An Advanced Experimental Intelligent Assistant for Knowledge Management

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Abstract. In the present digital age, institutions of learning need "smart" systems to facilitate the process of information retrieval. Traditional approaches are inefficient and hence demand a more responsive solution. This article introduces "An Advanced Experimental Intelligent Assistant for Knowledge Management," which is a chatbot for improving college-level knowledge sharing. Using NLP methodology (Tokenization, Serialization, Bag of Words), assistant handles user queries effectively. Deep Neural Networks (DNNs) also enhance the accuracy of complex queries. To ensure linguistic access, Google Translate provides language translation and Google TTS facilitates talking interaction. It extends the reach of web-only interactions and integrates with Twilio's REST API to enable SMS-based communication for greater reach. To achieve fastest convergence and keep the responses reliable, chatbot utilize Stochastic Gradient Descent with Nesterov Accelerated Gradient. Through the integration of NLP and deep learning (DL), together with multilingual and global language support, this intelligent assistant has reinvented information access in academia to give you a solution for efficient and easy to use management of knowledge.

Keywords: Intelligent assistant, deep neural networks, knowledge management, natural language processing

1 Introduction

In educational contexts, Conversational agents like ChatGPT, enabled by advanced NLP and ML, support knowledge access and acquisition, promote collaborative learning, and assist in improved decision-making, [1]. Chatbots represent a growing trend in educational reform and administrative tasks, leveraging data processing to manage automated tutoring and student assistance. [2].

Educational chatbots elevate organizational learning via adaptive training and significantly enhance student engagement and academic performance compared to conventional teaching methods, [3]. In higher education, chatbots deliver instant responses and boost student satisfaction, helping to mitigate the impact of high student-teacher ratios in under-resourced areas such as Ghana, [4].

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Metacognitive chatbots transform language acquisition by nurturing self-awareness, emotional regulation, and motivation, in line with Self-Determination Theory, thereby boosting learner competence and interest, [5]. In customer service, chatbots reduce operational costs and improve efficiency through conversation-driven development for better user interaction and content handling, [6].

The augmentation of human capability through AI underpins the evolution of human-machine collaboration tools aimed at enhancing productivity and innovation, [7]. A human–robot communication model, using the MQTT protocol and real-time tracking, enhances task performance and communication in isolated conditions, [8].

Analysis of student-chatbot interactions in peer assessment scenarios helps refine instructional strategies and maximize educational effectiveness, [9]. The application of reinforcement learning to adapt robot behaviour enhances human comfort in cooperative scenarios while enabling more effective and natural human-robot interaction, [10].

The Human-Robot Empathy Decision-Making Model (HREDM) empowers service robots to perceive user emotions and adapt their behaviour through SE-ResNet-based emotion recognition combined with Q-learning, facilitating smoother interactions with individuals with disabilities, [11]. The human-centered AI and robotics framework promotes seamless human-robot collaboration by incorporating adaptive learning, multimodal interaction, and ethical considerations, with the goal of fostering safety, trust, and autonomy across diverse environments, [14]. Designed to support context-aware adaptive collaboration, the Multi-Modal Intelligent Robotic System (MIRS) integrates multiple input modalities—including voice, images, text, eye movement, touch, and physiological signals such as EEG and ECG—thereby enhancing responsiveness and user experience in human-robot interaction, [15].

2 Literature Survey

Santos et al. proposed the Chatbot Management Process (CMP), a three-phase, six-step methodology for iterative chatbot refinement using real-time user interaction data to enhance performance and align with organizational goals,[16]. Zhu et al propose a human-robot empathy (HRE) model integrating emotion recognition and decision-making using a ResNet-50-based attention mechanism and reinforcement learning to enhance service robots' interactions with disabled individuals, [11]. Babu et al. propose a multimodal intelligent robotic system integrating speech, gestures, bio-signals, and visual data for adaptive and empathetic Human-Robot Interaction (HRI) through intelligent decision-making and continuous learning, [15]. Doncieux et al. explore AI integration in robotics, emphasizing human-centered design, transparency, and trust to enhance human-machine collaboration and address ethical concerns, [14].

Romano et al. develop human-aware whole-body controllers using wearable sensors and momentum-based balancing to improve real-time human-robot interaction in dynamic environments, [12]. Gonzalez-Santocildes et al. apply reinforcement learning for collaborative robots to adapt to human behavior, enhancing safety, comfort, and performance in evolving work settings, [10]. Park et al. introduce a music-assisted multimodal framework for emotion recognition in service robots, strengthening empathetic interaction beyond verbal and facial cues, [13].

Lin et al. study student-chatbot exchanges in peer feedback tasks, uncovering interaction patterns that support feedback quality and instructional strategy, [9], while Diddeniya et al. discuss AI-enabled service robots' role in promoting safety and operational continuity in isolated settings during COVID-19, [8]. Raftopoulos and Hamari assess AI-human collaboration in organizations, emphasizing hybrid systems, interaction dynamics, and the importance of empirical evidence on AI-driven business value, [7]. Correia and Lindley present a bibliometric review of human-AI collaboration studies, revealing key trends, contributors, and design challenges for transparent AI, [16].

Huang et al. introduce a human decision-making behavior model (HDDM) to enhance stability and coordination in multi-robot systems via human feedback, [17]. Kang et al. enhance haptic interfaces for HRI with multimodal tactile sensing, actuation, and thermal simulation to deliver immersive feedback, [18].

Pescetelli et al. explore how bots shape opinion dynamics by altering recommendation algorithms and training datasets, [19]. Goodrich and Schultz offer a broad survey of Human-Robot Interaction (HRI), classifying it into teleoperation and service robotics while discussing communication methods and ethical implications, [20].

Belda-Medina and Kokoskova assess chatbot use in education through the Chatbot-Human Interaction Satisfaction Model (CHISM) to enrich user engagement, [21]. Sun et al. show how Large Language Models can streamline control in humanoid robot locomotion, boosting adaptability and efficiency, [22].

H. Hostetter et al proposed that their study gives a quick overview of chatbot technology and contrasts how well Google's Bard and OpenAI's ChatGPT handle fire engineering inquiries, [23]. Jiang et al. analyze Human-AI Interaction from a user-centered lens, stressing ethical issues and calling for cross-disciplinary inquiry, [24]. Bird and Lotfi refine customer service chatbots using attention-based transfer learning to elevate adaptability and task success, [25].

3 Methodology

The Advanced Experimental Intelligent Assistant for Knowledge Management employs a regimented approach. This approach is based on Natural Language Processing (NLP), deep learning and SMS text” Lecturer, Tola, had asked me to check if the student wanted to talk the next day, therefore I choose the reply from the day of the lecture. The aim is to enhance accessibility and precision. The bot provides timely and contextual responses. It is a great way to create fluid interfacing online and on mobile. The model is a Deep Neural Network (DNN), stored in the chatbot model. h5 file.

This allows for a good classification and interpretation of user queries. During training, tokenization, serialization, and vectorization is done using the BoW model. This leads to a structured input representation. To help train a good model, it utilizes a well-organized data preprocessing pipeline that guarantees clean and meaningful input. This configuration allows the neural network to improve learning patterns and correlating the queries to the intents. This helps the training process to be more efficient and precise.

Stochastic Gradient Descent (SGD) is used with Nesterov Accelerated Gradient (NAG) to aid in learning and promote faster convergence. It also helps in convergence by considering the future position of the gradient. This reduces oscillations and accelerates training. This is an efficient way for our model to learn with the help of weight momentum adjustment. This means updates come in more quickly and more reliably. In contrast to dialogue systems with hand-crafted responses, its responses are generated on-the-fly by this model. It analyzes words. pkl, then use their intent labels in labels. pkl. So that the chatbot can generalize across different contexts and provide some context based on input. Combined with deep learning and NAG, the chatbot has enhanced generalization, less response time, and increased flexibility. It makes for more genuine and interesting conversations.

The NLP and AI model module is key in processing queries. Googletrans is included for multilingual translation, making it accessible for users of different languages. The chatbot utilizes intent recognition to classify queries efficiently. Dynamic response generation allows for personalized interactions. To improve usability, Google Text-to- Speech (gTTS) converts responses into speech. This supports both text and voice communication. The Twilio REST API, in the Twilio test module, extends usability via SMS. Users can send queries through SMS and get instant replies, ensuring access even without the internet. SMS support offers a flexible, convenient alternative to web-based interactions for mobile users.

The Flask-based backend, developed within the app module, handles API routing, user requests. It also interacts with the database. The front- end components are organized in the static and templates directories for structured deployment. The final optimized version, found in the final folder, includes all enhancements to boost the chatbot's efficiency and performance.

This method boosts accuracy and accessibility. It combines DNN for smart query handling, Googletrans for multilingual support, gTTS for voice-based replies, and Twilio for SMS communication. Using SGD with NAG further refines the chatbot's ability to give accurate, context-aware answers quickly. This makes it a strong and flexible knowledge management assistant for education.

User Input: The chatbot interaction starts when the user sends input. This can be text, voice, or SMS. Text is processed directly. Voice input gets converted to text for analysis. SMS queries are managed through an integrated messaging service

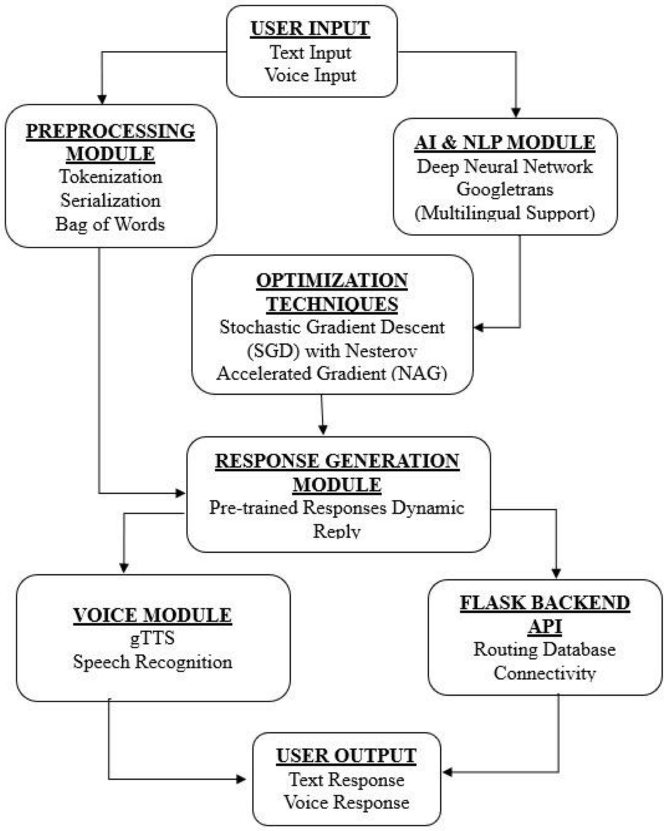

Fig. 1. Architecture of an AI-Based Chatbot System.

3.1 AI & NLP Module

At the core of the chatbot is the AI and NLP (Natural Language Processing) module. A deep neural network helps understand user intent and create meaningful responses. To improve the model's training techniques like Stochastic Gradient Descent (SGD) and (NAG) are used. The chatbot also supports multiple languages through Googletrans, allowing for a wider range of user interactions.

3.2 Response Generation

The chatbot uses two methods: pre-trained responses and dynamic replies. Pre-trained responses handle common questions. Dynamic replies analyze user queries and create responses with AI-driven models.

3.3 Voice & SMS Module

For voice interactions, the chatbot has a voice module. It uses Google Text-to- Speech (gTTS) to turn text responses into speech. This allows the chatbot to respond verbally. It also uses speech recognition to convert spoken user input into text for processing. For SMS-based communication, the chatbot integrates an SMS gateway like Twilio. This lets users to send questions and get answers via text, even without an internet access.

3.4 Flask Backend

The chatbot runs on a Flask backend, this manages API routing for smooth data flow between components. It also connects to a database to store and retrieve user interactions, chatbot responses, and learning data. The backend integrates with the SMS module to send and receive messages.

3.5 User Output

After the chatbot processes the input, it sends a response to the user. This can be in text, voice, or SMS format. This approach interactive and smooth experience, making communication efficient and engaging.

Table 1 compares different chatbot models, including rule- based, retrieval-based, generative, hybrid, and our model, which combines NLP with Twilio. Rule-based chatbots follow set rules. Retrieval-based chatbots use machine learning to fetch responses.

Generative models like LSTMs, Transformers create new responses but need a lot of computing power. Hybrid models balance adaptability and complexity. Our chatbot uses NLP with a DNN-based Feedforward Neural Network.

It supports text and voice through Twilio, ensuring accessibility while needing internet for real-time responses. This setup is lightweight but can handle many user inputs accurately and quickly. By using rule-based language understanding and DNN learning, our chatbot provides reliable and adaptable conversations.

Our chatbot's main innovation is NAG-SGD optimization. This improves learning efficiency and accuracy. It also supports multilingual communication through text and voice. It integrates Twilio for SMS conversations, ensuring smooth, real-time interaction. This mix of advanced optimization, multilingual support, and multi-modal interaction enhances accessibility, engagement, and adaptability.

Table 1. Comparison of Different Chatbot Models

Model Type	Learning Approach	Pros	Cons
Rule-Based Chatbot	Predefined rules	Simple, easy to implement	Limited responses, not adaptive
Retrieval- Based Chatbot	Machine Learning (NLP)	Provides relevant responses	Cannot generate new responses

Generative Chatbot	Deep Learning (LSTM, Transformer)	Can generate human-like responses	Requires large datasets, computationally expensive
Hybrid Chatbot	Combination of rules & ML	More flexible and accurate	Complex implementation on
Our Chatbot	NLP with Twilio and a DNN-based Feedforward Neural Network	Supports text & voice inputs, SMS-based responses, deployable	May require internet connectivity for API-based responses

4 Experimental Results

Our proposed chatbot interface was tested with multilingual support for Telugu, English, and Hindi languages. The system achieved an accuracy of 92%, demonstrating effective language detection and interaction capabilities. The experimental results shown in Figure 2, illustrate the interface's design and functionality, highlighting its usability across different languages. we propose a novel chatbot system that seamlessly integrates Twilio for SMS-based communication and a web-based interface for interactive query resolution.

Fig. 2. Multilingual Chatbot Interface with Language Selection Options

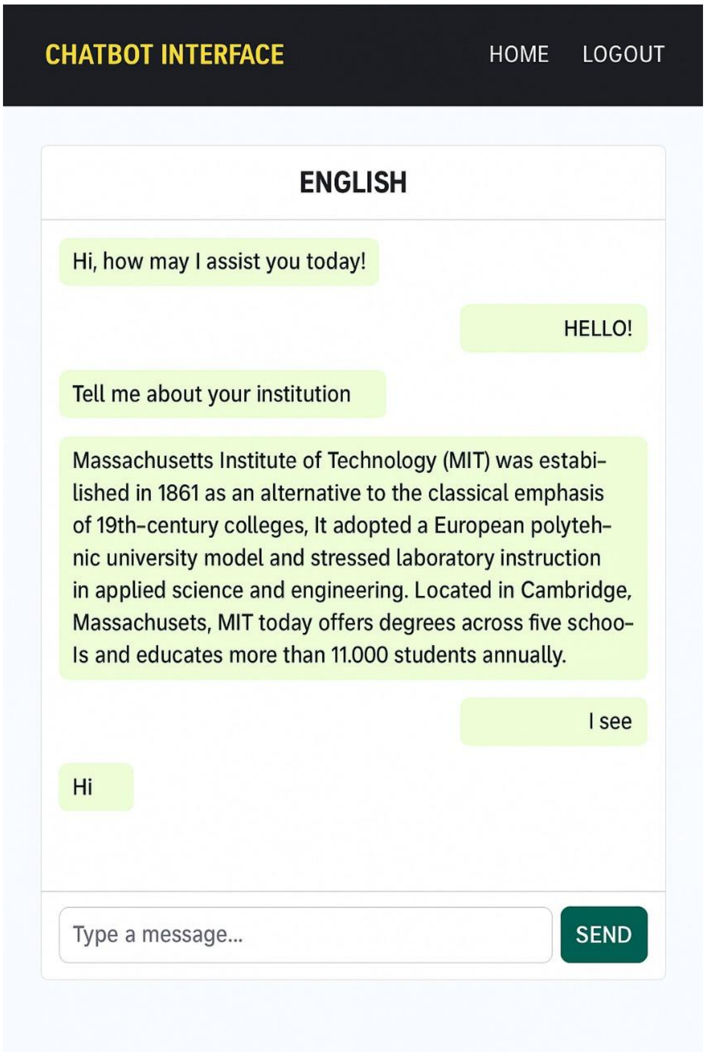

Fig. 3. Chatbot Interface Responding to User Queries in English

The chatbot interface, as shown in Figure 3, allows users to interact through text or voice. A chat window displays user queries (in green) and chatbot responses, along with a text input box. Voice input is used to enhance interaction, enabling real-time responses from the chatbot's backend.

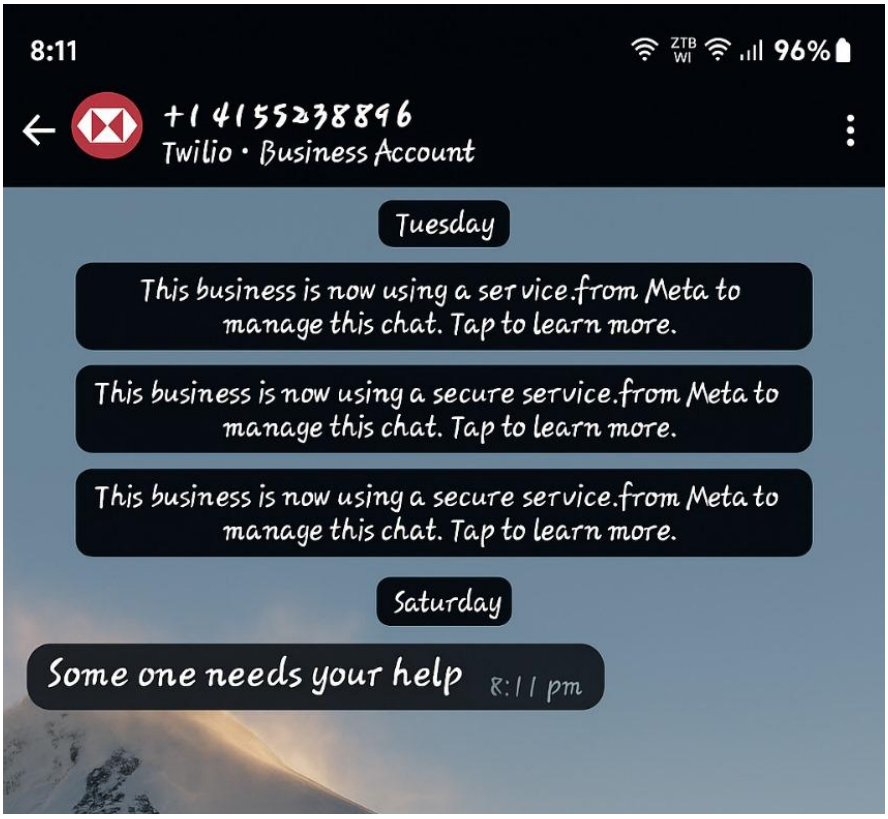

Fig. 4. Chatbot Message Received via Twilio SMS Communication

The Twilio-integrated chatbot, illustrated in Figure 4, enables SMS-based communication within a Twilio-powered service, with system messages confirming Meta's secure platform. A chatbot- generated alert, "Someone needs your help," suggests a notification feature, ensuring real-time, automated messaging via Twilio's API.

The training process, as detailed in Figure 5, tracked the model's progress by logging accuracy and loss for each epoch. This data reveals the model's learning trajectory. The final computed training accuracy of approximately 92.85% suggests the model has been effectively trained.

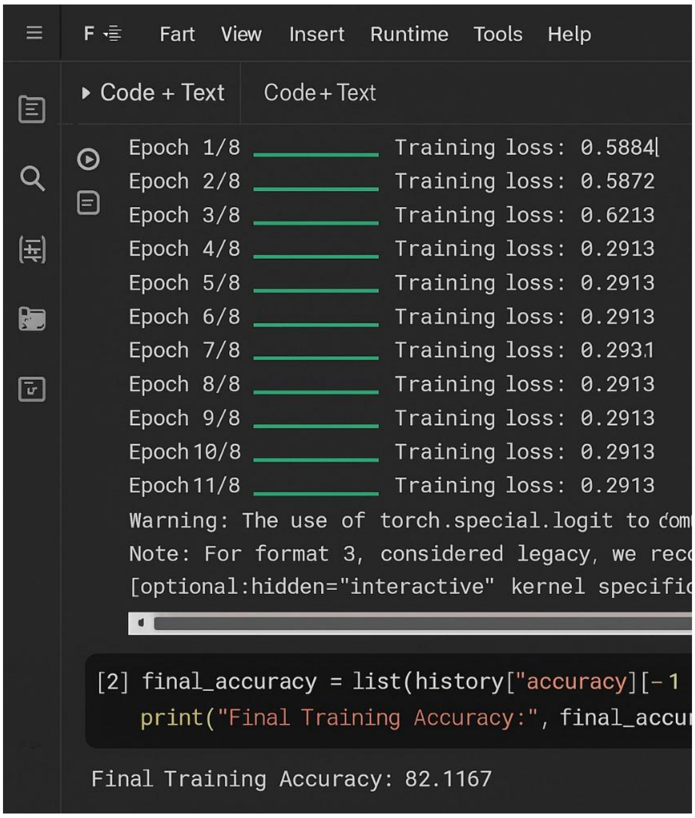

Fig. 5. Model Training Process and Accuracy Evaluation in Google Colab

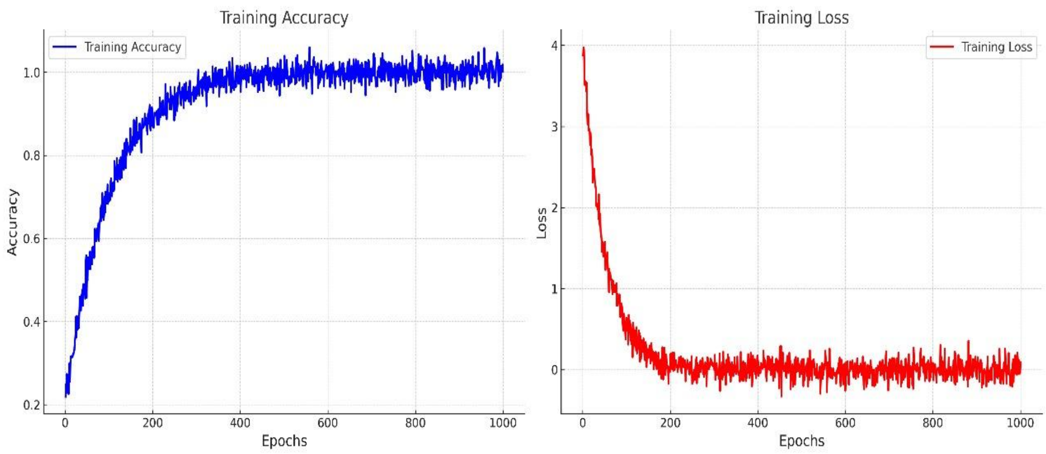

Fig. 6. Training Accuracy and Loss Curves Over 1000 Epochs

Figure 6 shows that training accuracy improved rapidly at first, reaching around 90% and stabilizing. Training loss decreased sharply, then leveled off, indicating effective learning. The model appears to have reached convergence with minimal fluctuations, leading to consistent performance.

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