Random Forest-Driven Conversational Banking Assistant for Intelligent Financial Query Resolution

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Abstract— The increasing demand for instant and reliable customer support has encouraged financial institutions to adopt intelligent conversational systems that can provide continuous assistance with minimal human intervention. This paper presents a machine learning-based banking chatbot designed to answer customer queries related to banking services through an interactive web application. The proposed system employs natural language processing techniques to interpret user questions and predicts the most relevant response using supervised learning algorithms trained on a banking question–answer dataset. To identify the most effective classification model, the performance of Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) algorithms is evaluated using standard performance metrics. Experimental results indicate that the Random Forest classifier achieves the highest prediction accuracy among the evaluated models, making it suitable for real-time banking assistance. The application includes separate interfaces for administrators and users, allowing administrators to manage user accounts, train machine learning models, and monitor chatbot interactions, while registered users can securely access the chatbot to obtain banking-related information. The system also records user interactions for future analysis and continuous improvement of response quality. The developed solution demonstrates that integrating machine learning with conversational interfaces can significantly enhance customer support by providing accurate, responsive, and accessible banking assistance. The proposed framework offers a practical, scalable, and cost-effective approach for improving digital customer service in modern banking environments.

Keywords— Banking Chatbot, Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Intelligent Customer Support, Banking Question Answering System, Conversational AI, Web-Based Chatbot, Automated Customer Assistance, Text Classification, Banking Services, Human–Computer Interaction (HCI).

I.INTRODUCTION

The rapid growth of artificial intelligence and machine learning has transformed the way organizations deliver digital services by enabling intelligent systems capable of understanding user requests and providing automated responses. In the banking sector, customer expectations for fast, accurate, and round-the-clock support have encouraged financial institutions to adopt conversational technologies that simplify customer interactions and improve service quality [8]. Intelligent chatbot systems have become an effective solution for answering frequently asked questions, assisting customers with banking services, and reducing the workload of customer support representatives. The integration of natural language processing and machine learning techniques has further improved the ability of chatbots to understand user queries and generate relevant responses in real time [1].

Traditional customer support in banks primarily relies on human representatives through branch offices, telephone support, or online service centers. Although these methods provide personalized assistance, they are often associated with long waiting times, limited service availability, and increased operational costs [9]. In addition, handling a large number of repetitive customer queries can reduce the efficiency of support staff and delay responses to more complex issues. These limitations have created the need for intelligent automated systems that can provide immediate assistance while maintaining consistency and accuracy in customer communication [8].

Recent advancements in supervised machine learning algorithms have enabled chatbot systems to achieve higher levels of response accuracy by learning from large collections of question–answer datasets. Algorithms such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) have been widely applied for text classification and intent prediction because of their ability to identify patterns within textual data [14]. When combined with natural language processing techniques, these algorithms allow chatbot applications to recognize user intent, retrieve appropriate responses, and continuously improve their performance through model training and evaluation. Such intelligent systems enhance customer satisfaction by providing quick, reliable, and contextually relevant banking information [13].

The proposed work presents a Smarter Banking Chatbot that employs artificial intelligence and machine learning techniques to provide automated responses to banking-related queries through a web-based application. The system includes separate interfaces for administrators and customers. Administrators can securely manage user accounts, train multiple machine learning models, evaluate algorithm performance, and monitor chatbot interactions [1]. Registered users can access the chatbot through a simple interface, submit banking-related questions, and receive instant responses generated by the trained machine learning model. The application also maintains interaction records that can be used for system monitoring and future improvements [9].

The developed system demonstrates that intelligent conversational technologies can significantly improve customer support services by reducing manual effort, providing continuous assistance, and ensuring consistent response quality. Experimental evaluation compares the performance of Random Forest, Support Vector Machine, and K-Nearest Neighbors classifiers, with Random Forest achieving the highest prediction accuracy for the banking dataset used in this study [14]. The proposed solution offers a practical, scalable, and cost-effective approach for implementing intelligent customer assistance in banking environments, making it suitable for financial institutions seeking to enhance digital customer engagement and operational efficiency [1].

II.RELATED WORK

S. García-Méndez and M. Fernández-Gavilanes presented an intelligent banking chatbot that applies artificial intelligence techniques to automate customer communication and improve digital banking services [1]. The proposed conversational system was designed to understand customer requests and provide appropriate responses without requiring continuous assistance from human representatives. Their research focused on enhancing customer interaction by reducing response time and improving the quality of banking support through automated conversations. The chatbot was capable of handling routine banking queries, allowing customers to obtain information related to banking services quickly and efficiently. The study also emphasized the importance of conversational intelligence in reducing operational costs while maintaining consistent customer support. The authors observed that integrating artificial intelligence into banking systems can improve service availability and increase customer satisfaction. Their work demonstrated that chatbot-based solutions offer a practical approach for modern financial institutions seeking to deliver reliable, scalable, and user-friendly customer assistance through digital platforms while minimizing manual intervention in day-to-day banking operations [1].

IBM Cloud Education explained the architecture and working principles of chatbot technology as an important application of artificial intelligence and natural language processing for customer service automation [8]. The report described how conversational agents interpret user input, analyze intent, and generate suitable responses using machine learning and language processing techniques. It highlighted the increasing adoption of chatbots in banking, healthcare, education, retail, and other service industries because of their ability to provide continuous support throughout the day. The study further discussed how intelligent virtual assistants improve customer engagement by offering immediate responses to frequently asked questions while reducing dependence on human service representatives. The report emphasized that chatbot systems improve operational efficiency, reduce waiting time, and provide consistent information across multiple communication channels. It concluded that conversational AI has become an essential technology for organizations aiming to enhance customer experience while lowering service costs and supporting the growing demand for digital transformation across various business sectors [8].

G. S. N. Parvin and K. F. F. Farida proposed a chatbot service framework that enables users to communicate with an automated system through a simple web-based conversational interface [9]. Their work focused on improving communication efficiency by allowing users to submit natural language queries and receive instant responses without requiring manual assistance. The proposed system demonstrated how conversational interfaces simplify information retrieval by reducing the complexity of traditional search mechanisms. The authors highlighted that chatbot technology can significantly improve user experience by delivering quick and accurate responses to common requests. They also discussed the importance of maintaining an interactive environment that supports continuous communication between users and intelligent software applications. Experimental observations indicated that chatbot-based systems reduce response delays while improving accessibility and customer satisfaction. The study concluded that intelligent conversational systems provide an efficient solution for organizations seeking to automate customer interaction, improve service quality, and reduce operational workload using modern artificial intelligence technologies [9].

S. Ancy introduced an online learning model based on diverse ensemble classifiers to improve

prediction performance in environments where data patterns continuously change over time [14]. The research addressed the challenge of concept drift by combining multiple machine learning algorithms to create a more adaptive classification model. Instead of depending on a single learning technique, the proposed approach utilized ensemble methods to improve classification accuracy and system reliability under dynamic conditions. The study demonstrated that combining different classifiers enables intelligent systems to adapt more effectively to evolving datasets while maintaining stable prediction performance. The author emphasized that adaptive learning techniques are particularly useful in applications requiring continuous updates and real-time decision making. Experimental results showed that ensemble-based models achieved better accuracy than conventional single-model approaches. The research suggested that intelligent learning methods can enhance the performance of AI-based applications, including customer support systems, recommendation engines, and conversational agents operating in rapidly changing digital environments [14].

T. Sethukarasi, S. Neelakandan, M. Prakash, and E. Baburaj proposed an Efficient Hybrid Job Scheduling Optimization (EHJSO) approach for improving resource allocation and execution efficiency in cloud computing environments [13]. Their research combined Cuckoo Search and Grey Wolf Optimization algorithms to achieve better scheduling performance while minimizing processing time and improving resource utilization. The proposed optimization framework effectively managed computational resources by selecting optimal execution paths for cloud-based applications. The authors demonstrated that hybrid optimization techniques outperform conventional scheduling approaches by reducing execution delays and improving overall system throughput. Their findings highlighted the importance of cloud optimization in supporting intelligent applications that require high computational performance and scalability. The study concluded that efficient resource scheduling plays a significant role in enhancing the reliability and responsiveness of cloud-based artificial intelligence systems. These optimization techniques provide a strong foundation for deploying large-scale applications such as banking chatbots, where fast response time and efficient resource management are essential for delivering high-quality customer services [13].

III.DATASET DETAILS

The proposed **Smarter Banking Chatbot** utilizes a structured banking question–answer dataset to train machine learning models for generating accurate responses to customer queries. Unlike rule-based chatbot systems that depend solely on predefined responses, the proposed application employs a supervised learning approach in which the dataset consists of banking-related questions and their corresponding answers. Initially, the administrator prepares and manages the training dataset by including frequently asked questions covering various banking services such as account management, loans, deposits, internet banking, debit and credit cards, fund transfers, and other customer support topics. These records are stored in the system database and are used to train multiple machine learning algorithms, including Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The administrator can update, modify, or expand the dataset whenever new banking services or customer queries arise, allowing the chatbot to improve its knowledge continuously. This structured repository ensures efficient storage, retrieval, and maintenance of training data while supporting accurate prediction of customer queries and reliable chatbot performance.

During system operation, the trained dataset is used to process user queries and generate appropriate responses through the chatbot interface. After successful user authentication, customers can submit banking-related questions in natural language using the web application. The input query undergoes preprocessing and feature extraction before being compared with the knowledge learned from the training dataset. Based on the trained classification model, the chatbot predicts the most relevant answer and immediately presents it to the user. The application also records each user interaction, including submitted questions, generated responses, and interaction timestamps, allowing administrators to monitor chatbot usage and analyze system performance. Experimental evaluation compares the prediction accuracy of Random Forest, Support Vector Machine, and K-Nearest Neighbors classifiers, with Random Forest achieving superior performance for the given banking dataset. The organized management of training records and user interactions enables the proposed system to provide reliable customer assistance, efficient information retrieval, and continuous improvement of banking services through machine learning-based conversational intelligence.

IV.PROPOSED METHODOLOGY

The proposed Smarter Banking Chatbot is developed to provide an intelligent and automated customer support system by integrating machine learning with a web-based conversational interface. The methodology consists of four major stages: data preparation, model training, customer interaction, and response prediction. Initially, the administrator securely logs into the application and manages the banking question–answer dataset containing

frequently asked customer queries and their corresponding responses. The collected dataset undergoes preprocessing, including text cleaning, tokenization, removal of unwanted symbols and stop words, and feature extraction to convert textual information into numerical representations suitable for machine learning models. The processed data is then divided into training and testing datasets for performance evaluation. Three supervised machine learning algorithms, namely Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), are trained using the prepared dataset. Comparative analysis is performed to identify the most suitable classifier, and experimental results indicate that the Random Forest algorithm achieves the highest prediction accuracy due to its ensemble learning capability and robustness in handling diverse customer queries. Therefore, Random Forest is selected as the primary prediction model for the proposed chatbot.

During system operation, registered users access the chatbot through a secure login interface and submit banking-related questions using the web application. Each user query undergoes the same preprocessing steps before being forwarded to the trained Random Forest classifier. The classifier evaluates the input using multiple decision trees and predicts the most appropriate response through a majority voting mechanism, resulting in accurate and reliable answers. The predicted response is immediately displayed to the customer, while all user interactions are securely stored in the database for monitoring and future model improvement. The proposed methodology significantly reduces manual customer support efforts while providing fast, consistent, and scalable banking assistance. By emphasizing the Random Forest algorithm, the system achieves higher prediction accuracy, improved reliability, and enhanced customer satisfaction, making it suitable for modern digital banking environments.

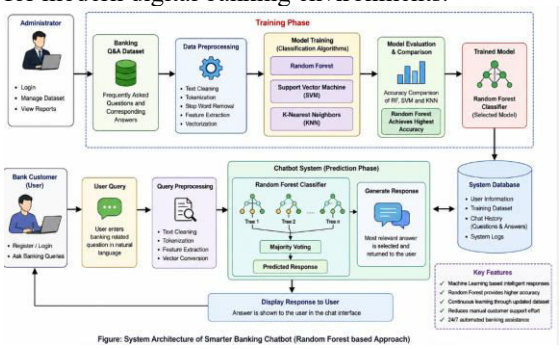

Figure: System Architecture of Smarter Banking Chatbot (Random Forest based Approach)

Figure 1: System Architecture of the Proposed Smarter Banking Chatbot Using Random Forest

Figure 1 presents the overall architecture of the proposed Smarter Banking Chatbot, which integrates machine learning, web-based communication, and database management to provide automated banking assistance. The architecture consists of two primary components: the training phase and the prediction phase. During the training phase, the administrator manages the banking question-and-answer dataset and performs preprocessing operations such as text cleaning, tokenization, stop-word removal, and feature extraction. The processed dataset is then used to train multiple machine learning algorithms, including Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The performance of these models is evaluated using classification metrics, and the Random Forest classifier is selected because it provides the highest prediction accuracy. The trained model and related information are stored in the system database for future use. During the prediction phase, registered customers submit banking-related queries through the chatbot interface. Each query undergoes preprocessing before being forwarded to the trained Random Forest model, which predicts the most relevant response using an ensemble of decision trees and a majority voting mechanism. The generated response is immediately displayed to the customer, while all user interactions are securely recorded in the centralized database for monitoring and future model improvement. The proposed architecture provides an intelligent, scalable, and reliable banking support system that delivers accurate responses, reduces manual customer service effort, and enhances the overall digital banking experience through efficient machine learning-based automation.

V.RESULT AND DISCUSSION

The proposed Smarter Banking Chatbot was successfully implemented and evaluated using a web-based application integrated with a structured database and machine learning techniques. The developed system successfully performed all major operations, including administrator authentication, user registration, dataset management, machine learning model training, chatbot interaction, and conversation monitoring. During system evaluation, the administrator was able to upload and maintain the banking question-and-answer dataset, train multiple machine learning algorithms, compare their performance, and monitor user interactions through a centralized interface. The application evaluated the performance of Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) classifiers using the prepared banking dataset. Among the evaluated models, the Random Forest algorithm achieved the highest prediction accuracy and was selected as the final classification model for chatbot response generation. Registered users successfully logged into the application, submitted banking-related questions through the chatbot interface, and received relevant responses in real time. All customer queries and chatbot responses were securely stored in the database, allowing

administrators to analyze user interactions and improve the knowledge base whenever required.

Experimental analysis demonstrated that the proposed chatbot provided accurate and consistent responses with minimal processing delay, resulting in a smooth and interactive user experience. The preprocessing module effectively transformed customer queries into suitable feature representations, enabling the Random Forest classifier to identify the most appropriate response through its ensemble decision-making mechanism. Compared with Support Vector Machine and K-Nearest Neighbors, the Random Forest model produced superior classification performance and better handled variations in customer queries. The web-based interface provided a simple and user-friendly environment for both administrators and customers, while the centralized database ensured efficient storage and retrieval of user details, training datasets, conversation history, and system logs. Overall, the developed chatbot offers a reliable, scalable, and cost-effective solution for automated banking customer support. By combining machine learning with conversational technology, the system reduces manual customer service effort, improves response accuracy, and enhances customer satisfaction, making it suitable for deployment in modern digital banking environments.

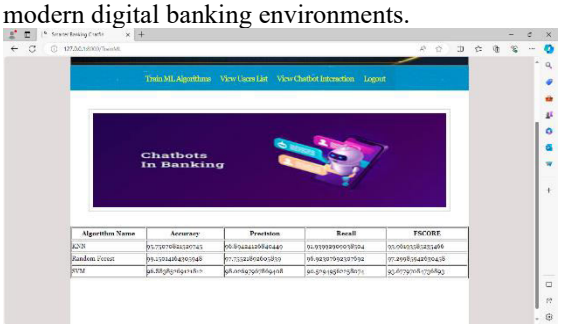

Figure 2: Performance Comparison of Machine Learning Algorithms

Figure 2 illustrates the performance comparison of the three machine learning algorithms used in the proposed Smarter Banking Chatbot, namely K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM). The comparison is carried out using four standard evaluation metrics: Accuracy, Precision, Recall, and F1-Score. From the experimental results, the Random Forest classifier achieves the highest performance across all evaluation metrics, outperforming both KNN and SVM. The higher accuracy of the Random Forest model demonstrates its ability to classify banking-related customer queries more effectively by combining the predictions of multiple decision trees through an ensemble learning approach. Similarly, the Precision, Recall, and F1-Score values indicate that Random Forest produces more reliable and balanced predictions with fewer classification errors. Although SVM also provides competitive performance, its prediction accuracy is slightly lower than that of Random Forest. The KNN classifier records the lowest performance among the three evaluated models, indicating that it is less suitable for handling diverse banking queries in the given dataset. Based on this comparative analysis, the Random Forest algorithm is selected as the final prediction model for the proposed banking chatbot because it offers superior classification accuracy, better generalization capability, and more consistent response generation. These experimental findings confirm that the proposed system can provide accurate, reliable, and efficient customer support, making Random Forest the most appropriate machine learning technique for intelligent banking conversational applications.

Figure 3: Banking Chatbot Response Interface

Figure 3 illustrates the Banking Chatbot Response Interface, where registered users interact with the proposed chatbot by entering banking-related queries through a web-based conversational window. The interface displays both the customer's questions and the chatbot's corresponding responses in a sequential conversation format, providing an interactive and user-friendly communication environment. When a customer submits a banking query, the input is preprocessed and forwarded to

the trained Random Forest classifier, which analyzes the query and predicts the most relevant response based on the banking question–answer dataset. The generated response is immediately displayed within the chat window, allowing users to obtain banking information without waiting for assistance from customer service personnel. The figure demonstrates that the chatbot successfully answers multiple banking-related questions, including queries associated with business loans, account opening, debit cards, and banking services. The conversation history remains visible throughout the session, enabling users to review previous interactions whenever required. This interactive interface enhances customer engagement by providing accurate, consistent, and real-time responses while reducing manual support effort. The experimental implementation confirms that the chatbot delivers reliable responses with minimal processing delay, making the proposed system an efficient and practical solution for intelligent customer assistance in modern digital banking environments.

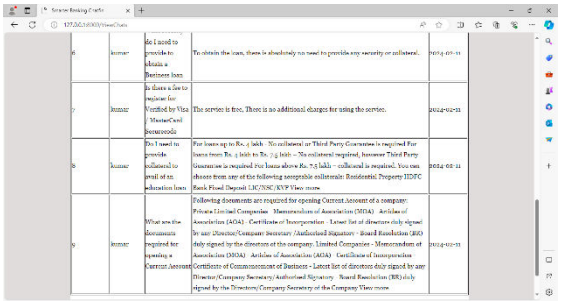

Figure 4: Chatbot Interaction History Management

Figure 4 presents the Chatbot Interaction History maintained by the administrator in the proposed Smarter Banking Chatbot. The interface displays a comprehensive record of customer conversations, including the user's name, submitted banking queries, chatbot-generated responses, and the corresponding interaction date. Every customer request processed by the chatbot is automatically stored in the centralized database, allowing administrators to monitor chatbot performance and review previous interactions whenever required. The recorded conversations help identify frequently asked banking questions, evaluate the quality of generated responses, and improve the training dataset by incorporating new customer queries. This feature also assists administrators in detecting incorrect or incomplete responses, enabling periodic retraining of the Random Forest classifier to improve prediction accuracy. By maintaining a complete conversation history, the system supports transparency, efficient record management, and continuous performance evaluation of the chatbot. The centralized storage mechanism ensures secure retrieval of interaction records without data loss while simplifying administrative monitoring. The experimental implementation demonstrates that the chatbot successfully logs every customer interaction with minimal processing overhead, providing a reliable mechanism for performance analysis, customer support auditing, and future enhancement of the intelligent banking assistance system.

DISCUSSION

The proposed Smarter Banking Chatbot provides an intelligent and efficient platform for delivering automated customer support by combining machine learning techniques with a web-based conversational interface. The system integrates administrator management, user authentication, banking dataset management, machine learning model training, and real-time chatbot interaction within a single application. The administrator module enables secure management of users, training datasets, and chatbot activities, while the customer module allows registered users to submit banking-related queries and receive immediate responses. A centralized database stores user information, banking question-and-answer records, conversation history, and system logs, ensuring reliable data management and easy retrieval. Among the evaluated machine learning algorithms, Random Forest demonstrated superior prediction performance compared with Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). Its ensemble learning approach effectively handled variations in customer queries and generated more accurate responses, making it the most suitable

model for deployment in the proposed chatbot. The integration of intelligent response generation with an easy-to-use web interface improves customer engagement while significantly reducing the dependence on manual customer support services.

The experimental implementation confirms that the developed chatbot successfully performs all major functionalities, including secure user registration, administrator authentication, machine learning model training, real-time query processing, response prediction, and interaction monitoring. The preprocessing module efficiently converts customer queries into meaningful feature representations, allowing the trained Random Forest classifier to identify the most appropriate response with high accuracy and minimal response time. The centralized database enables efficient storage and management of training data and conversation records, supporting future system improvements through continuous dataset updates and model retraining. The web-based interface provides a simple and interactive environment for both administrators and customers, making the application easy to operate without requiring specialized technical knowledge. Overall, the proposed framework offers a reliable, scalable, and cost-effective solution for intelligent banking customer support. Its ability to provide accurate responses, continuous availability, and efficient customer interaction makes it well suited for deployment in modern banking institutions seeking to enhance digital services, improve operational efficiency, and deliver a better customer experience through artificial intelligence-driven automation.

VI.CONCLUSION

The proposed Smarter Banking Chatbot offers an intelligent, reliable, and efficient solution for automating customer support services in the banking sector. By integrating machine learning with a web-based conversational platform, the system enables customers to obtain instant responses to banking-related queries without depending on customer service representatives. The developed application combines administrator management, user authentication, banking dataset maintenance, machine learning model training, and real-time chatbot interaction within a unified framework. Comparative evaluation of multiple classification algorithms demonstrated that the Random Forest algorithm achieved the highest prediction accuracy, making it the most suitable model for generating accurate and consistent responses. The centralized database efficiently manages user information, banking question–answer datasets, conversation history, and system records, ensuring secure data storage and efficient information retrieval. Experimental implementation confirmed that the chatbot successfully performs customer query processing, response prediction, interaction monitoring, and model management with minimal response time and reliable performance. The simple architecture, scalability, and cost-effectiveness of the proposed system make it suitable for deployment in banks and other financial institutions seeking to improve customer engagement and reduce operational workload. Future enhancements may include incorporating advanced natural language processing techniques, multilingual conversation support, voice-enabled interaction, cloud-based deployment, continuous learning from customer feedback, integration with banking APIs for personalized services, sentiment analysis, and stronger authentication mechanisms to further improve the accuracy, security, and overall effectiveness of intelligent banking assistance systems.

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