Smart Chatbot System for Banking using Natural Language Processing Tools

Clement Amama (clementamama82@yahoo.com)
National Open University of Nigeria
Ugochi Okengwu
University of Port Harcourt

Article

Keywords:

Posted Date: August 31st, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3285543/v1

Abstract

This research work focuses on creating a Smart Chatbot System for banking that leverages Natural Language Processing Toolkit and Machine Learning. The study involves gathering and preprocessing a dataset of user queries and responses. Key words are defined for pattern matching, and a decision tree algorithm is used to train the model. The Chatbot's performance is evaluated, and the results demonstrate the successful development of a functional Chatbot with a high F1 score of 0.97, indicating 97% accuracy in understanding user queries and providing relevant responses. User testing and a comparison with an existing system reveal significant improvements achieved through the incorporation of NLP and machine learning algorithms. The Chatbot is designed with an intuitive and user-friendly interface accessible through a web application, and administrators have a separate back-end access to effectively manage the knowledge base. The research also identifies areas for future improvement, such as enhancing accuracy, incorporating system memory and anaphora resolution, and integrating a logging system. Addressing these limitations will contribute to the advancement and effectiveness of conversation agents in the banking sector.

Introduction

The banking industry is undergoing digital transformation, and chatbots have emerged as a convenient solution for providing online banking services. To develop a successful chatbot system for banking, it is crucial to understand customer needs and preferences. Technologies like natural language processing (NLP) and machine learning (ML) algorithms can help chatbots interpret customer queries accurately. Challenges include data security, regulatory compliance, and accessibility for all customers. Developing a smart chatbot system using NLP and ML algorithms can enhance the customer experience, reduce wait times, and lower operational costs. This study aims to create a banking chatbot that meets customer needs, incorporating NLP, ML, and accessibility features. The research contributes to the growing body of knowledge on chatbots in the banking industry.

AI has moved from academic research to industry, with businesses increasingly developing AI applications. Various AI technologies like neural networks, planning systems, speech synthesis systems, and voice recognition systems are being utilized alongside knowledge-based expert systems [11]. Machine learning is a crucial aspect of AI, encompassing algorithms that learn from data and address challenges such as image recognition and natural language processing [3]. Neural networks and deep learning are prominent techniques in machine learning, inspired by the human brain.

NLP focuses on algorithms that understand and generate human language, enabling applications like chatbots, language translation, and sentiment analysis. Significant progress has been made in developing algorithms that comprehend human language nuances [4]. Computer vision analyzes and interprets images and videos, finding applications in self-driving cars, facial recognition, and medical imaging. Recent advancements enable accurate object and scene recognition. Ethics and societal implications are important considerations in AI research, including employment, privacy, and human values. Concerns arise regarding potential AI misuse, such as facial recognition for surveillance.

Machine learning (ML) refers to a computer's ability to adapt and change based on previously seen data. It involves the acquisition of knowledge or skills through study, experience, or teaching. ML can be defined as a computer program that learns from experience to improve its performance on specific tasks. ML is used in various domains, including predicting future events and training chatbots in natural language processing (NLP) [7].

The realm of natural language processing (NLP) centers around empowering computers to comprehend human language. NLP comprises two distinct subfields: natural language understanding (NLU) and natural language generation (NLG). NLU plays a crucial role in extracting valuable information from unstructured data, such as text, videos, audio, and images [1]. It helps in tasks like analyzing social media data, customer feedback, and complaints. NLP technology provides efficient and accurate criteria for language-based tasks, contributing to improved efficiency and accuracy. It also enhances the user-friendliness of machines by allowing them to interpret human language and decipher information [4].

NLU, or Natural Language Understanding, is a subfield of AI that enables computers to understand human language. It involves analyzing and processing textual or spoken input to bridge the gap between human language and machine understanding. NLU components include intent and entity recognition, sentiment analysis, language parsing, question answering, and information extraction [6]. NLU is applied in virtual assistants, customer support, and information retrieval. Ongoing research aims to improve the accuracy and naturalness of NLU systems for smarter and context-aware interactions.

NLG, or Natural Language Generation, is a subfield of AI that generates human-like text or speech based on data and predefined rules. It has applications in data-to-text generation, personalized messaging, chatbots, report generation, content creation, and language translation [7]. NLG systems analyze structured or unstructured data to convert it into coherent narratives. They enhance customer engagement, automate content generation, and simulate natural conversations. Challenges include generating diverse outputs, ensuring accuracy, handling ambiguity, and addressing ethical considerations. Ongoing research aims to improve NLG capabilities and its impact on communication, automation, and content creation.

Chatbots utilize NLP and AI technologies to simulate human conversation [2]. They can be developed using supervised, unsupervised, or reinforcement learning. Supervised learning trains chatbots on labeled data, unsupervised learning is used with unstructured data, and reinforcement learning involves a reward-based system. Chatbots understand user input through NLP and generate responses using machine learning. They can learn from user interactions to improve over time. Chatbots have applications in various industries, including commerce, science, and entertainment. They automate tasks, engage users, and personalize responses based on past interactions. Chatbots can appear more personable by linking them to avatars or animations. They analyze user inputs to predict personality and preferences, providing data-driven recommendations [8].

The history of chatbots dates back to the mid-20th century, with early examples like ELIZA and PARRY simulating conversation using pattern matching and language processing techniques [9]. The emergence of ALICE in the late 1990s highlighted progress in chatbot development, and SmarterChild gained popularity as an interactive companion on instant messaging platforms. The advent of smartphones brought chatbots mainstream, exemplified by Apple's Siri. IBM Watson's success in Jeopardy! demonstrated the potential of AI in chatbots. The mid-2010s saw the proliferation of chatbot platforms on messaging apps, and voice-activated virtual assistants like Google Assistant and Amazon Alexa became prominent [10]. OpenAI's GPT-3 language model in 2020 further advanced chatbot technology. Throughout history, chatbots have evolved from rule-based systems to AI-powered models, integrating into various domains and modern-day interactions [1].

Chatbot systems are widely utilized in various fields due to their flexibility. They have been integrated into education, healthcare, and business industries for different purposes. Major companies like Facebook, Google, Apple, and Microsoft have incorporated chatbots into their systems, such as Facebook Messenger, Google Assistance, Siri, and Cortana. For instance, Facebook has integrated chatbot systems into Messenger for automated customer responses. In education, chatbots serve as intelligent tutors for online learners. Their natural language analysis capabilities enhance conversation accuracy, making them valuable tools for education [12]. Chatbots can support and solve problems for multiple students simultaneously. In healthcare, chatbots assist healthcare professionals in providing support to patients through computer and application mediums [5]. They act as conversational assistants, facilitating long-term adherence to health promotion interventions. Chatbots serve as communication channels connecting healthcare experts and users, providing guidance on diet, physical activities, and weight gain journeys. In the business sector, chatbot systems are extensively used for marketing purposes. For example, Collect.chat is an interactive chatbot designed to collect customer data on company websites. It can gather information, conduct surveys, answer inquiries, and facilitate registrations and bookings.

Results

Model’s performance

The model's performance was evaluated and visualized, showing the Loss and Accuracy over Epoch as a line graph in Fig. 1. The graph demonstrates that the model effectively learns as the loss consistently decreases and the accuracy increases. There are no signs of overfitting or underfitting, indicated by the absence of stagnation or increases in loss, as well as the absence of plateaus or decreases in accuracy.

Output of the Proposed System

The web user interface has a white background with the tittle written in black text as Fig. 2 illustrates. There is an input section for users to enter text and click the send button. The user text is highlighted in green, while the Chatbot’s response is highlighted in red as Fig. 3 illustrates. These color variations provide visual contrast and improves usability.

Machine Learning Evaluation

Initially, the F1 score is perfect at 1 for the first dataset. However, at dataset 15, there is a noticeable drop to 0.93, indicating a potential error or anomaly in the classification process as Fig. 4 illustrates. After dataset 15, there is a gradual recovery in the F1 score, steadily increasing until the end of the datasets. This recovery suggests that the error was addressed, leading to improved performance. Further investigation is needed to identify and rectify the error for consistent and improved performance across all datasets.

Discussion

To compare the proposed system with the existing system, two performance indicators were used: Accuracy and Error Rate. Accuracy measures the percentage of correct responses provided by each system, calculated as the number of correct responses divided by the total number of queries, multiplied by 100. The Error Rate measures the percentage of incorrect responses generated by each system, calculated as the number of incorrect responses divided by the total number of queries, multiplied by 100. These calculations involved comparing the chatbot's responses with a reference set of responses for 30 test questions. The test result is plot in a line graph shown in Fig. 5.

The comparison between the Existing system and the Proposed system revealed their strengths and weaknesses. In terms of "Accuracy," the Existing system initially had a poor start but improved to 93% before dropping to 90%. The Proposed system started strong and showed a steady increase, reaching 97% accuracy. The Proposed system outperformed the Existing system by 7% in terms of accuracy. Regarding "Error rate," the Existing system had a sharp increase to 63% before steadily declining to 7%. The Proposed system started with a 0% error rate, decreased to 3% by the end. The Existing system had an error rate 60% higher than the Proposed system. These results highlight the advantages of utilizing advanced NLP and Machine learning techniques in the Proposed system

Methods

Existing System

Eliza, a pioneering chatbot developed in the 1960s by Joseph Weizenbaum, exemplifies an early conversational agent. Initially implemented in the MAD-SLIP programming language, a dialect of LISP known for its use of parentheses and list processing, Eliza utilized a rule-based approach. By matching user input against predefined patterns, Eliza generated responses based on corresponding templates. The system's patterns followed a straightforward template structure, often reflecting the user's input back in the form of a question or statement, fostering the illusion of conversation as Fig. 6 depicts.

Eliza is a rule-based chatbot that follows a structured approach. Eliza’s architecture is illustrated in Fig. 7 which shows that user input is received and parsed by the Input Processor, then compared to predefined patterns using the Pattern Matcher. The Rule Database stores these patterns and associated response templates, which are used by the Response Generator to construct relevant responses. The Output Formatter ensures the responses are presented in a user-friendly format. The User Interface allows users to interact with Eliza through text-based interfaces or integration with larger systems. Eliza offers three advantages: engaging users by reflecting their statements and encouraging elaboration, simplicity in implementation compared to complex machine learning-based chatbot models, and its historical significance as a pioneer in chatbot technology, contributing to the understanding of natural language processing and human-computer interaction.

Proposed System

These components collaborate in a sequential manner as depicted in the System Flow chat (Fig. 8) and Architecture (Fig. 9). The input from the user is received by the user interface, which is then passed to the Natural Language Processor. The NLP tokenizes the words and compares the key words against predefined patterns stored in the knowledgebase. If a match is found, the Dialogue Manager generates a response using the relevant dataset associated with the matched keywords for the Response Generator to format the response, otherwise, a default response is selected. Finally, the formatted response is presented to the user through the web interface. The system administrator can Chat with the bot and view, update and add information as illustrated in Fig. 10.

In conclusion, the research focused on developing a smart chatbot system for banking using NLPTK to provide accurate and accessible banking information. The chatbot had a user-friendly web interface. Testing showed 97% response accuracy and spelling error detection. It had a separate back end for administrators. Limitations included occasional incorrect answers, lack of system memory leading to repetitive responses, and no anaphora resolution. Hosting the chatbot online was highlighted for wider access and insights. Suggestions were made for enhancing the user interface and implementing a logging system for analysis. Addressing these aspects would improve the chatbot's accuracy, comprehensiveness, and user-friendliness.

Declarations

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The author(s) declare no competing interests.

References

1. S et al. Dynamic NLP Enabled Chatbot for Rural Health Care in India. Second Int. Conf. Comput. Sci., Eng. Appl. (ICCSEA), Gunupur, India (2022).
2. Bandhu, K. C. et al. Health Care Chatbot using Natural Language Processing with SGD and ADAM Optimizer Parameter Optimization. IEEE World Conf. Appl. Intell. Comput. (AIC), Sonbhadra, India (2022).
3. Canonico, M. & De Russis, L. A Comparison and Critique of Natural Language Understanding Tools. Cloud Comput. Ninth Int. Conf. Cloud Comput., GRIDs, Virtualization (2018).
4. George, A. S. et al. Survey on the Design and Development of Indian Language Chatbots. Int. Conf. Commun., Control, Inf. Sci. (2021).
5. Gupta, J., Singh, V. & Kumar, I. Florence- A Health Care Chatbot. 7th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS), Coimbatore, India (2021).
6. Kaburuan, E. R., Kelvin, A. & Jery. Analyzing and Designing Conversational Banking Service Architecture for Banking Company. 8th Int. Conf. Orange Tech. (ICOT), Daegu, Korea (2020).
7. Kasthuri, E. & Balaji, S. A Chatbot for Changing Lifestyle in Education. Third Int. Conf. Intell. Commun. Tech. Virtual Mob. Networks (2021).
8. Mangla, D., Aggarwal, R. & Maurya, M. Measuring perception towards AI-based chatbots in Insurance Sector. Int. Conf. Intell. Innov. Tech. Comput., Electr. Electron. (IITCEE), Bengaluru, India (2023).
9. Samuel, I., Ogunkeye, F. A., Olajube, A. & Awelewa, A. Development of a Voice Chatbot for Payment Using Amazon Lex Service with Eyowo as the Payment Platform. Int. Conf. Decis. Aid Sci. Appl. (DASA), Sakheer, Bahrain (2020).
10. Savanur, A. et al. Application of Chatbot for consumer perspective using Artificial Intelligence. 6th Int. Conf. Commun. Electron. Syst. (ICCES), Coimbatre, India (2021).
11. Shinde, V. R. et al. Chatbot for college related FAQs. Int. J. Res. Eng. Appl. & Manag. (2019).
12. Sobhana, M., Yamini, A., Hindu, K. & Narayana, Y.L. Navbot—College Navigation Chatbot Using Deep Neural Network. In IoT Based Control Networks and Intelligent Systems (eds Joby, P.P., Balas, V.E. & Palanisamy, R.) vol. 528, (Springer, Singapore, 2023).
13. Syamsuddin, I. & Warastuti, S. W. Selecting ChatBot Platform for Health Enterprise Training: A Fuzzy AHP Approach. Int. Conf. Decis. Aid Sci. Appl. (DASA), Sakheer, Bahrain (2021).
14. Srinivas, K. K., Peddi, A., Srinivas, B. G. S., Vardhini, P. A. H., Prasad, H. L. P., & Choudhary, S. K. Artificial Intelligence Techniques for Chatbot Applications. International Mobile and Embedded Technology Conference (MECON), Noida, India (2022).
15. Van Thin, D. et al. A Human-like Interactive Chatbot Framework for Vietnamese Banking Domain. 9th NAFOSTED Conf. Inf. Comput. Sci. (NICS), Ho Chi Minh City, Vietnam (2022).

Figures

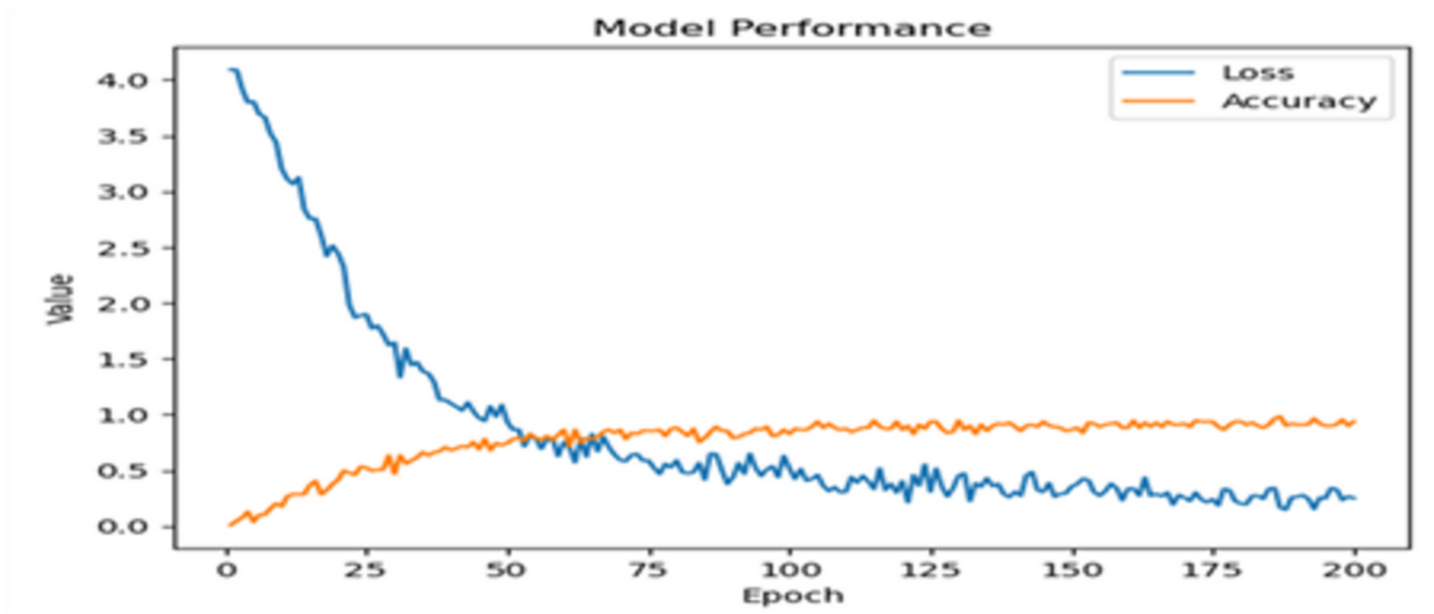

Figure 1

Loss and Accuracy of the Proposed Model

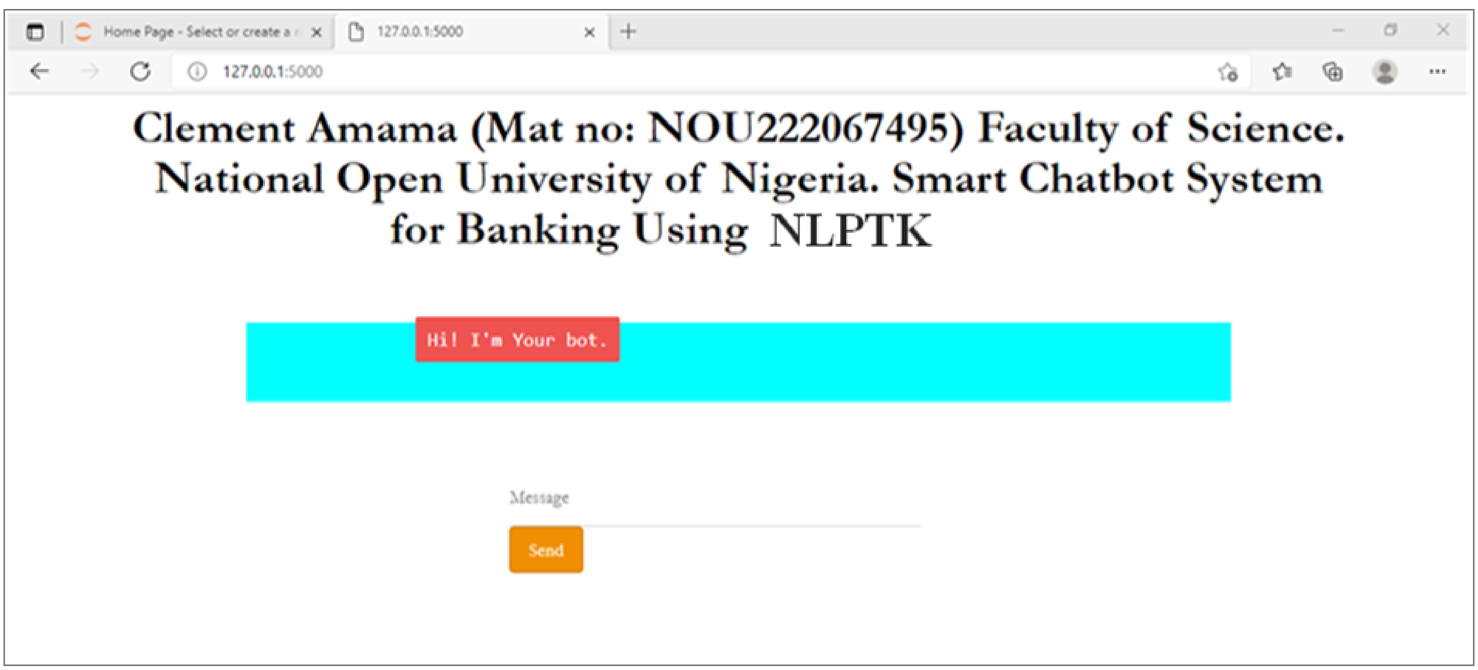

Figure 2

User Interface of the Proposed System

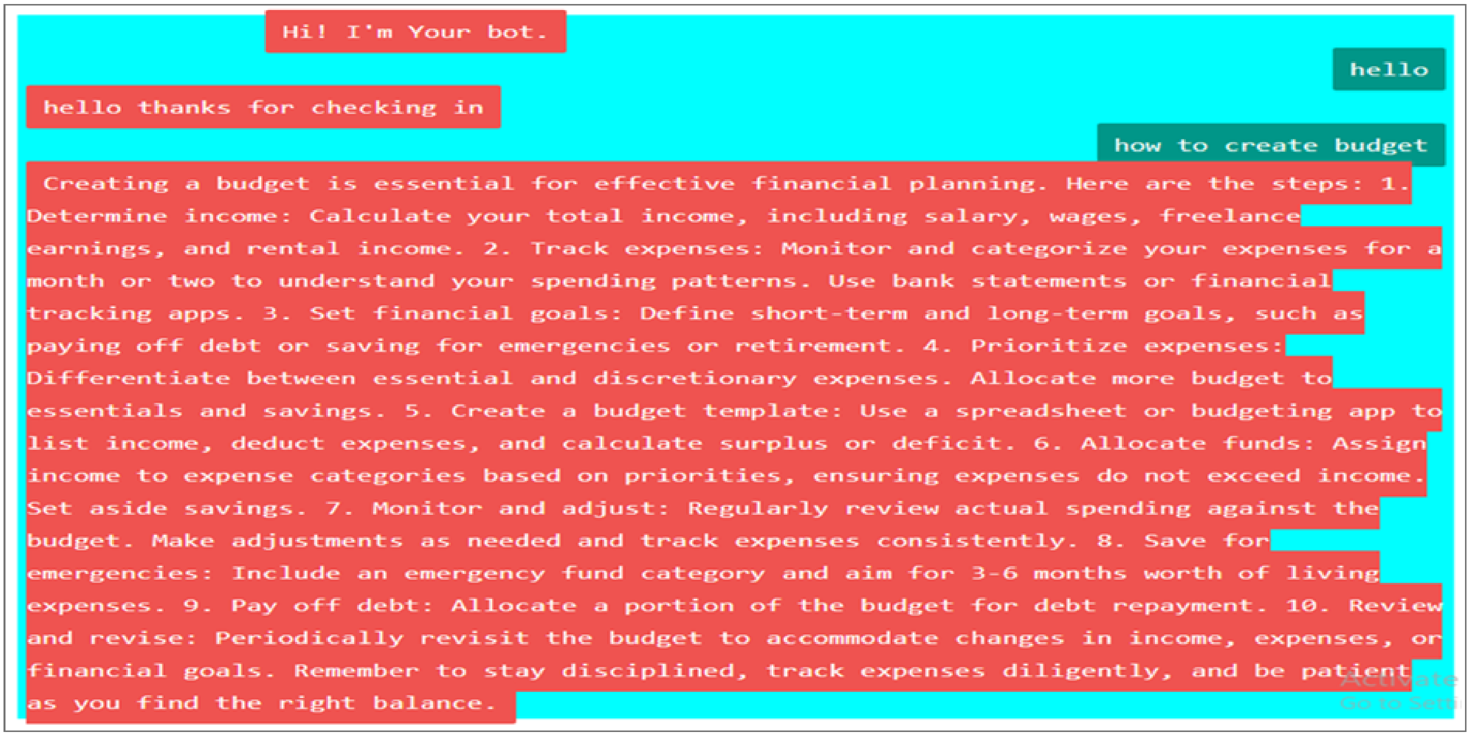

Figure 3

Conversation with the Proposed System

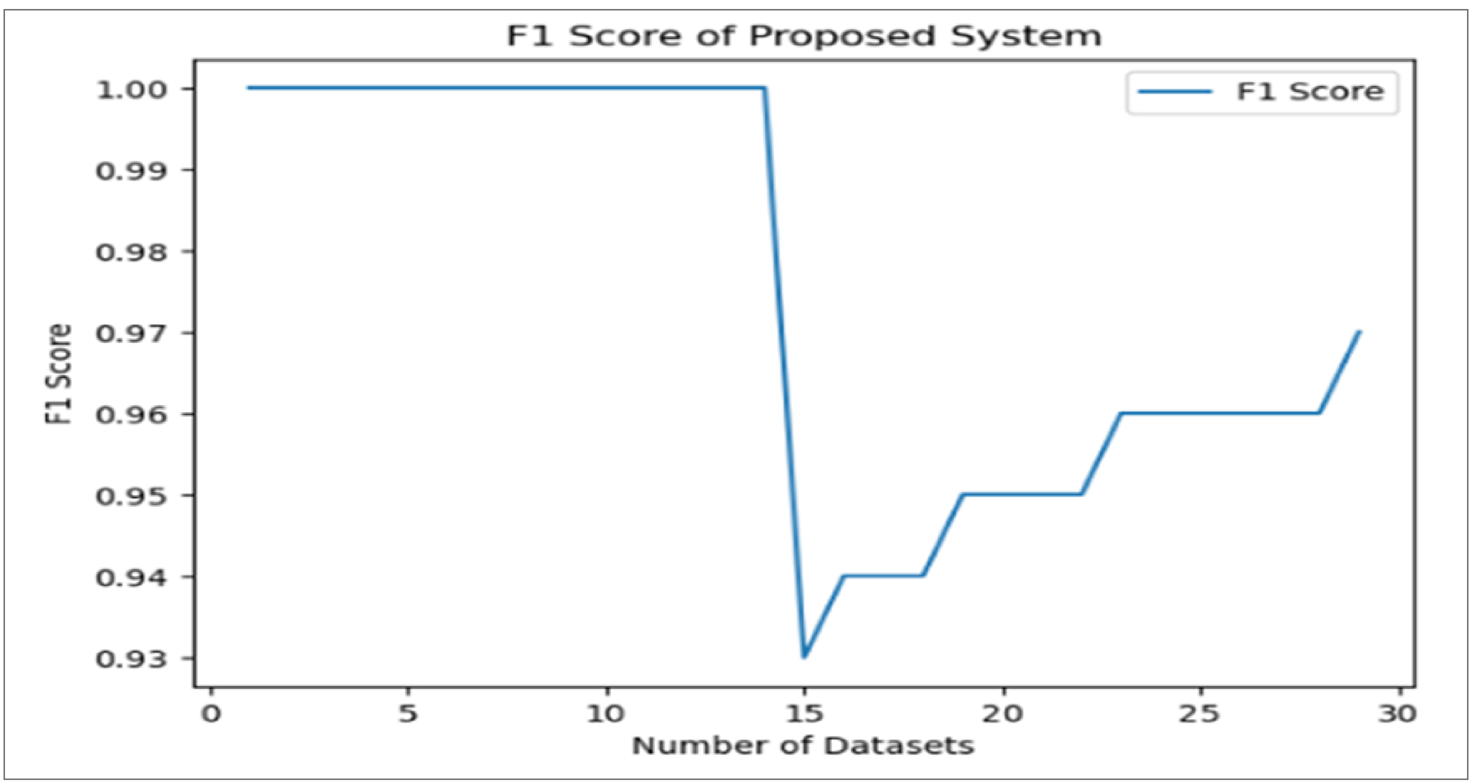

Figure 4

F1 Score of the Proposed Model

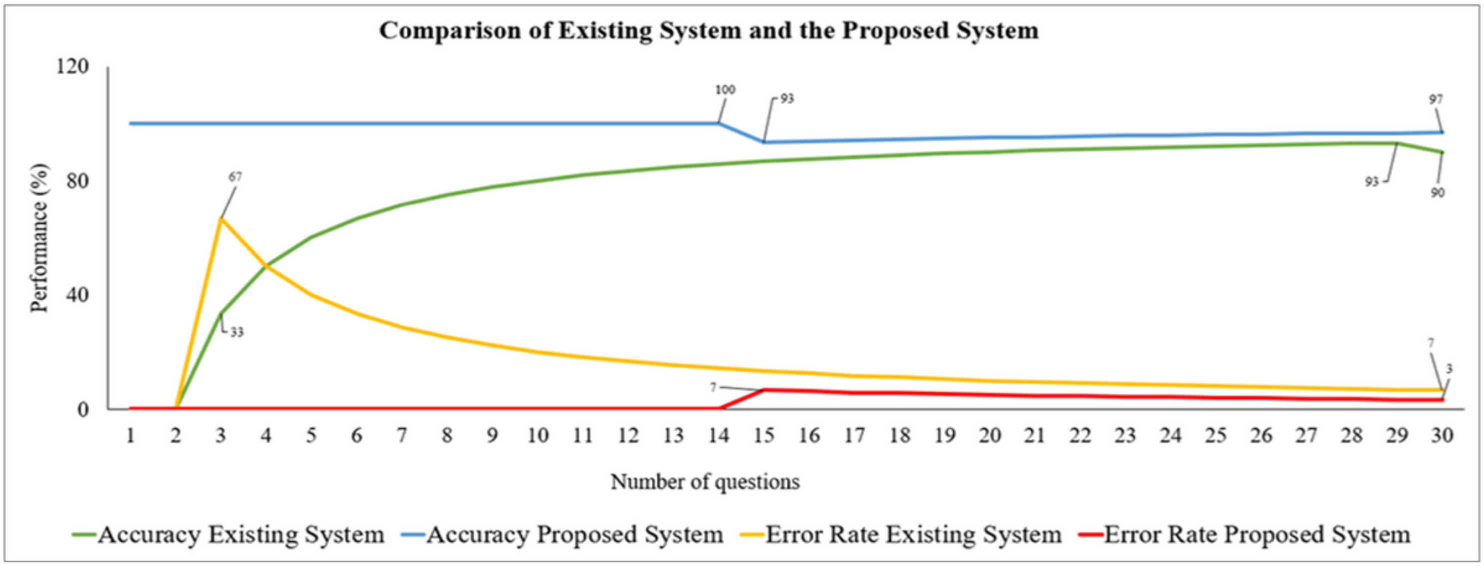

Figure 5

Existing and Proposed Systems Performance

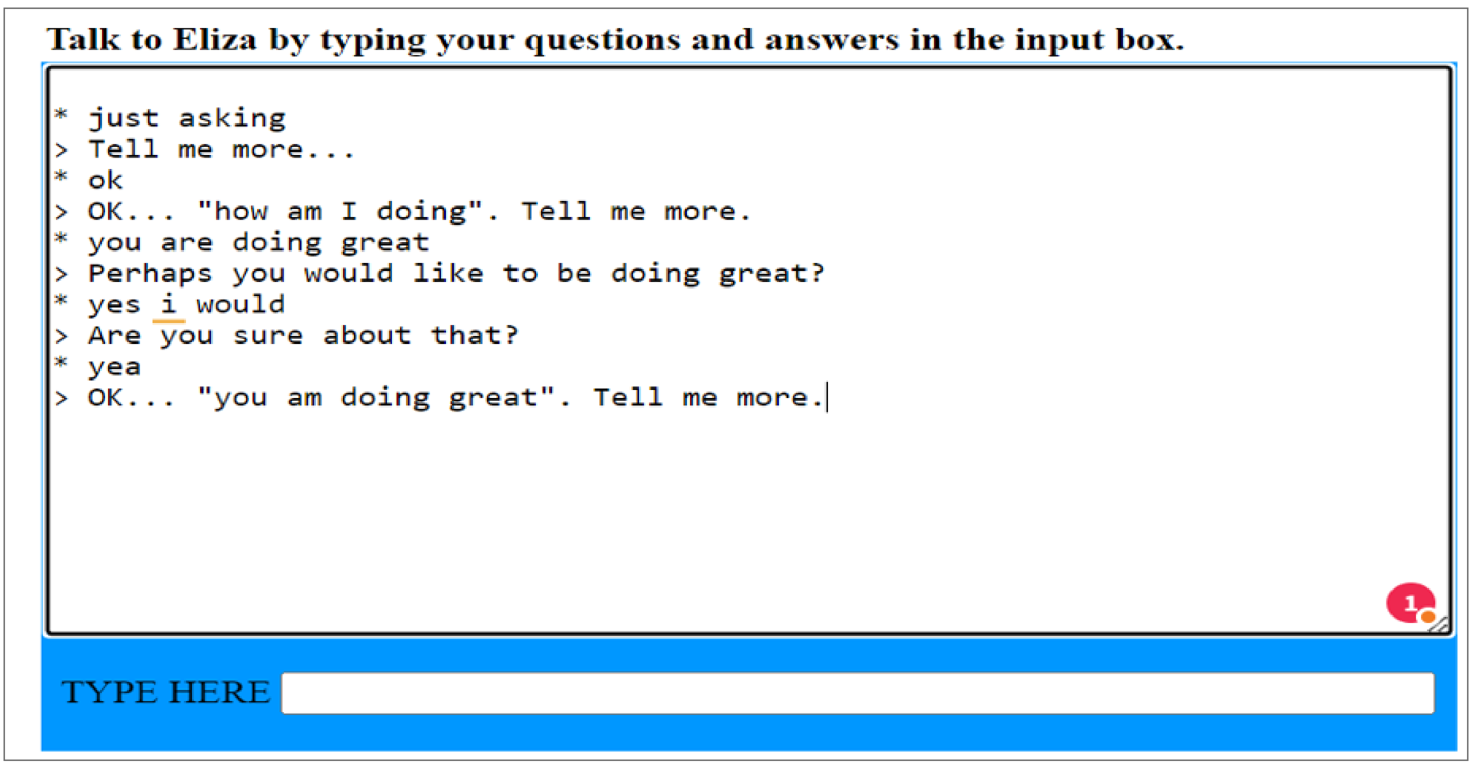

Figure 6

Eliza (GetSkilla, 2016)

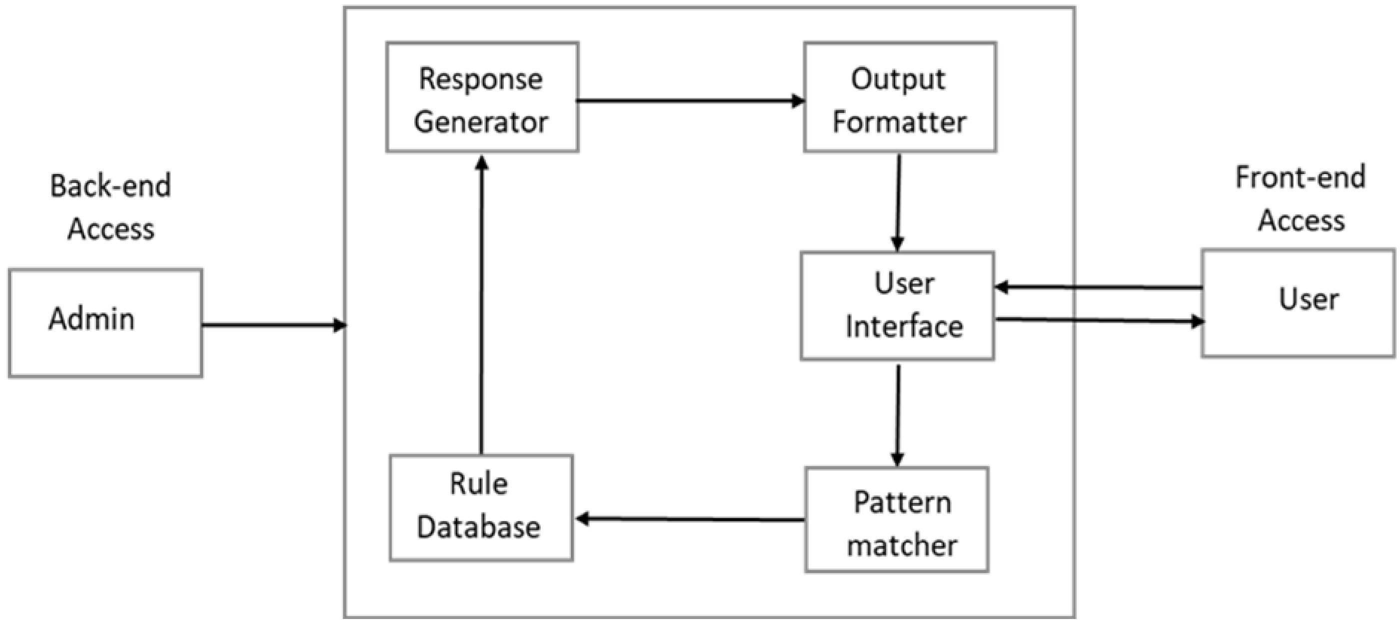

Figure 7

Architecture of the Existing System

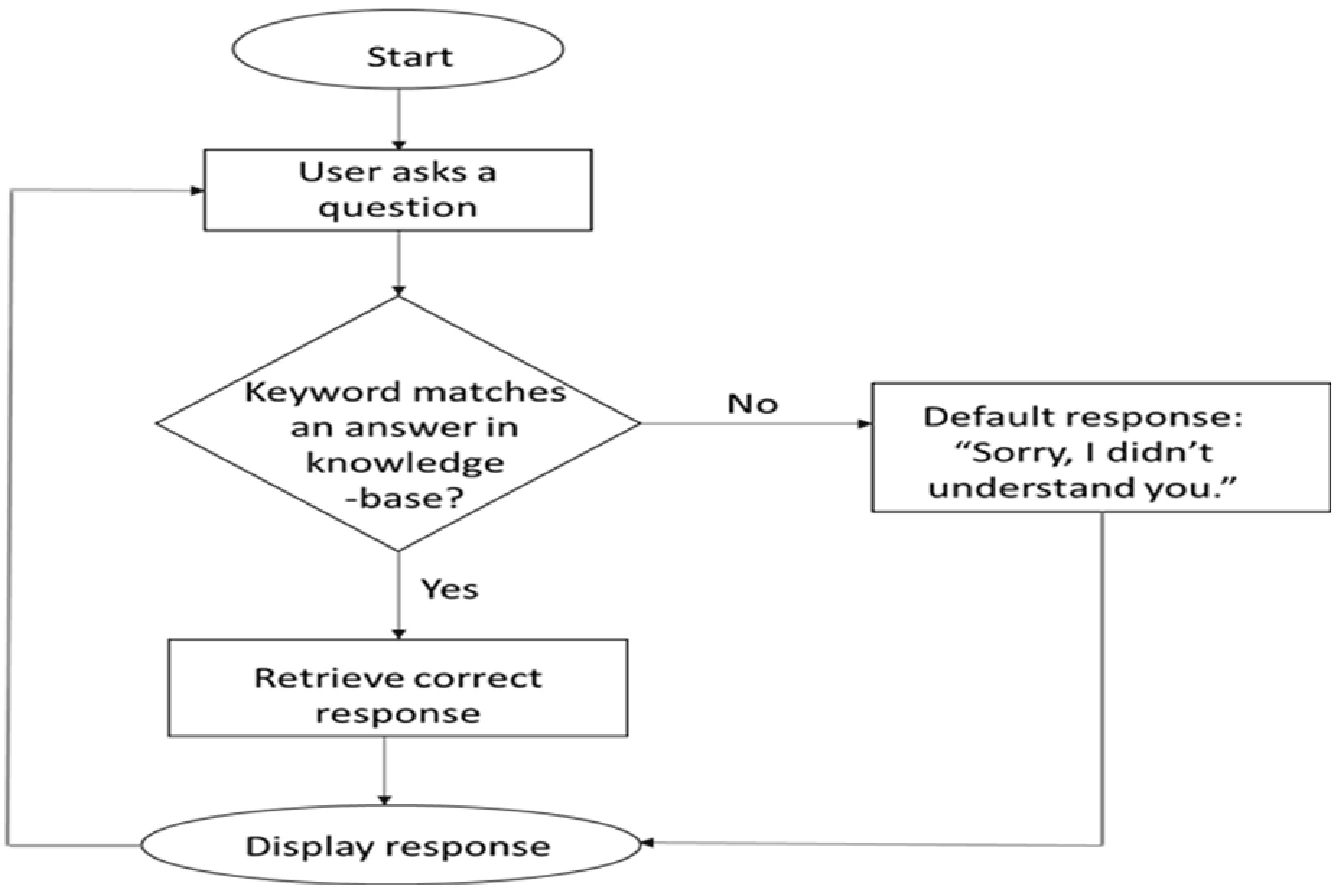

Figure 8

Flowchart of the Proposed System

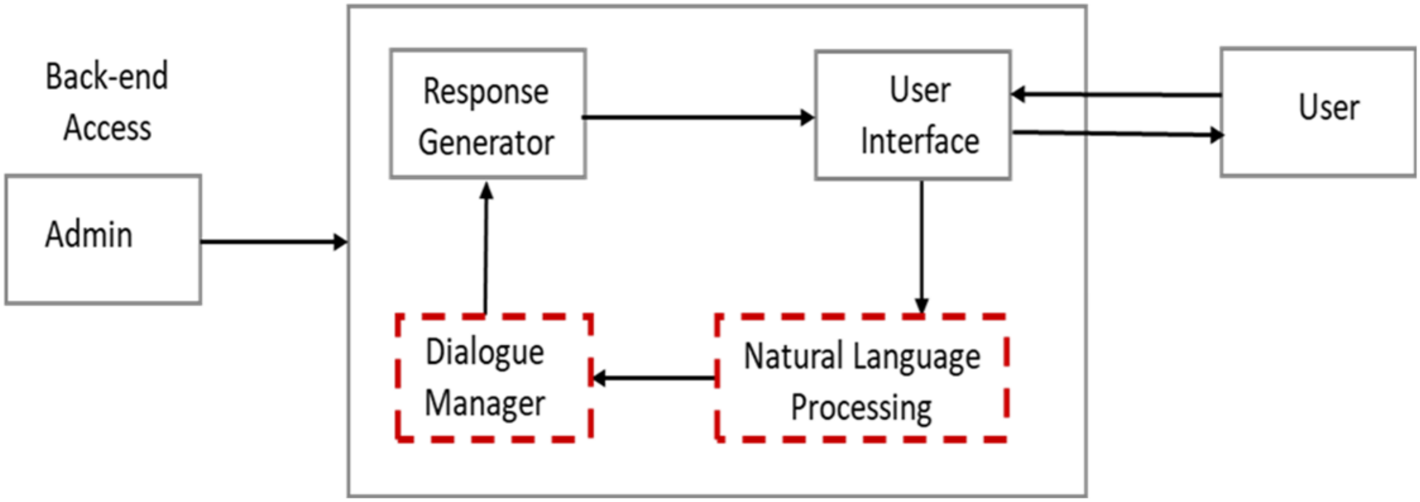

Figure 9

Architecture of Proposed System

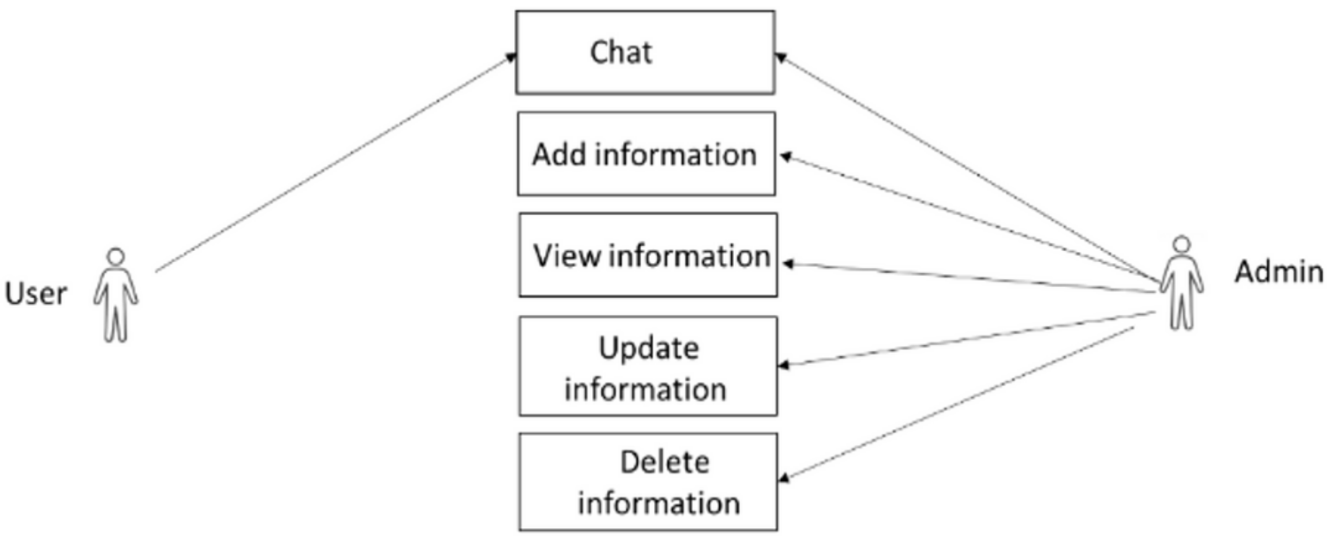

Figure 10

Use case of Proposed System

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Responseaccuracytest.docx