of positive classifications were relevant. Similarly, the LSTM with GOA) achieved a high precision of 97%, showcasing the effectiveness of optimization techniques in fine-tuning LSTM architectures. The LSTM model with Seq-Seq architecture also performed exceptionally well, with a precision score of 98%, highlighting its ability to capture patterns accurately. Ensemble methods like Random Forest and AdaBoost achieved precision scores close to LSTM models, while simpler models like Decision Trees and K-Nearest Neighbors (KNN) had respectable scores. However, models like Gated Recurrent Unit (GRU) and Bidirectional LSTM (Bi-LSTM) had slightly lower precision, suggesting challenges in capturing relevant patterns. Overall, these results emphasize the superiority of LSTM-based models, especially when optimized with advanced algorithms, in classifying relevant responses for fashion industry chatbots.

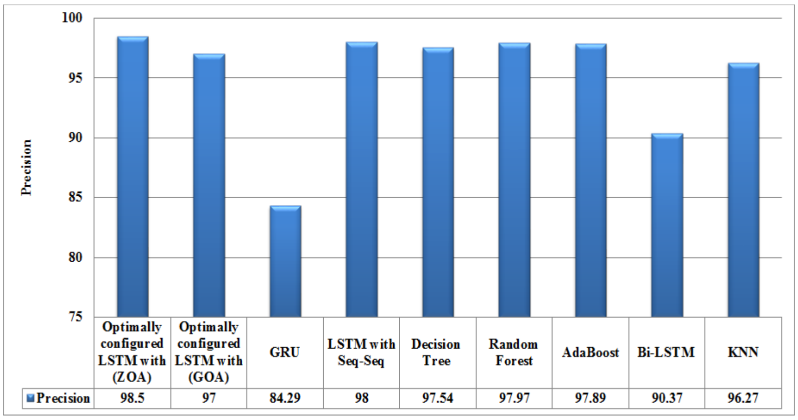

Fig. 6. Precision to evaluate the performance of chatbot's response

F1-Score is the harmonic mean of precision and recall, offering a balanced measure of the chatbot's performance in identifying relevant responses, as shown in Equation (6).

$$\text{F1-Score} = \frac{2 * \Pr ecision}{\Pr ecision + \operatorname{Re} call} \quad (6)$$

The F1-score analysis in Figure 7 reveals that optimally configured LSTM models with ZOA and GOA achieved the highest scores, demonstrating excellent balance between precision and recall. Other models, such as Seq-Seq LSTM, decision trees, Random Forest, and AdaBoost, also performed well. However, GRU and Bi-LSTM exhibited lower F1-scores, indicating challenges in achieving balanced performance. Overall, LSTM-based models optimized with advanced algorithms proved most effective for fashion industry chatbots.

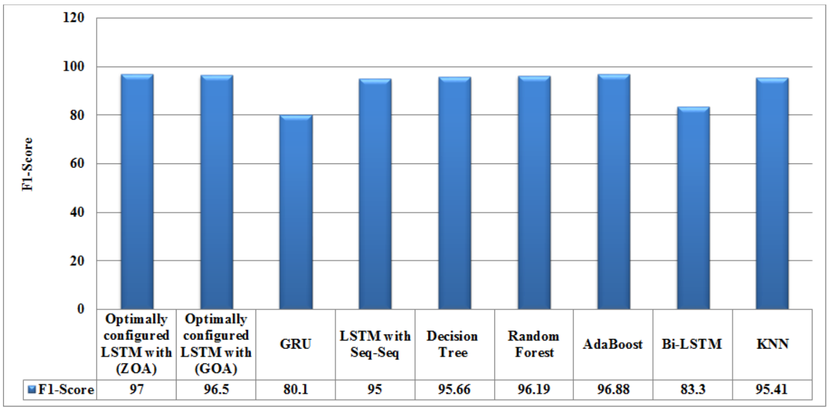

Fig. 7. F1-score to evaluate the performance of chatbot's response

4.2. Bilingual Evaluation Understudy Score

BLEU is the score to evaluate how well the translation from one language to another was done. Perfect BLEU is considered to be 1, where the mismatch score is 0. BLEU score is used to evaluate the predicted responses, in which we compared the predicted response with the reference from the dataset. Calculating the BLEU score for a chatbot involves comparing the generated responses of the chatbot to a set of reference responses, which are considered to be correct or ideal. BLEU score is commonly used to evaluate the quality of machine-generated text by comparing it to human-generated text. Equation (7) describes the BLEU score.

$$BLEU = BP \times \exp\left(\sum_{n=1}^{N} w_n \cdot \log p_n\right) \quad (7)$$

The BLEU score calculation involves factors such as the brevity penalty (BP), maximum n-gram size (N), and weights assigned to the precision of n-grams. However, while BLEU score is commonly used to evaluate chatbots and other natural language processing systems, it's crucial to consider additional metrics and qualitative assessments to capture aspects like fluency, coherence, and semantic quality. In assessing the effectiveness of the optimally configured LSTM with ZOA model, BLEU scores are compared. The Figure 8 shows that the optimally configured LSTM with ZOA outperforms existing models, achieving a BLEU score of 0.82. Conversely, K-Nearest Neighbors (KNN) exhibits the weakest performance among classifiers, with a BLEU score of 0.20.

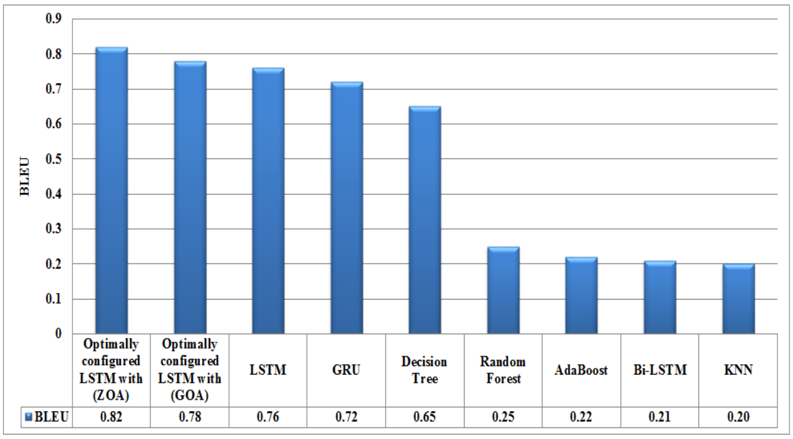

Fig. 8. Bilingual Evaluation Understudy Score to evaluate the performance of chatbot's response

4.3. Recall-Oriented Understudy for Gisting Evaluation

ROUGE is a statistic used to automatically evaluate the quality of a computer-generated word summary to that of a person, which is a more evolved way of recall. ROGUE is a metric commonly used to evaluate the quality of machine-generated text, such as chatbot responses, in comparison to reference texts. It calculates the similarity between the generated text and reference text based on the overlap of n-grams (contiguous sequences of n items, typically words) between the two. Our experiment reveals that the optimally configured LSTM with (ZOA) stands out, demonstrating the better performance of ROGUE Score of 0.79, as illustrated in Figure 9. Moreover, the KNN displays the weakest performance among the classifiers, achieving a bleu rate of 0. 07 in this scenario.

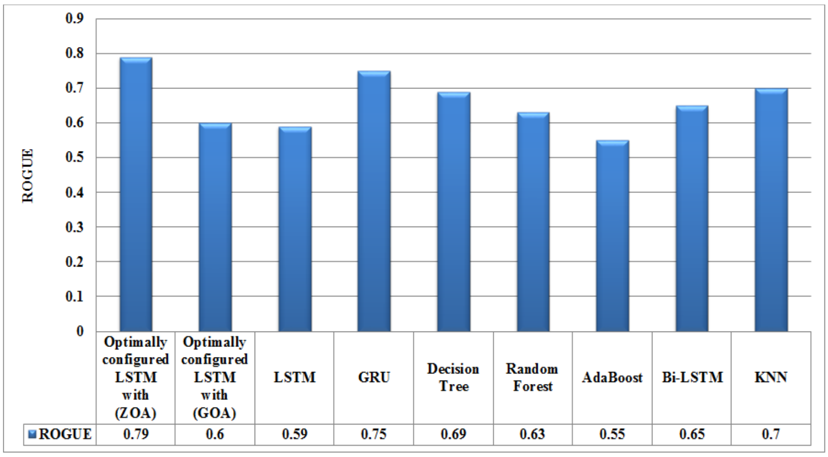

Fig. 9. Recall-Oriented Understudy for Gisting Evaluation to evaluate the performance of chatbot's response

5. Conclusion

The incorporation of chatbots has become increasingly essential within the fashion sector, transforming interactions between customers and brands and fostering e-commerce growth through tailored shopping experiences. This study aims to narrow the divide between high-end fashion labels and smaller businesses by investigating strategic approaches and translating insights into actionable suggestions. By examining the impact of chatbot integration on customer sentiment, this research emphasizes the importance of intelligent chatbot design in improving overall customer satisfaction. The primary goal is to enhance chatbot performance, ensuring accurate and efficient responses to user inquiries, thereby delivering significant value to businesses. Notably, the optimally configured LSTM, combined with attention mechanisms, demonstrates outstanding effectiveness in handling both lengthy and concise sentences, achieving an impressive accuracy rate of 99% during thorough testing. These results underscore the efficacy of the applied techniques in substantially improving chatbot performance, leading to enhanced customer interactions and satisfaction within the fashion industry.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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