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Sentiment aware interactive Chatbot AI using multi agent processing model

Vinod Kumar Shukla[1], Sumithra Alagarsamy[2], Vijaylakshmi Nagarajan[2], Gavaskar Shanmugam[3]
[1]Department of Information Technology, School of Engineering Architecture Interior Design, Amity University Dubai, Dubai International Academic City, Dubai, United Arab Emirates
[2]Department of Computer Science and Engineering, SNS College of Technology, Coimbatore, India
3Department of Computer Application, Bharthiyar University, Coimbatore, India

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ABSTRACT

Understanding user sentiment has become more important for organizations and consumers due to the rapid growth of social media platforms such as marketplaces, platforms for connecting brands and consumers, and public discussion platforms. Emotions that are based on aspects, nuanced within context, and multifaceted often require complex sentiment analysis algorithms to interpret properly. Furthermore, these systems do not provide real-time information to help companies make better decisions and enhance consumer satisfaction. To tackle these challenges, a novel Interactive Chatbot artificial intelligence (IChat-AI) approach has been proposed in this paper for sentiment-aware chatbot interaction. The word to vector (W2V), term frequency-inverse document frequency (TF-IDF), and bag of words (BoW) are utilized to effectively extract essential features. The deep Kronecker neural network (DKNN) is utilized to predict and classify the emotions into five classes, such as sad, happy, neutral, angry, and fearful. Python has been used to simulate the suggested model. The efficacy of the suggested system is examined employing parameters including recall, execution time, F1-score, complexity, precision, scalability, accuracy, and response time. The developed IChat-AI strategy performs better regarding accuracy than the existing methods, including RoBERTa, TLSA, and multimodal transformers fusion for desire, emotion, and SA (MMTF-DES) approaches, by 5.33%, 4.73%, and 14.39%.

Corresponding Author:

Sumithra Alagarsamy
Department of Computer Science and Engineering, SNS College of Technology
Coimbatore, Tamil Nadu 641035, India
Email: sumithra.a.cse@snsct.org

1. INTRODUCTION

In today's digital landscape, the nature of interaction between companies and consumers has been significantly transformed by social media platforms [1], [2]. Beyond serving as promotional tools, these platforms have become critical sources of consumer-generated content, generating massive volumes of real-time user opinions, feedback, and sentiment [3], [4]. For businesses to remain competitive, it is essential to monitor and analyze these sentiment trends accurately and efficiently [5]–[7]. Users often encounter frustrating experiences when a chatbot fails to recognize sarcasm, empathy, or tone, which are crucial for maintaining meaningful and satisfying interactions [8], [9]. Moreover, conventional sentiment analysis (SA) methods typically based on lexicon or basic machine learning (ML) approaches are inadequate in capturing the complexity of human emotions in the heterogeneous space of social media communication [10], [11].

Existing techniques have struggle with several drawbacks including lack of contextual awareness, poor handling of multilingual or multicultural data, and limited real-time responsiveness [12], [13]. As user expression on social media becomes increasingly sophisticated, static sentiment tools cannot capture the intricacies of human emotion [14], [15]. Some systems have made progress by introducing interactive chatbot layers and real-time visualization dashboards, but challenges remain in sentiment accuracy and emotional alignment [16]–[18]

In 2022, Tan *et al.* [19] suggested the robustly optimized BERT approach (RoBERTa), and the simulation findings show that the suggested hybrid approach outperforms the new techniques with F1-scores of 90%, 93%, and 91%. In 2023, Kaur and Sharma [20] offered a hybrid method for accurately conducting SA from the perspective of the consumer review summarization method. Regarding F1-score precision, and recall, the method's average results are 92.81%, 94.46%, and 91.63%, respectively. In 2023, Harita [21] created an end-to-end system that can predict the sentiment of a collection of tweets and the price of Bitcoin based on the sentiment prediction. In 2023, Gothane *et al.* [22] provided a deep learning (DL) model to detect the degree of polarity in Twitter postings. This approach improves performance by 81% accuracy ranging from 54 to 59%. In 2024, Neelakandan *et al.* [23] provided a proficient SA technique in Twitter data performed the best regarding recall, accuracy, F-score, and precision.

In 2024, Zhao *et al.* [24] suggested a transformer and lexicon-based SA (TLSA) for accurate and trustworthy SA of English text and it offer recommended practices for accurate and trustworthy SA. In 2025, Aziz *et al.* [25] provided a unified architecture of multimodal transformers fusion for desire, emotion, and SA (MMTF-DES) model for the multimodal human desire understanding challenge. This technique performs 2.2% better for emotion analysis. In 2025, Brun *et al.* [26] discovered that the emotion-sensitive chatbot was perceived as more competent and trustworthy. Here, the user feelings are compared during interactions with an emotion-sensitive chatbot versus an emotion-insensitive chatbot. According to the findings, users have a better experience with an emotionally sensitive chatbot than with one that is emotionally insensitive. In 2025, Abinaya *et al.* [13] suggested a novel hybrid chatbot system named text emotion BERT CNN network (TEBC-Net), which interprets user emotions and produces more sympathetic answers by combining text and video analysis. A convolutional neural network (CNN) model that has been particularly trained for emotion recognition analyzes the processed image and assigns probabilities to various emotions, achieving 74.14% accuracy. Additionally, challenges like a lack of scalability, absence of interactive questioning and chatbot assistance are the critical limitations. To tackle these problems a new IChat-AI methodology has been suggested for sentiment-aware chatbot interaction. The key objectives of the developed IChat-AI have been given as follows: i) The key objective of this work is to enhance user interaction by integrating sentiment analysis into chatbot conversations using a multi-agent architecture; ii) The proposed method employs word2vec (W2V), bag of words (BoW), and term frequency–inverse document frequency (TF-IDF) models for feature extraction, effectively converting textual data into numerical representations for accurate sentiment classification; iii) The proposed IChat-AI model utilizes a deep Kronecker neural network (DKNN) for sentiment classification, categorizing emotions into sad, happy, neutral, fearful, and angry for precise sentiment identification; iv) The proposed framework incorporates an interaction layer that enables scalable and personalized conversations across diverse platforms; and v) The performance of the developed IChat-AI approach is evaluated using key parameters including accuracy, precision, recall, F1-score, execution time, throughput, complexity, error rate, scalability, and response time.

The rest of the suggested approach are provided as follows. Section 2 offers a literature survey. Section 3 provides the suggested IChat-AI technique. Section 4 details the findings and discussion. Section 5 explains the conclusion.

2. PROPOSED SYSTEM

In this section, a novel interactive Chatbot with Gen-AI (IChat-AI) approach has been proposed for sentiment-aware chatbot interaction. Initially, the raw data are gathered from the database. Figure 1 shows the proposed IChat-AI framework.

2.1. Data collection

The procedure commences with raw, unstructured text data. This could include tweets, product reviews, consumer feedback, comments on social media, and so on. The information is accumulated from a variety of sources, comprising social media platforms, websites, customer surveys, and more.

2.2. Data pre-processing

Pre-processing is an essential step in text analysis that prepares data for further processing. Stop words are often used English words that don't contribute to SA. The stemming process helps eliminate unnecessary word computation by converting various word tenses into their most basic form. Combining two or more words into a single word is known as lemmatization. Tokenization divides lengthy passages of text, known as chunks of text, into tokens, which are essentially sentences. Correcting inaccurate data, removing some incorrect data from the data set, and reducing superfluous detail are all examples of data cleansing activities.

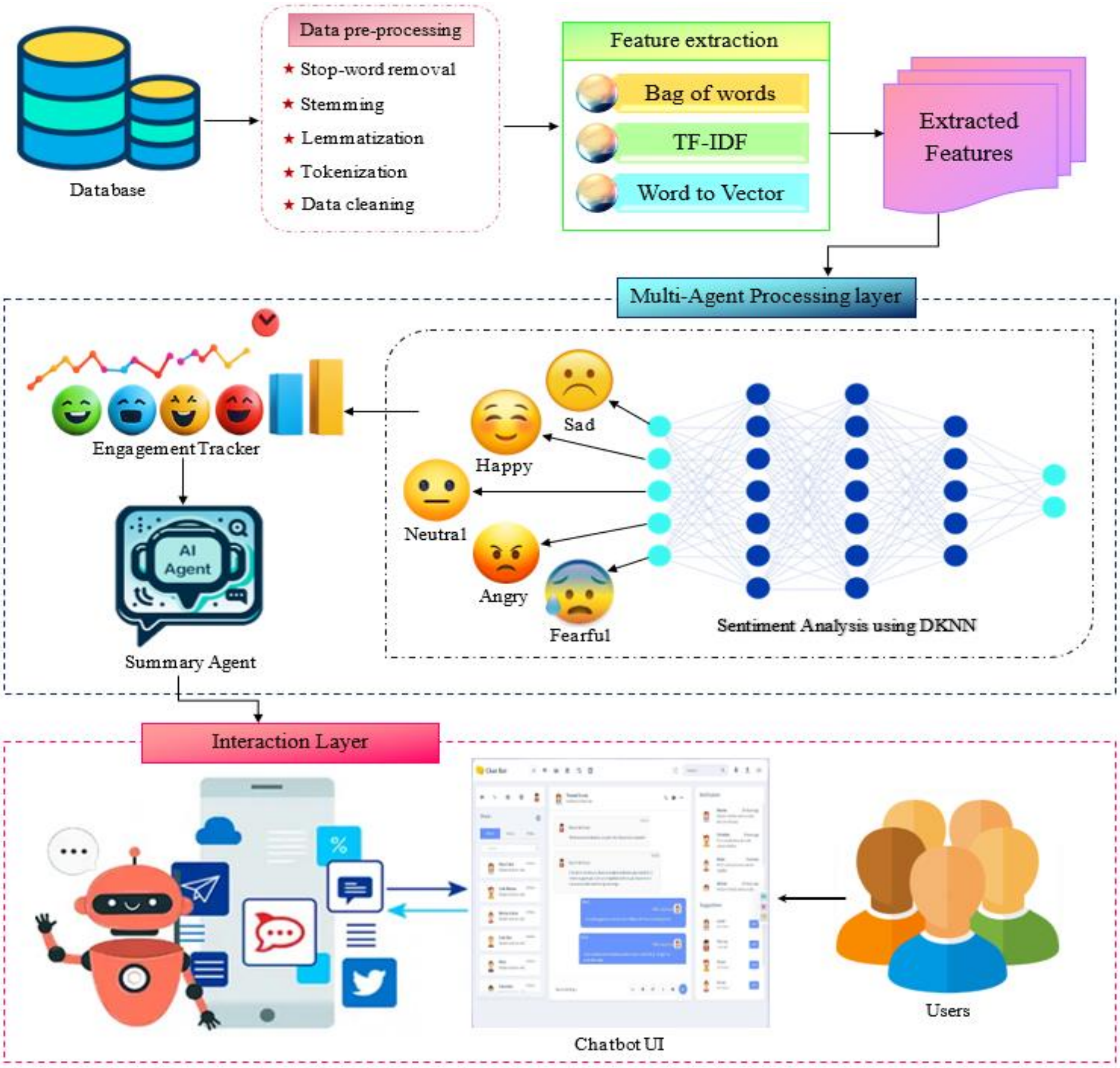


Figure 1. Proposed IChat-AI framework

2.3. Feature extraction (FE)

FE is a critical step that focuses on detecting and extracting the significant features to enhance model performance. It ensures the conversion of raw text into structured integer forms, which can be effectively processed by models. Techniques like BoW, TF-IDF, and W2V methods create a vocabulary of unique terms and count their occurrences in each text sample.

2.3.1. Bag of words (BoW)

The BoW is utilized for FE method in natural language processing (NLP). The BoW algorithm aims to convert a chunk of text into a numerical vector by ignoring word order and focusing solely on word frequency. Equation (1) provides the formula for representing a document as a BoW, where s denotes vocabulary size and the document as d_n, $bow(d_n)$ denotes the BOW representation.

$$bow(d_n) = [count(j_{n\_}1, d_n), count(j_{o\_}2, d_n) \dots \dots, count(j_{n\_}m, d_n)] \quad (1)$$

2.3.2. TF-IDF

TF-IDF is employed to extract the text's keyword information as a text feature. TF-IDF is a statistical technique for assessing a word's significance inside a text. Certain distinguishing words can be recognized more accurately by TF-IDF. To determine the IDF score, we utilize (2).

$$TF - IDF = TF(T, I) * \log\left(\frac{M}{AS+1}\right) \tag{2}$$

2.3.3. Word to vector (W2V)

The method's initial step focuses on finding word representations using the W2V model. Assume that a corpus C comprises a collection of texts $C = \{c1, c2, c3, .., ci\}$ and a vocabulary $V = \{v1, v2, v3, \ldots, vj\}$. For the classifier in the sentiment analysis challenge, the resultant set of vectors for every term in the corpus is high-dimensional and ineffective. The set of terms in the vocabulary V is thus represented by the set of vectors $T_v = \{\vec{t_1}, \vec{t_2}, \vec{t_3}, \ldots, \vec{t_j}\}$ hat are found by this first component. Equation (3) represents the W2V model.

$$V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_y \end{bmatrix} \Rightarrow \vec{T_v} = \begin{bmatrix} \vec{t_1} \\ \vec{t_2} \\ \vdots \\ \vec{t_x} \end{bmatrix} \tag{3}$$

2.4. Multi-agent processing layer

This layer includes sentiment analysis, an engagement tracker, and a summary agent. Here sentiment analysis is done by the use of DKNN, which classifies the emotions into sad, happy, neutral, fearful, and angry. Then the engagement tracker monitors the user's emotions using textual comments. And the summary agent summarizes user interactions and sentiment trends. These modules are explicitly explained below.

2.4.1. Sentiment analysis classification using DKNN

This work uses DKNN to classify emotions for improving accuracy in high-dimensional data. We actually utilize the KDNN to method $pb(q_v|o_v)$ the state's posterior probability given the observation vector o_v. Figure 2 displays the architecture diagram of the DKNN approach.

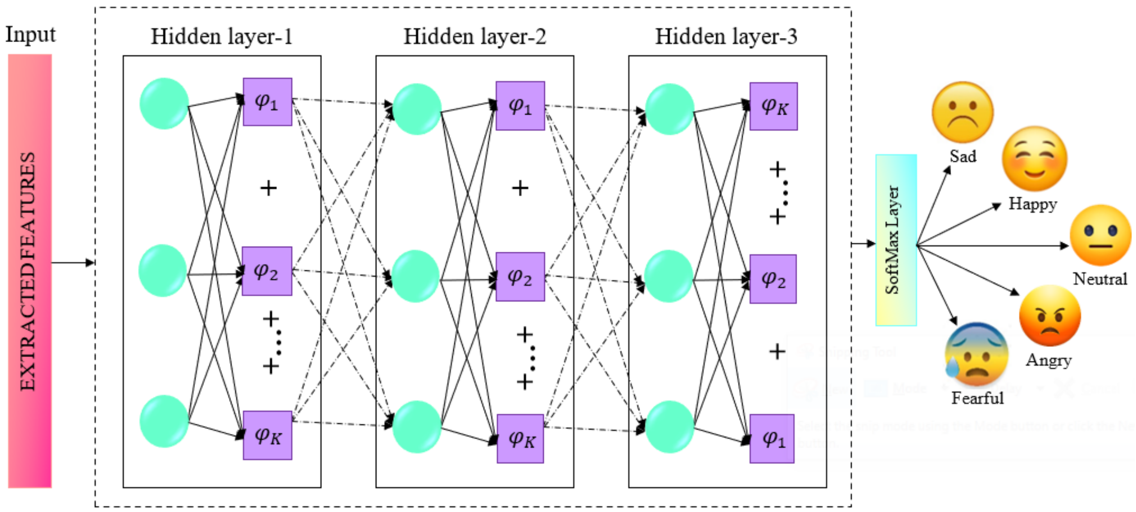


Figure 2. Architecture of DKNN model

a. DKNN classification procedure

For classification, given an input sequence $O = (o_1, o_2, \ldots, o_{rc})$, the goal is to assess the probability $pb(O|\gamma_{rc})$ for each vector class c and determine the optimal vector using a scoring criterion. The routing process with DKNN proceeds as follows.

- The input sequence O is passed through DKNN, producing posterior probabilities $\{pb(La_x|o_v)\}_{x=1,\ldots,RC\times Q}$ as outputs. The posterior probability $pb(q_v = T_s^{rc}|o_v)$ is derived from $pb(La_x|o_v)$ by mapping label La_x to stake s of the routing rc.
- Based on Bayesian principles, the likelihood probability $pb(o_v|q_v)$ is calculated as $pb(o_v|q_v) = \frac{pb(q_v|O_v).pb(o_v)}{pb(q_v)}$
  Here, $pb(q_v)$ is computed from the training data, and $pb(o_v)$ is treated as a constant, assuming independent observation feature vectors.
- For each vector model γ_{rc}, the Viterbi algorithm computes $pb(O|\gamma_{rc})$, substituting $b_{q_v}(o_v)$ with $pb(o_v|q_v)$ calculated using the above equation. The output vector with the highest probability is chosen as the SA classification.

This DKNN-based classification approach improves the precision of sentiment prediction, which ensures a more reliable understanding of user opinions. Finally, this DKNN model classifies the emotions into five categories such as sad, neutral, fearful, happy, and angry.

2.4.2. Engagement tracker

The engagement analysis agent tracks user interaction behavior like likes, shares, responses, and other engagement metrics from social media platforms. The agent applies time series analysis and anomaly detection methods to identify aberrant engagement patterns that indicate viral sentiment or a crisis in the making. Through correlation of engagement with sentiment scores, the agent can determine if well-engaged content is positive or negative in sentiment, attributing meaning to popularity surges or engagement bursts.

2.4.3. Summary agent

The comment summarization agent applies extractive and abstractive summarization techniques to shorten lengthy user comments into concise, informative summaries with the most important sentiment and points. The summarization procedure is based on sentiment-carrying sentences and aspect-related content so that the most important content is preserved in the summary.

2.5. Interaction layer

The interaction layer serves as the communication link between the chatbot system and its end-users. Follow-on questions or further questions seeking clarification may be asked without restatement of the original question by the users while engaging with the system through the chatbot interface. The chatbot is a game-changer in the user experience with sentiment analysis data. Instead of having to dig through static dashboards or templated reports to locate data, users can simply ask questions in natural language and get instant, contextually relevant responses. With the guided exploration approach, the users can find relevant findings they would not have requested consciously.

3. RESULTS AND DISCUSSION

In this section, the suggested IChat-AI framework is implemented in a Python simulator. To examine the performance of the developed IChat-AI framework, it has been compared with other techniques, including RoBERTa [19], TLSA [24], and MMTF-DES [25]. A number of important efficacy key parameters including recall, execution time, complexity, F1-score, precision, scalability, accuracy, and response time were evaluated to determine how well the IChat-AI method performed.

3.1. Dataset description

In this work, the GoEmotions dataset has been utilized. The GoEmotions dataset is a corpus of 58k Reddit comments manually classified by humans into 28 different emotion categories. The following list of emotions is organized into different categories: amusement, caring, love, relief, nervousness, excitement, curiosity, surprise, approval, gratitude, fear, disapproval, grief, joy, pride, disappointment, anger, remorse, sadness, realization, desire, optimism, embarrassment, disgust, confusion, admiration, and annoyance.

As shown in Figure 3, we will be implementing the fundamental Chatbot configuration into practice to make sure that the same bot may be utilized to offer various services. The fundamental setup can be changed to suit a given situation based on the needs and demands of the user. The service manages user requests and inquiries such that responses are dynamically tailored to the user during the discussion.

Figure 4 shows an example of a scatter plot that was made using a sample of comments' polarity and subjectivity. From a cybersecurity perspective, the upper left quadrant of Figure 5 is of importance since it shows certain remarks that are highly subjective and negatively polarized. These could be referred to as data outliers that merit further examination.

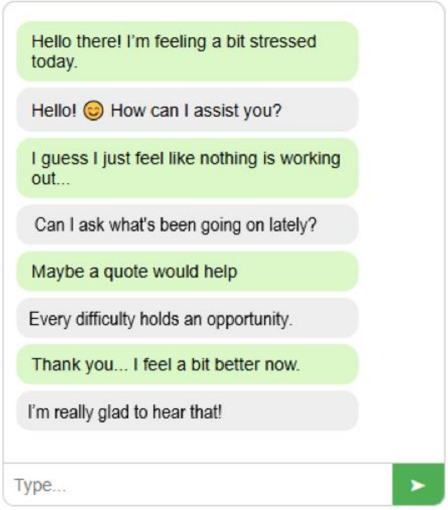


Figure 3. Actual implementation of Chatbot

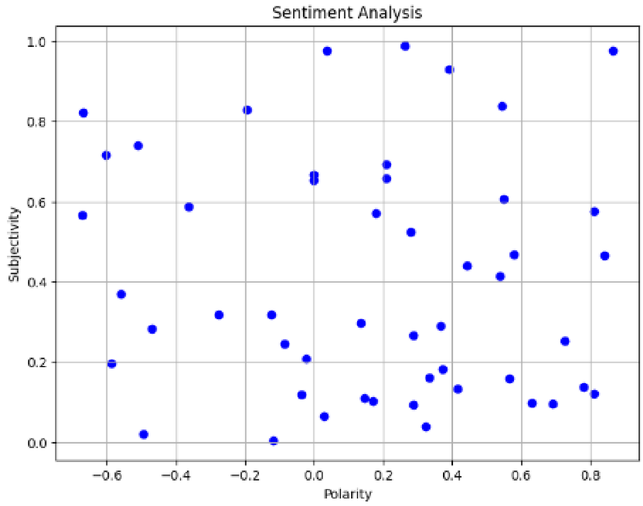


Figure 4. Subjectivity vs polarity of a sample of comments

Figure 5(a) presents a comparison of evaluation parameters. The accuracy of the proposed IChat-AI approach is 5.33%, 4.73%, and 14.39% higher than the existing RoBERTa, TLSA, and MMTF-DES methods, respectively. On the majority of techniques, the suggested model attains excellent precision, accuracy, recall, and f1-score. This demonstrates how well the suggested technique accurately classifies the sentiment detection. The response time fluctuation with SA query arrival rate is shown in Figure 5(b). The average response time was 15 seconds for 30 inquiries per second at a 600-sentence arrival rate. The suggested system attains significant SA performance is scalable with streaming data, and facilitates online reaction.

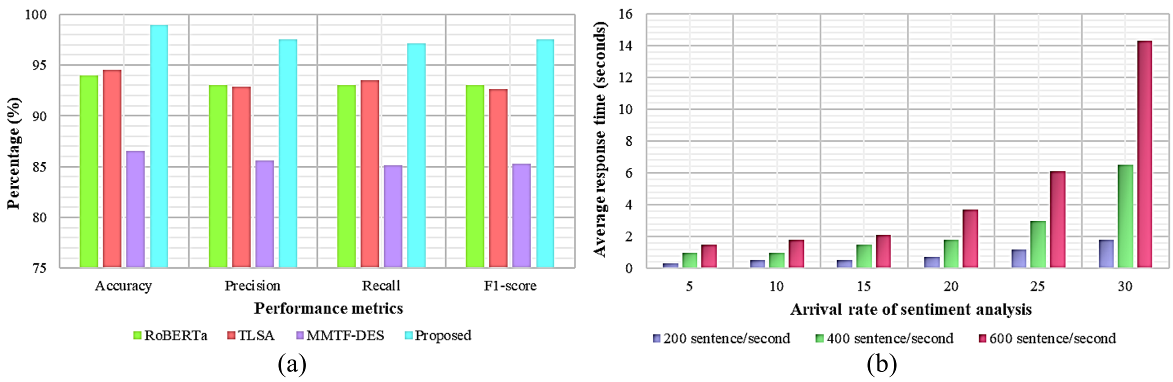


Figure 5. Performance metrics and response time: (a) metrics comparison and (b) response time

The suggested IChat-AI model as shown in Figure 6 responds more quickly than the existing models. The RoBERTa method demonstrates the highest query execution time, maintaining a relatively stable increase, while TLSA and MMTF-DES show moderate growth in execution time as the number of queries rises. In contrast, the proposed method exhibits the lowest query execution time across all query levels, with a steep upward trend, indicating that it is less efficient in handling larger numbers of queries compared to the other methods.

Figure 7(a) represents the comparison of computational complexity. Among the analyzed techniques, IChat-AI exhibits the highest execution and inference time due to its integrated DL and feature-rich pipeline. However, this added complexity supports enhanced classification accuracy, making it a suitable trade-off in high-stakes decision-making environments. The suggested IChat-AI model's scalability is compared to various models that are currently in use in Figure 7(b). The trend shows a linear increase in scalability as the data size increases, with IChat-AI maintaining the best performance throughout. The suggested IChat-AI framework offers a faster reaction time than the current techniques because of the previously mentioned advantages.

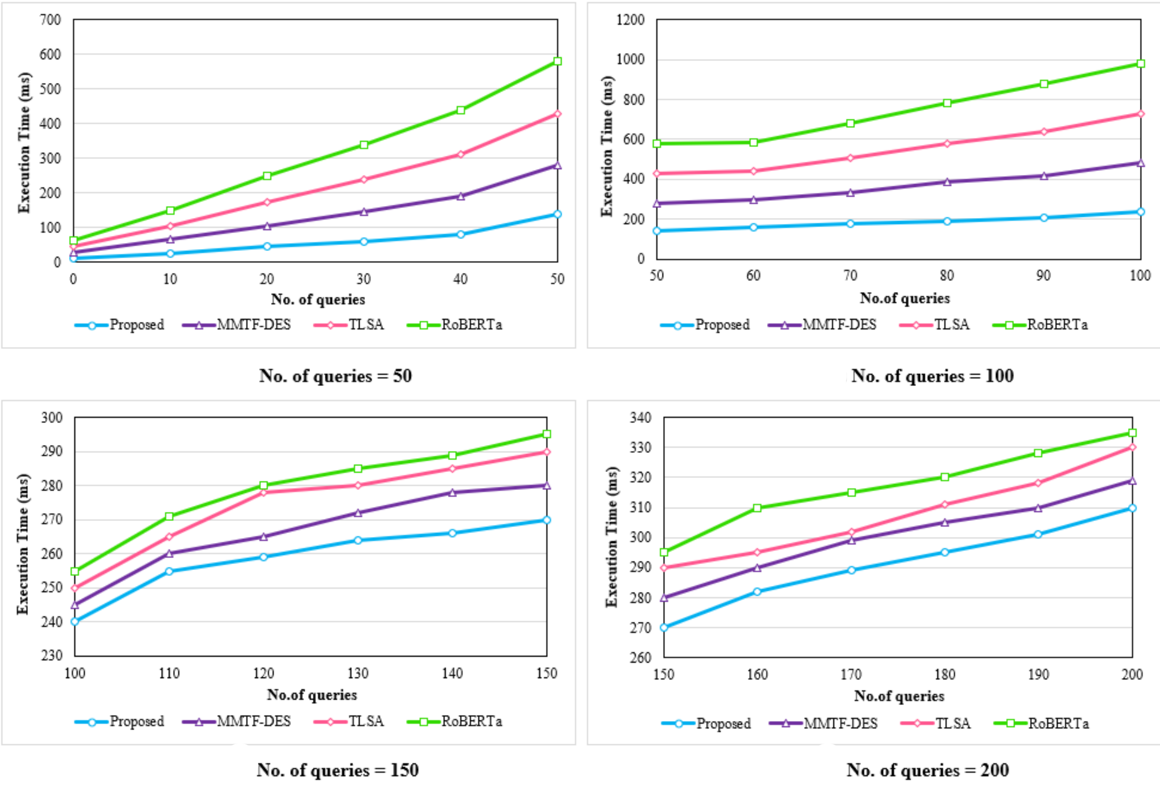
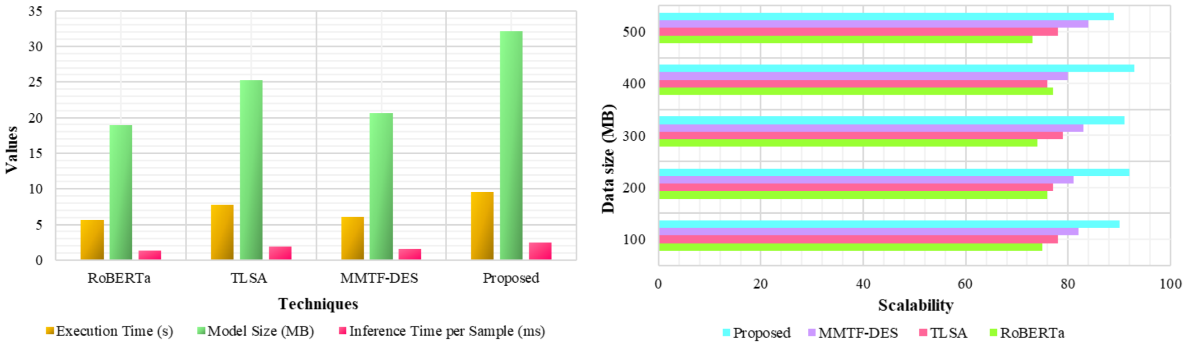


Figure 6. Execution time comparison



(a) (b)

Figure 7. Comparison in terms of (a) complexity and (b) scalability

Figure 8(a) illustrates the comparative examination of error rate between the suggested IChat-AI approach and existing approaches. The proposed IChat-AI model achieved an error rate of 6.23%, which is significantly lower than that of RoBERTa (15.44%), TLSA (10.83%), and MMTF-DES (11.56%). This indicates that the IChat-AI framework misclassifies fewer user sentiments, thereby enhancing trust and reliability in chatbot-based interactions. The model's processing speed to process user sentiment queries per second is determined by the throughput. Figure 8(b) presents a comparative comparison of throughput in terms of time. The existing systems have lower throughput. The proposed system shows that the involvement of DKNN network enhances the throughput in speed, making it highly effective for real-time SA detection in emotionally sensitive chatbot interactions.

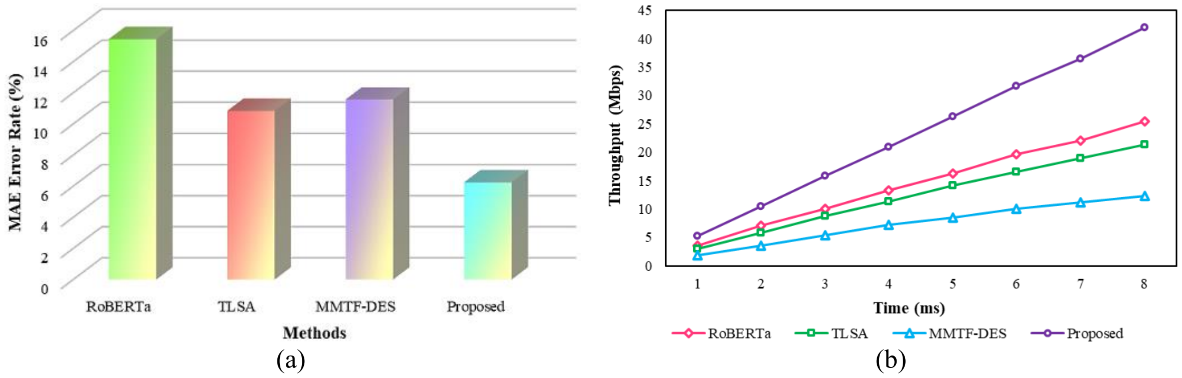


Figure 8. Comparison of error rate and throughput (a) error rate and (b) throughput.

4. CONCLUSION

In this paper, a novel interactive Chatbot with Gen-AI (IChat-AI) approach has been proposed for sentiment-aware chatbot interaction. The proposed model achieves the intelligent and interactive chatbot by accurately detecting user sentiments through the DKNN model. The suggested IChat-AI system has been assessed using a Python simulator. The comparative analysis demonstrates the superiority of the suggested IChat-AI method regarding throughput, recall, execution time, F1-score, complexity, precision, scalability, accuracy, and response time when compared to existing RoBERTa, TLSA, and MMTF-DES methodologies. The accuracy of the developed IChat-AI approach is 5.33%, 4.73%, and 14.39% higher than the existing RoBERTa, TLSA, and MMTF-DES methods respectively. The proposed framework enhances reliable and interactive chatbot interaction but faces challenges like limited adaptability across diverse languages and inaccuracies in high-volume environments. Future research will concentrate on using reinforcement learning models to overcome these constraints and change over time in response to user input.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vinod Kumar Shukla		✓	✓			✓		✓	✓			✓		
Sumithra Alagarsamy	✓		✓		✓			✓	✓		✓		✓	
Vijaylakshmi Nagarajan		✓		✓		✓	✓			✓		✓		
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C : **C**onceptualization
M : **M**ethodology
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Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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BIOGRAPHIES OF AUTHORS

Vinod Kumar Shukla is currently working with Amity University, Dubai, U.A.E., as an Associate Professor and Head of Academics for the Engineering, Architecture, and Interior Design department. He completed his Ph.D. in Semantic Web and Ontology. Dr. Vinod Kumar Shukla appeared in the prestigious Stanford University list of the top 2% of scientists in 2022. His research areas include cybersecurity, IoT, and blockchain. He can be contacted at vshukla@amityuniversity.ae.

Sumithra Alagarsamy is currently working as an associate professor in the Department of Computer Science and Engineering at SNS College of Technology, Coimbatore. She obtained her Ph.D. in Information and Communication Engineering from Anna University in 2019. She completed her B.E. degree in Computer Science and Engineering in 2008 at Sethu Institute of Technology. Her areas of interest include wireless networking, IoT, data mining, artificial intelligence, machine learning, MANET, and cloud computing. She can be contacted at sumithra.a.cse@snsct.org.

Vijaylakshmi Nagarajan is currently working as an assistant professor in the Department of Computer Science and Engineering at SNS College of Technology, Coimbatore. She obtained her master’s degree in computer science and engineering from SASTRA University, Thanjavur, in 2010. Her areas of interest include networking, cloud computing, image processing, and data analytics. She can be contacted at vlakshmi.n.cse@snsct.org.

Gavaskar Shanmugam is currently working as an assistant professor in the Department of Computer Applications at Bharathiar University. He obtained his postgraduate degree from the University of Madras. His areas of interest include cloud computing, IoT, machine learning, computer security, and cryptography. He can be contacted at gavaskar@buc.edu.in.