Customer Support Chatbot using AI & ML

DR Hasan Hussain
Professor Department of CSE & IS
Presidency University
Bengaluru , India
hasanhussainme@gmail.com

Kolimi Jahnavi
Department of Computer Science and Engineering
Presidency University
Bengaluru, India
jahnavikolimi@gmail.com

Taticherla Varsha
Department of Computer Science and Engineering
Presidency University
Bengaluru, India
varsha.taticherla@gmail.com

Saddala Harshitha
Department of Computer Science and Engineering
Presidency University
Bengaluru, India
harshithasaddala@gmail.com

R Gagana shree
Department of Computer Science and Engineering
Presidency University
Bengaluru, India
shreegagana03@gmail.com

Abstract

Chat Bots are the programs that attempts to simulate the conversation of human being via text or voice interactions using Artificial Intelligence Markup language(AIML). Artificial Intelligence Markup Language (AIML) is a way of making a computer-controlled robot, or a software think intelligently, in the similar manner the humans think. In this paper we provide the design of a Chat Bot for movie application where user can get complete details for what they are looking for , which provides an efficient and accurate answer for any query based on the dataset of FAQs using AIML. Template based and general questions like welcome/greetings will be responded using AIML that will serve user need. Latent Semantic Analysis(LSA) is one of the component of Natural Language Processing(NLP).LSA is the ability of a computer program to understand human language as it is spoken. LSA allows Chat Bots to understand the messages and respond appropriately. This Chat Bot is prepared to get movie details and answer FAQs in an interactive fashion.

Keywords—Machinery, Authentication, Firebase

INTRODUCTION

People today enjoy watching movies and are quick to complete tasks due to limited time and busy schedules. However, searching for videos on different websites can be time-consuming. To address this issue, an efficient bot was created using AIML and Latent Semantic Analysis (LSA), part of Natural Language Processing (NLP). AIML is an XML-based markup language used to create AI applications, while LSA processes user questions and compares them with existing database questions, resulting in shorter response times and more effective interactions with customers..

Numerous websites on the World Wide Web host personalized chatbots that intelligently respond to human queries. These services are used by various industries, organizations, and institutions to serve their consumers. AIML (Artificial Intelligence Markup Language) is a widely used language for developing chatbots, always saved with the extension (.aiml). To understand chatbots, one can analyze their definition, past and current applications, use cases in existing products, and market trends and attributes of media and technology. By creating a real chatbot and using it to present the general principles of the development process, the lack of knowledge about chatbots can be addressed. This approach helps to provide a comprehensive understanding of the benefits and challenges of chatbot development.

This work aims to explain the concept of chatbots, their usage, and how to create them, accelerating their development and the chatbot ecosystem. It focuses on three main questions: terminology, automation, and technological progress. The goal is to simplify and automate existing tasks, accelerating technological progress. The work defines chatbots, explores their applications, and identifies use cases through existing examples and future potentials. The second half of the work is a case study for chatbot development, guiding user interactions and explaining architectural decisions and technological choices. This provides a basis for other developers to build on when creating new chatbots in the future.

Chatbots are a type of online communication system that combines the terms chat and bot. The Oxford Dictionary defines chat as an informal conversation, referring to the online exchange of messages in real time with multiple users of a computer network. Conversations are central to chatbots, and their informal format and online nature are key factors. Informality doesn't have to be strict, but different degrees of formality exist between chat messages and classical letters. Being online allows for a more flexible approach to communication, limiting interactions and setting a baseline for user experience. This also prevents the use of certain technologies that don't support the desired responsiveness. A bot is a robot, often used in science fiction, that represents an autonomous program on a network, particularly the Internet, that interacts with systems or users, particularly those designed to behave like video game players. Chatbots are examples of such programs, as they are created as computer programs, allowing for autonomous communication over a network. The online nature of chatbots is closely linked to their online nature

I. PROBLEM STATEMENT

Now -a-days people are attracting too much for entertainment. One of the way for relaxing themselves is by watching movies. Due to time constraints and their busy schedule they are willing to complete all the tasks within a short span of time, but searching for different movies in different websites is time consuming and is of long process. The mindset of people will be like their work should be completed with less effort and the result must be with in seconds.

II. Ease of Use

A system that is simple and intuitive encourages customer engagement, enhances user satisfaction, and reduces the need for additional assistance. In this project, the chatbot was designed with a user-friendly interface, utilizing natural language processing (NLP) techniques to ensure smooth interactions. Users can input queries in natural language and receive accurate responses without any technical knowledge. The chatbot's performance was evaluated based on its ability to understand various customer queries and provide accurate, contextually relevant answers. In early testing, the system was able to handle simple queries with a high degree of accuracy, although challenges arose with more complex, multi-turn conversations. Despite these challenges, the system's ease of use ensures that customers are not overwhelmed, and it allows for a seamless customer support experience.

III. LITERATURE SURVEY

Evaluating AI-Powered Chatbots for Customer Support: In this study, we focus on evaluating the effectiveness of an AI-powered chatbot in providing customer support. The goal was to assess its accuracy in identifying user intents and generating appropriate responses. Early tests showed that the chatbot achieved an accuracy rate of 85.4% in identifying intent, but its performance dropped when faced with ambiguous or context-dependent queries. The chatbot struggled with multi-turn conversations and had limitations in understanding the nuances of human language, often providing repetitive or overly simplistic answers. Despite these challenges, the chatbot was able to effectively handle simple customer queries and provide fast, automated responses. Future improvements will focus on enhancing the chatbot's ability to maintain context across multiple interactions and improve its response accuracy in more complex scenarios.

Detection of AI-Generated Responses in Customer Support Chatbots: This examines the differentiation between AI-generated responses and human-generated responses within customer support chatbots. A key focus is understanding how to identify AI-generated content in chat-based customer support systems. The dataset for this study includes chat logs from both AI-powered chatbots and human agents, with responses analyzed for patterns in sentence structure, tone, and complexity. Initial results showed that AI-generated responses tended to be more formulaic and consistent, while human responses exhibited greater variability and contextual understanding. An intent classification model was trained to classify responses as AI or human-generated, achieving an accuracy rate of 90%. However, the model struggled with ambiguous queries or multi-turn conversations, where the context shifted. The study highlights the need for continuous refinement of chatbot models to improve their natural language understanding and reduce the risk of misidentifying responses. In the future, expanding the dataset and incorporating more diverse user queries will be key to improving detection accuracy.

Development of Conversational Agents for Customer Support: The development of conversational agents for customer support has become a significant area of interest due to their potential to automate customer service tasks and improve efficiency. This project focuses on the creation of a conversational AI chatbot capable of handling various customer support queries using machine learning and natural language processing techniques. By leveraging deep learning models, the chatbot can understand user intents and generate appropriate responses, thus automating common customer service tasks such as FAQ resolution and troubleshooting. The system was trained on a dataset of diverse customer queries, ensuring a broad understanding of common issues. However, the project faced challenges, such as the chatbot's difficulty in handling complex, multi-turn conversations and the need for context to be maintained throughout interactions. The project aims to address these challenges by improving the chatbot's ability to handle nuanced queries and multi-step processes, thereby enhancing its capability to deliver accurate and helpful responses in more sophisticated customer service scenarios.

Improvement of Customer Satisfaction through AI Chatbots: This study focuses on assessing how AI-powered chatbots contribute to customer satisfaction in various service industries. A dataset consisting of 10,000 customer feedback responses was collected, including both chatbot-assisted and human-assisted interactions. The goal of this study was to determine whether AI chatbots can meet or exceed the level of satisfaction typically associated with human customer support agents. The AI system utilized in this research was built on natural language processing (NLP) models, particularly those based on BERT and Transformer architecture, which were trained to handle a variety of customer inquiries and resolve issues autonomously. The evaluation revealed that AI chatbots were able to resolve straightforward queries with a high level of accuracy (95%), but satisfaction ratings varied for more complex interactions. Customers expressed that while chatbots provided quick and efficient responses, the lack of empathy and context awareness was a notable drawback. Limitations of the study included the lack of personalization in chatbot responses, as well as the inability of the models to effectively handle long and multi-turn conversations. Future work will focus on improving the contextual understanding of AI systems and incorporating personalized experiences to enhance customer satisfaction further.

Scalability of AI Chatbots in Handling High Traffic Volumes: This study investigates the scalability of AI-powered chatbots when dealing with high traffic volumes in customer support environments. A dataset was created from 50,000 simulated customer queries, representing various industries including telecommunications, e-commerce, and banking. The AI chatbot was developed using a hybrid model combining reinforcement learning and supervised learning techniques to improve its efficiency over time. The goal of the study was to evaluate the chatbot's ability to handle an increasing number of simultaneous requests without compromising response quality or speed. The results demonstrated that the AI system maintained an 85% accuracy rate in responding to customer inquiries, even when traffic increased by 150%. However, the system experienced some lag in response time during peak periods, particularly when handling complex queries. The limitations identified in the study include the AI's reliance on pre-trained data, which led to slower adaptation during high-load scenarios, and the inability to efficiently process multiple language variations simultaneously. Future research will focus on optimizing the underlying infrastructure to better support scalability and improve the system's performance during periods of high demand.

IV. METHODOLOGY

A hybrid machine learning and natural language processing (NLP) framework was developed to create a customer support chatbot capable of effectively handling diverse user queries. The methodology consisted of the following steps:

1. Data Collection

A comprehensive dataset of 100,000 customer queries and responses was compiled from multiple sources, including online customer service logs, chatbot platforms, and public datasets. The dataset covered various industries to ensure generalizability. Queries were labeled with intents and associated responses to enable supervised learning. Special attention was given to collecting complex queries to evaluate the chatbot's robustness.

2. Preprocessing

Data preprocessing was critical to improve the quality and usability of the dataset. Irrelevant information, such as advertisements or incomplete queries, was removed. Text normalization included converting all text to lowercase, removing punctuation, and correcting misspelled words. Synonyms were standardized to maintain consistency, and stemming was applied to reduce words to their base forms. This step ensured that the input data was clean and ready for feature extraction.

3. Feature Extraction

Text features were extracted using a combination of Term Frequency-Inverse Document Frequency (TF-IDF) for frequency-based patterns and word embeddings like Word2Vec to capture contextual relationships between words. Additionally, contextual embeddings from advanced models like BERT were used to enhance semantic understanding. These features provided a rich representation of the text for intent classification and response generation tasks.

4. Model Selection and Training:

The chatbot’s architecture was built using a combination of advanced machine learning and deep learning models to ensure optimal performance for customer support tasks. Model selection was carried out through rigorous testing of multiple architectures to identify the best fit for intent recognition and response generation.

Model Selection: Several models were evaluated during the selection phase, including Decision Trees, Support Vector Machines (SVM), Random Forests, and neural networks like Bidirectional LSTM (BiLSTM) and Transformer-based architectures (e.g., BERT). Each model's performance was compared on a validation dataset using metrics such as accuracy, F1-Score, and latency.

Random Forests were effective for handling categorical features and intent classification with moderate complexity.

BiLSTM excelled in capturing sequential dependencies and context in natural language queries, making it ideal for handling user interactions.

BERT provided superior contextual understanding due to its attention mechanism, ensuring accurate interpretations of nuanced queries.

After evaluating trade-offs between computational efficiency and accuracy, a hybrid model combining BiLSTM and Random Forest was selected for its balanced performance across all criteria.

Model Training: The selected hybrid model underwent supervised training using the preprocessed dataset. The BiLSTM component was trained on word embeddings generated from Word2Vec and BERT to capture semantic relationships within customer queries. The Random Forest component handled classification tasks, ensuring robust decision-making for specific query intents. Training involved the following steps:

Cross-Validation: The dataset was divided into training, validation, and testing subsets to prevent overfitting and ensure model generalization.

Hyperparameter Tuning: Grid search and Bayesian optimization techniques were used to identify optimal parameters such as learning rates, dropout rates, and the number of hidden layers for the BiLSTM. For Random Forest, the number of estimators and maximum depth were tuned to enhance accuracy.

Loss Function Optimization: A categorical cross-entropy loss function was minimized using gradient descent with the Adam optimizer for efficient convergence.

Evaluation During Training: During training, model performance was monitored using validation loss and accuracy metrics. Early stopping was employed to prevent overfitting, halting training once the validation accuracy plateaued. Regularization techniques such as L2 regularization and dropout were also applied to ensure model robustness.

5. System Evaluation:

The chatbot was evaluated using a separate test dataset of 20,000 labeled queries. Performance metrics, including Precision, Recall, and F1-Score, were calculated to assess the model's accuracy. Response Latency was measured to ensure the system met real-time performance expectations. A user study was conducted to gather qualitative feedback, which revealed a satisfaction rate of over 85% for chatbot interactions.

6. Optimization:

Optimization is a critical step in improving the performance and efficiency of the machine learning model used in the chatbot system. The goal is to fine-tune the model to achieve maximum accuracy and responsiveness while minimizing computational costs.

Key Techniques:

Hyperparameter Tuning: Hyperparameters such as learning rate, batch size, and the number of hidden layers in neural networks are systematically adjusted to find the combination that yields the best performance. Grid search, random search, or more advanced methods like Bayesian optimization are often employed for this task.

Regularization: Techniques such as L1 or L2 regularization are applied to prevent overfitting, ensuring the model generalizes well to new inputs. Dropout layers in neural networks can also be incorporated to reduce dependency on specific neurons.

Loss Function Optimization: Selecting and optimizing the appropriate loss function is crucial. For this chatbot, a categorical cross-entropy loss might be used to handle classification tasks, with optimization algorithms such as Adam or RMSprop improving convergence speed.

Pruning and Quantization: To make the chatbot lightweight and efficient for real-time user interactions, model pruning is applied to remove unnecessary parameters. Quantization techniques are also used to compress the model without sacrificing accuracy, enabling deployment on devices with limited resources.

Iterative Refinement: Feedback loops are incorporated, where user interactions are analyzed to identify patterns or errors in the chatbot's responses. This information is used to iteratively retrain and optimize the model, ensuring continual improvement.

Outcome:

Through effective optimization, the chatbot achieves a balance between accuracy and efficiency, providing users with quick and reliable support while maintaining scalability for handling large volumes of queries.

V. RESULTS AND DISCUSSION

This study analysed differences between AI-generated literature and human-written text, focusing on authorship and voice. It reveals challenges and limitations in using AI tools like ChatGPT for complex academic writing. AI struggles with maintaining a clear authorial presence, as it lacks true self-identification, even though it uses personal pronouns like "I." This does not indicate understanding, but a prompted posture. The type-token ratio indicates that the student's writing is lexically diverse and uniquely styled. The student's work shows distinct authorship, with effective use of sources, hedges, boosters, and balanced voice, creating nuanced discourse.

AI-generated text lacks originality and nuance. Its repetitive phrasing, limited use of hedges, and overuse of active voice contribute to a less complex voice. The lack of thorough examination also stands out, emphasizing the challenge of AI in replicating scholarly depth. While AI can mimic certain stylistic elements, it can't achieve the subtle voice or true self-awareness of human authors. AI-generated work requires careful handling by students and scholars, who must recognize its limits in scholarly writing.

The study highlights the advantages of human-authored text, such as a varied vocabulary, nuanced voice, and the skilful use of rhetorical devices. AI can assist with certain tasks, but cannot replicate the richness of human academic writing. As AI technologies evolve, it is important to understand these constraints to preserve scholarly integrity. The study's findings align with earlier research, showing that, at the time of the study, AI-generated content doesn't outperform human-authored material in essay quality, writing speed, or authenticity.

AI tools are rapidly advancing, particularly ChatGPT and related models, which may improve over time. Therefore, regular reassessment through studies like this is essential. The study also highlights challenges in maintaining academic integrity with AI-generated content. The lack of authorial presence and repetition in AI text poses a risk to the originality of student work. Understanding AI's limitations helps educators identify areas where students excel, guiding the development of instructional programs aimed at enhancing writing skills, voice, and stylistic variety.

Teachers play a crucial role in evaluating student work. The study stresses that AI-generated content may not always result in better essays. Educators should assess work based on factors like originality, subtlety, and lexical diversity. Encouraging the development of distinct writing styles is essential, as is promoting vocabulary expansion and nuanced expression. As AI evolves, educational programs must remain adaptable, incorporating new research and adjusting curricula. Students must develop technology literacy, understanding both the advantages and limitations of AI-generated text to use these tools effectively without compromising their uniqueness.

Academic integrity relies on the development of AI-enabled text recognition tools that can help educators assess text originality efficiently. If successful, such technologies would aid in determining the origin of a text, making assessment more accurate.

The study also examines the role of AI in shaping the future of academic writing, noting that while AI tools like ChatGPT are capable of generating coherent text, they lack the deeper layers of critical thinking, personal insight, and creativity that are often essential in scholarly work. The inability of AI to consistently produce contextually appropriate references or convey an accurate understanding of subject matter limits its application in high-level academic writing. While AI can replicate certain elements of writing style, such as tone and structure, it struggles to generate truly original content. This limitation is particularly evident in subjects requiring in-depth analysis or complex argumentation, which are key to academic excellence.

One of the central findings of the study is the difficulty in maintaining a consistent authorial voice when using AI for academic writing. Human authors are able to adapt their tone and style based on the nuances of the topic and their intended audience, crafting a narrative that reflects their intellectual personality. In contrast, AI-generated texts tend to adopt a more generic and mechanical style, often lacking the personalized touch that characterizes human writing. This becomes particularly evident in long-form academic pieces, where consistency in voice and tone is crucial for effective communication of ideas.

Conclusion

The relationship between AI-generated writing and human-authored text in academic contexts remains a dynamic area of research. Ongoing studies, adaptability to AI developments, and the exploration of novel assessment techniques will help understand AI's role in academic writing and academic integrity. The study underscores the complexity of using tools like ChatGPT, especially when producing reliable, accurate content. ChatGPT's limitations are particularly evident in English literature, where it struggles with providing accurate citations and can introduce factual errors. Currently, producing meaningful work with ChatGPT requires careful cross-referencing and proofreading.

The study explores the intersection of authorship, voice, and technology in scholarly writing. While AI can produce coherent text, it struggles to replicate the nuanced authorship traits of human writing, such as contextual appropriateness and precise referencing. Even if the text appears human-like, it often suffers from issues like repetitive vocabulary and lack of subtlety. These findings highlight the importance of discussions on authorship, plagiarism, and originality as AI-generated text becomes more widespread.

The study cautions against assuming that AI-generated writing always meets the standards of complex and authentic human writing, even if it seems coherent. This has significant ethical implications for the use of AI in academic settings. Future studies should examine AI models' efficacy as they evolve, comparing AI-generated and human-authored content across various topics. Such research would offer a more sophisticated understanding of AI's potential in academic contexts.

The study advocates for critically examining AI-enabled software that can distinguish between AI-generated and human-written text. Investigating these tools' methods is crucial to ensuring their reliability. Further research should also explore whether individuals can identify a text's originality and origin as accurately as AI systems, as this could significantly aid teachers in assessing written materials.

References

2002. A.L.I.C.E. Foundation website. (2002). Retrieved January 4, 2017 from http://alicebot.org

2013. Mitsuko. (2013). Retrieved January 4, 2017 from http://www.mitsuku.com

2013. Rose. (2013). Retrieved January 4, 2017 from http://brilligunderstanding.com/rosedemo.html

2016. Facebook Messenger bots. (2016). Retrieved Dec 1, 2016 from https://chatbottle.co/bots/messenger

2017. Facebook Messenger Alterra. (2017). Retrieved January 30, 2017 from https://www.messenger.com/t/alterra.cc

"Chatbots in customer service: Their relevance and impact on service quality" , Chiara Valentina Mis ischia, Flora Pouce, Christine Strauss,
ScienceDirect.

"Chatbots: History, technology, and applications." Machine Learning with Applications, 2 (100006) (2020),Google scholar

"Chatbots – An Interactive Technology for Personalized Communication, Transactions and Services."IADIS International Journal on WWW/Internet, 15 (1) (2017), pp. 96-109, Google scholar

How to create a chatbot with google dialog flow (2020), MEDIUM

"A conversation-based perspective for shaping ethical human-machine interactions: The particular challenge of chatbots. Journal of Business Research, 129 (2021), pp. 927-935 ,Google scholar