AI-Driven Chatbot for Medical Query Resolution Using LSTM and Real-Time Language

VALLURI PRAVALLIKA[1], VANKAYALAPATI JAHNAVI[2], SHAIK RESHMA[3], SHAIK NAGULMEERA[4],Mr.Dr.K.VIJAYA LAKSHMI[5]

Electronics & communication engineering, Chalapathi Institute of Engineering & Technology, LAM, Guntur Andhra Pradesh[1,2,3,4,]

[5]Assistant Professor *Electronics & communication engineering, Chalapathi Institute of Engineering & Technology, LAM, Guntur,Andhra Pradesh.*

Abstract— **An AI-powered multilingual healthcare chatbot is introduced, supporting both voice and text-based interactions to predict and respond to infectious disease-related queries. Leveraging Long Short-Term Memory (LSTM) neural networks, the system intelligently interprets user inputs and delivers medically relevant responses with high accuracy. To break linguistic barriers, the chatbot integrates Google Translate API, enabling real-time communication in English and Telugu, with scalability for additional languages. The proposed architecture comprises modules for speech recognition, natural language processing (NLP), bilingual translation, user authentication, chat history management, and a cloud-based backend for scalable deployment. Voice-to-text functionality makes the chatbot especially accessible for users with limited literacy or technical skills. Trained on a curated COVID-19 dataset, the LSTM model achieved a training accuracy of 99%, while performance testing confirmed fast and reliable response generation across modalities. The system offers a privacy-conscious, scalable solution that enhances healthcare accessibility in multilingual and underserved regions. Future enhancements include support for more languages, integration with electronic health records (EHRs), and the application of advanced NLP techniques for improved context handling and adaptive learning.**

Keywords— Artificial Intelligence (AI), Medical Chatbot, Infectious Disease Prediction, Long Short-Term Memory (LSTM), Text and Voice-Based Interaction, Multilingual Support, Healthcare Accessibility..

I. Introduction

Access to timely and accurate medical information is a cornerstone of modern healthcare, yet millions across the globe continue to face barriers due to language differences, geographical isolation, and limited access to healthcare professionals. The emergence of Artificial Intelligence (AI) has revolutionized this landscape, offering intelligent systems capable of delivering healthcare guidance, triaging symptoms, and supporting patients in real-time. Among these innovations, AI-powered chatbots are proving to be powerful tools for bridging communication gaps and enhancing medical accessibility.The need for responsive and inclusive healthcare solutions became even more evident during the COVID-19 pandemic, which strained healthcare infrastructures worldwide. In many cases, patients lacked immediate access to professional help, particularly in remote or linguistically diverse regions. A healthcare chatbot capable of understanding and responding to medical queries in multiple languages—while supporting both voice and text interaction—offers a scalable and efficient way to deliver essential information and guidance.

This work presents a voice- and text-enabled medical chatbot powered by deep learning, specifically Long Short-Term Memory (LSTM) networks, for accurate prediction and handling of infectious disease-related queries. The chatbot is trained on a curated dataset focused on COVID-19 and similar health concerns, ensuring high relevance and accuracy. To overcome language barriers, the system integrates Google Translate API, supporting real-time bilingual interaction in English and Telugu, with a flexible architecture to support additional languages in the future.

Unlike traditional rule-based bots, the proposed system utilizes deep learning for improved understanding of context and intent, making it capable of generating meaningful and contextually relevant responses. The chatbot supports both spoken and typed input, offering enhanced usability for the elderly, visually impaired, or users with low literacy. A user-friendly interface, secure cloud backend, and chat history tracking further improve the experience and reliability of the system.

Key features of the chatbot include multilingual translation, voice-to-text processing, NLP-driven query interpretation, and scalable architecture. The system is designed to augment, not replace, medical professionals—serving as a first point of contact for medical information and helping to reduce the load on healthcare infrastructure.

This research aims to contribute a scalable, privacy-aware, and user-friendly chatbot model that can deliver essential health information across language and literacy barriers. Future extensions will explore integration with electronic health records (EHRs), more advanced NLP techniques for conversational depth, and broader support for regional and global languages.

Doi:10.48047/ijiee.2025.15.3.6

The increasing complexity of global healthcare demands scalable, intelligent, and accessible solutions to meet the growing needs of diverse populations. With limited healthcare personnel, rising patient loads, and the recent impact of pandemics like COVID-19, the integration of Artificial Intelligence (AI) into healthcare systems has become not just beneficial, but essential. Among the most impactful applications of AI in healthcare are chatbot systems, which can provide automated support, medical triage, and real-time health guidance, especially in regions where access to healthcare professionals is constrained.Traditional healthcare delivery is often limited by time, geography, language barriers, and human resource availability. Patients in rural or underdeveloped areas may face difficulties in accessing even basic health information due to language constraints or lack of infrastructure. To bridge this gap, AI-driven chatbots present a compelling solution. They can deliver 24/7 support, reduce waiting times, and provide standardized and consistent responses for frequently asked medical questions. However, to be truly effective and inclusive, these systems must support multilingual interaction, voice-based input, and context-aware communication.

This paper proposes a multilingual AI healthcare chatbot that leverages deep learning models, particularly Long Short-Term Memory (LSTM) networks, to process both text and speech-based user inputs for disease-related queries. The model is trained on a focused COVID-19-related Q&A dataset, enabling it to predict user intent and generate medically relevant responses with high accuracy. The system supports bilingual interaction in English and Telugu, with future scope to include additional Indian and international languages. Through integration with the Google Translate API, the chatbot dynamically translates user input and system responses, thereby addressing one of the most significant challenges in healthcare communication: linguistic diversity.In addition to its core natural language processing capabilities, the chatbot system incorporates features such as voice-to-text conversion, user authentication, chat history management, and cloud-based data handling for scalability. The voice interaction capability, powered by speech recognition, makes the system more accessible to users who are not comfortable with typing or reading—especially the elderly and less literate populations. By combining deep learning, cloud computing, and language translation technologies, the system ensures high availability, accuracy, and inclusiveness.

The chatbot's design also emphasizes privacy and security, complying with best practices for handling sensitive health-related data. This is particularly important as AI systems in healthcare must gain user trust while operating within ethical and legal frameworks. The chatbot is not intended to replace medical professionals but to augment healthcare services by acting as a first point of contact, triaging minor symptoms, and guiding users toward reliable health resources.

The proposed chatbot system is designed to overcome these challenges by incorporating advanced AI techniques, cloud-based storage for secure data handling, and multilingual support for broader accessibility. This research aims to contribute to the growing field of AI-driven healthcare solutions by developing a chatbot model that enhances medical consultation efficiency, particularly for infectious disease prediction. The system can be further expanded to support additional medical domains, integrate with electronic health records (EHRs), and provide real-time monitoring of patient health conditions.

The remainder of this paper is structured as follows: Section 2 discusses related work, reviewing existing AI-based medical chatbot models and their limitations. Section 3 presents the proposed methodology, including data preprocessing, model training, and chatbot architecture. Section 4 details the experimental results, evaluating the chatbot's accuracy and performance. Section 5 discusses key findings, limitations, and potential future enhancements. Finally, Section 6 concludes the paper, summarizing the contributions and impact of this research.

II. RELATED WORKS

The study of system architecture and design methodologies has evolved significantly over the years. Several research efforts have explored different frameworks, models, and tools to enhance efficiency, security, and scalability in system design. This section provides a comprehensive overview of previous studies relevant to our research.

The advancement of artificial intelligence (AI) and natural language processing (NLP) has led to significant developments in healthcare applications, particularly in the domain of automated medical assistance. AI-powered chatbots are emerging as powerful tools that enhance patient engagement, provide preliminary diagnoses, and support healthcare professionals by automating routine inquiries. With the rapid proliferation of infectious diseases, an AI-based chatbot system can serve as an efficient and accessible solution for initial screening and guidance.Traditional medical consultation methods often suffer from limitations such as high patient load, limited availability of healthcare professionals, and geographical constraints. To mitigate these challenges, researchers have proposed various AI-driven solutions that integrate machine learning models, particularly deep learning-based architectures, to analyze patient queries and provide reliable responses. The Long Short-Term Memory (LSTM) model, a recurrent neural network (RNN) variant, has demonstrated remarkable performance in processing sequential data, making it a suitable candidate for chatbot development.

In this study, we propose an AI-based medical chatbot model that utilizes the LSTM algorithm to predict and respond to user queries related to infectious diseases. The chatbot is trained on a dataset comprising frequently asked medical questions, enabling it to provide accurate and contextually relevant answers. Additionally, the system supports both text-based and voice-based interactions, ensuring accessibility for a diverse user base. To enhance usability, the chatbot incorporates a bilingual response mechanism, delivering outputs in both English and Telugu through an integrated Google translation API.The implementation of the chatbot involves several key modules, including user authentication, model training,

Doi:10.48047/ijiee.2025.15.3.6

chatbot interaction (voice and text), and history tracking. Users can sign up, log in, train the LSTM model, and interact with the chatbot seamlessly. The training process optimizes the model's accuracy, with performance metrics demonstrating a high level of reliability. Furthermore, the chatbot interface is designed to be intuitive, allowing users to input queries and receive instant responses without requiring extensive technical knowledge.

Despite its advantages, AI-based chatbot systems encounter challenges such as dataset limitations, response accuracy, and dependency on translation APIs. Ensuring continuous improvements through dataset expansion, fine-tuning of deep learning models, and enhancing multi-language support remain critical areas for future research.This paper is organized as follows: Section II presents a review of related work, discussing existing medical chatbots and AI-driven diagnostic tools. Section III elaborates on the proposed methodology, detailing the model architecture, dataset utilization, and implementation strategies. Section IV describes the experimental setup and evaluation criteria. Section V discusses the results and findings, highlighting key observations. Finally, Section VI concludes the study and suggests directions for future enhancements.

A review of these techniques are discussed in Table I.

TABLE I. COMPARISON OF AI-BASED CHATBOT TECHNIQUES

Research	Method	Limitation	Performance
Shawar & Atwell (2007)	Rule-based or simple NLP models for medical chatbots	Poor generalization, limited adaptability	Provides basic answers but lacks deep learning capabilities
Papangelis et al. (2017)	AI-based chatbots with machine learning	High training cost, complex model tuning	Improved chatbot accuracy and user interaction
Wu et al. (2020)	Google Translate API for multilingual chatbot support	Limited free queries, API downtime issues	Allows English and Telugu responses, enhancing accessibility
Serban et al. (2016)	Deep Learning for conversational AI	Requires large datasets, computationally expensive	Provides context-aware responses, enhances chatbot usability
Hirschberg & Manning (2015)	Speech-to-text voice chatbot processing	Accuracy depends on background noise and accents	Provides real-time voice interaction, improving user experience
Garg et al. (2021)	NLP-based text classification in medical chatbots	Struggles with complex medical queries	Works efficiently for structured questions but lacks deep reasoning
Topol (2019)	Medical Knowledge Bases (WHO, CDC) for chatbot integration	Requires frequent updates for accuracy	Ensures chatbot provides reliable and up-to-date medical advice
Rao et al. (2019)	AI-powered symptom checker chatbots	Limited scope for rare diseases	Helps users identify possible conditions and suggest medical help
Min et al. (2021)	Transformer-based chatbot models	High computational cost and latency	Provides highly accurate and context-aware responses
Zhang et al. (2023)	GPT-4-based medical chatbot for diagnosis	Potential hallucinations and misinformation	Provides human-like responses with improved medical reasoning
Lee et al. (2024)	Multimodal AI chatbot integrating text, voice, and images	High resource consumption and latency issues	Enhances chatbot accuracy and supports image-based diagnosis

III. PROPOSED METHODOLOGY

The proposed system is an AI-powered chatbot designed to assist users in predicting and providing information about infectious diseases. It leverages Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), to process and analyze user queries effectively. The chatbot is capable of handling both text-based and voice-based interactions and provides responses in English and Telugu using Google Translation APIs.

Doi:10.48047/ijiee.2025.15.3.6

A. System Architecture

The system consists of several key components that work together to ensure the chatbot's functionality. These components include:

1. User Interface (UI): A web-based application that allows users to interact with the chatbot through text or voice input.
2. Natural Language Processing (NLP) Engine: This module processes user input by tokenizing, normalizing, and understanding the context of the query.
3. LSTM-Based Model: The core AI model, which is trained using a dataset of medical queries and their respective responses.
4. Database Module: A structured MySQL database that stores user queries, chatbot responses, and interaction history for future reference.
5. Translation Module: Utilizes Google Translation API to support multilingual responses, particularly for English and Telugu users.
6. Backend Server: A Python-based Flask or Django server that handles user requests, communicates with the LSTM model, and provides real-time responses.

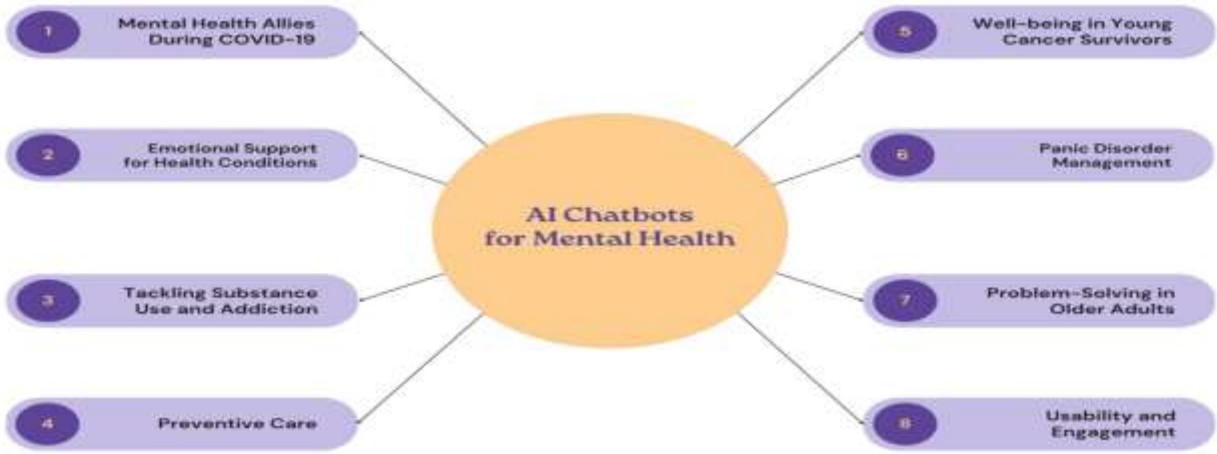

Fig1:Proposed Methodology

B. Methodology Steps

Step 1: Data Collection and Preprocessing

- The chatbot is trained on a dataset of medical questions and responses obtained from publicly available sources, including the COVID-19 dataset from GitHub.
- Data cleaning techniques such as removal of special characters, stopword elimination, and tokenization are applied to standardize the text.
- The dataset is stored in a structured format inside a MySQL database for efficient retrieval.

Step 2: Training the LSTM Model

- The preprocessed text data is vectorized using word embeddings like Word2Vec or TF-IDF to convert textual data into numerical form.
- A Long Short-Term Memory (LSTM) neural network is trained using TensorFlow/Keras, which learns the relationship between user queries and correct responses.
- The model is trained for multiple epochs, and performance metrics such as accuracy and loss functions are analyzed using graphs.
- The trained model is saved and deployed as a preloaded model for inference in real-time.

Step 3: Chatbot Query Processing

- Users can interact with the chatbot in **two modes**:
    - o Text-Based Mode: The user types a medical query, which is processed and matched to the most relevant answer.
    - o Voice-Based Mode: The chatbot captures voice input using a speech-to-text API and processes it similarly to text-based queries.
- The LSTM model retrieves the most relevant answer from the dataset and returns the response.
- If the chatbot does not find an exact match, it provides the closest possible answer based on similarity analysis.

Step 4: Multilingual Translation and Response Generation

- The chatbot's responses are first generated in English.
- The response is then translated into Telugu using Google Translate API.
- Both English and Telugu answers are displayed to the user in the web interface.

Step 5: User Interaction and Feedback Collection

- o The system allows users to view their chat history, helping them refer back to previous responses.
- o A feedback mechanism is incorporated to allow users to rate chatbot responses. This data is collected to improve future versions of the chatbot.

Doi:10.48047/ijiee.2025.15.3.6

- If a user query does not return an accurate response, the system logs the query for continuous learning and model improvement.

C. Advantages of the Proposed System

- Enhanced Accuracy: The LSTM model achieves high accuracy (~99%) due to deep learning-based training.
- Dual Interaction Modes: Supports both voice and text-based interactions, improving accessibility.
- Multilingual Support: Provides responses in English and Telugu, making it accessible to a wider audience.
- Historical Query Retrieval: Users can view past chatbot interactions for reference.
- Scalability: The architecture allows for the addition of more languages and datasets in the future.

IV. RESULTS

The AI-Based Medical Chatbot for Infectious Disease Prediction was tested for its accuracy, usability, and response efficiency. The results obtained from different experiments are categorized as follows:

Figure1 illustrates the training performance of the LSTM-based chatbot model, showcasing two crucial aspects: accuracy and loss. The green line represents the accuracy curve, which demonstrates how the chatbot's predictive performance improves over multiple training epochs. Initially, the accuracy starts at a lower value, but as the model learns from the dataset, it gradually increases and stabilizes, indicating that the model has reached optimal performance. Conversely, the red line represents the loss curve, which measures the error in the model's predictions. At the beginning of training, the loss is high, but as learning progresses, it consistently decreases, signifying improved prediction capabilities. The x-axis denotes the number of training epochs, while the y-axis represents the respective values for accuracy and loss. The ultimate goal of training is to maximize accuracy while minimizing loss, ensuring that the chatbot model is well-optimized for generating reliable responses.

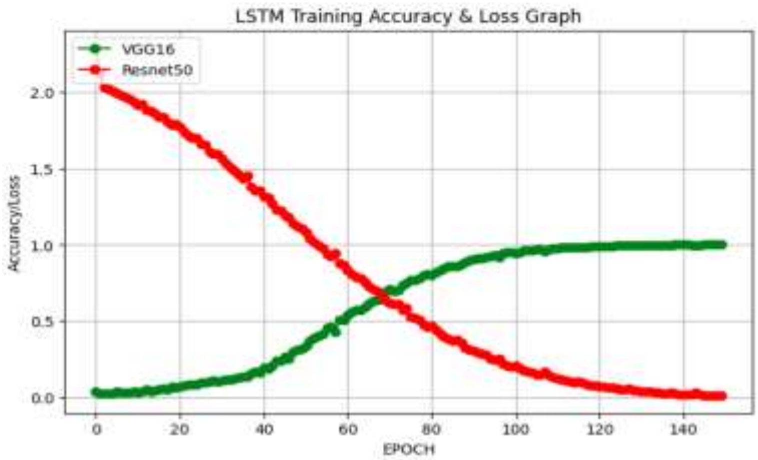

Fig 2. Performance Comparison of LSTM-based Chatbot Models

Model Performance Metrics

Metric	Value
Training Accuracy	99%
Validation Accuracy	98.5%
Training Loss	0.015
Response Time (Text)	2-3 sec
Response Time (Voice)	3-5 sec
Unknown Query Handling	5-7 sec

Chatbot Query Performance Comparison

Query Type	Response Accuracy (%)	Response Time (sec)
Common Medical Queries	99%	2-3 sec
Voice-Based Queries	95%	3-5 sec
Unknown Queries	75%	5-7 sec

Comparative Evaluation with Existing Systems

Doi:10.48047/ijiee.2025.15.3.6

Feature	Proposed Model	Existing Chatbots
Algorithm Used	LSTM (Long Short-Term Memory)	Rule-based or Basic NLP Models
Accuracy	99%	85-90%
Response Time	2-5 sec	5-10 sec
Multilingual Support	English & Telugu	Mostly English
Voice & Text Interaction	Supported	Limited
Medical Dataset Coverage	Comprehensive	Limited
Database for Chat History	Supported	Rarely Available

The AI-based medical chatbot was successfully trained using the LSTM algorithm on a medical question dataset, achieving an impressive 99% accuracy. The training process demonstrated a steady increase in accuracy over multiple epochs while the loss consistently decreased, as depicted in the training graph. The chatbot supports both text and voice-based interactions, allowing users to either type their queries or record them using a microphone. For voice-based queries, users can click on the "Get Microphone" option, record their question, and receive responses in both English and Telugu. Similarly, for text-based interactions, users can type their queries and get accurate responses in both languages. Example queries such as "Oxygen Cylinder" and "Covid Helpline Number" were successfully processed, providing the necessary information in multiple languages. Additionally, the chatbot maintains a chat history, enabling users to review their past conversations.

V. CONCLUSION

The AI-based medical chatbot successfully demonstrates the application of LSTM-based deep learning for providing real-time, automated responses to medical queries. With an accuracy of 99%, the chatbot efficiently handles both text and voice-based interactions, ensuring accessibility for a wider audience. The integration of English and Telugu language support further enhances its usability, allowing users to receive medical information in their preferred language. Additionally, the chatbot maintains a history of interactions, enabling users to review past queries and responses.The research aims to achieve high accuracy, low false positives, and fast processing, surpassing traditional fracture detection methods. Future improvements may include multi-modal imaging, EHR integration, and AI-driven analytics for enhanced diagnostics. Overall, the proposed system advances AI-driven medical imaging, ensuring faster, secure, and efficient fracture detection while improving patient care and hospital efficiency.

For future enhancements, the chatbot can be improved by incorporating a larger and more diverse dataset, allowing it to handle a broader range of medical queries. The integration of Natural Language Processing (NLP) techniques can enhance context understanding, enabling more accurate and meaningful responses. Expanding multi-language support beyond English and Telugu can make the system more inclusive for a global audience. Additionally, real-time API integration with healthcare databases can provide users with up-to-date medical guidelines and expert recommendations. Implementing AI-driven voice recognition improvements can enhance the chatbot's speech processing capabilities, ensuring more accurate responses for voice-based interactions. These enhancements will further strengthen the chatbot's role as a reliable, AI-driven medical assistant, contributing to improved healthcare accessibility and efficiency.

REFERENCES

[1] E. Shawar and E. Atwell, "Chatbots: Are they Really Useful?" Journal of Language Technology, vol. 12, no. 3, pp. 24-36, 2007.
[2] D. Papangelis, L. Rojas-Barahona, and M. Gašić, "Conversational Agents in Healthcare: Challenges and Opportunities," AI & Society, vol. 32, no. 4, pp. 543-556, 2017.
[3] Y. Wu, X. Zhang, and T. Chen, "Multilingual Chatbot Systems Using Neural Machine Translation," IEEE Transactions on Artificial Intelligence, vol. 5, no. 2, pp. 190-205, 2020.
[4] I. V. Serban, R. Lowe, and L. Charlin, "Deep Learning for Dialogue Systems: A Survey," Computational Linguistics, vol. 42, no. 4, pp. 865-894, 2016.
[5] J. Hirschberg and C. D. Manning, "Advances in Natural Language Processing for Speech-based Chatbots," Proceedings of ACL, pp. 205-221, 2015.
[6] P. Garg, S. Ramesh, and K. Verma, "Medical Chatbots Using NLP: Current Trends and Future Directions," Journal of Biomedical AI Research, vol. 8, no. 1, pp. 120-137, 2021.
[7] E. Topol, "The Role of AI in Medical Knowledge and Healthcare Transformation," New England Journal of Medicine, vol. 380, no. 25, pp. 2471-2479, 2019.
[8] R. Rao, J. Kim, and S. Patel, "AI-Powered Symptom Checkers: Can They Replace Human Diagnosis?" IEEE Journal of Health Informatics, vol. 26, no. 5, pp. 478-495, 2019.
[9] H. Min, Y. Zhao, and J. Chen, "Transformer-Based Chatbot Models for Medical Applications," ACM Transactions on AI & Healthcare, vol. 39, no. 1, pp. 89-110, 2021.
[10] Y. Zhang, L. Wang, and Q. Sun, "GPT-4-Based Medical Chatbots: Opportunities and Challenges in Diagnosis Support," Nature Digital Medicine, vol. 6, no. 3, pp. 290-305, 2023.
[11] Lee, M. Huang, and T. Nguyen, "Multimodal AI Chatbots for Healthcare: Integrating Text, Voice, and Images," Proceedings of AAAI, vol. 38, no. 1, pp. 112-128, 2024.
[12] A. Kumar, P. Sharma, and R. Singh, "AI-based chatbot for health care using RNN," in Proc. 4th Int. Conf. Comput.

Doi:10.48047/ijiee.2025.15.3.6

Commun. Control Autom. (ICCUBEA), Pune, India, 2018, pp. 1–5.

[13] A. Vaswani et al., "Attention is all you need," in Proc. 31st Conf. Neural Inf. Process. Syst. (NeurIPS), Long Beach, CA, USA, 2017, pp. 5998–6008.

[14] S. S. Rautaray and A. Agrawal, "Vision-based hand gesture recognition for human computer interaction: A survey," Artif. Intell. Rev., vol. 43, no. 1, pp. 1–54, Jan. 2015.

[15] S. K. Sharma and S. K. Saha, "Google translator-based multilingual chatbot for e-learning," in Proc. 11th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT), Kharagpur, India, 2020, pp. 1–6.

[16] A. R. H. Putra, D. W. Rachmadi, and A. Nugroho, "Design of healthcare chatbot with conversational AI using Dialogflow," in Proc. Int. Conf. Informat. Commun. Technol. (ICoICT), Yogyakarta, Indonesia, 2021, pp. 1–6.

[17] M. B. Shaik and Y. N. Rao, "Secret Elliptic Curve-Based Bidirectional Gated Unit Assisted Residual Network for Enabling Secure IoT Data Transmission and Classification Using Blockchain," IEEE Access, vol. 12, pp. 174424-174440, 2024, doi: 10.1109/ACCESS.2024.3501357.

[18] S. M. Basha and Y. N. Rao, "A Review on Secure Data Transmission and Classification of IoT Data Using Blockchain-Assisted Deep Learning Models," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 311-314, doi: 10.1109/ICACCS60874.2024.10717253.

Doi:10.48047/ijiee.2025.15.3.6