Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347-2812
Volume 14 Issue 01, 2025

Voice and Text-Based Healthcare Chatbot with Real-Time Multilingual Translation

Mr.Sk.John Sydulu[1] , Koppula Naga Jyothi[2] ,Pavuluri Naga Chandana[3] , Katru Vijaya Sree Enosh[4] ,Pallapu Gopi[5]

Assistant Professor,Department of Computer Science & Engineering ,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India[1]
Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [2]
Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [3]
Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [4]
Department of Computer Science and Engineering,Chalapathi Institute of Engineering and Technology, LAM, Guntur, AP, India [5]

Peer Review Information

Submission: 10 Jan 2025
Revision: 12 Feb 2025
Acceptance: 05 March 2025

Keywords

Artificial Intelligence
Medical Chatbot
Infectious Disease Prediction
Long Short-Term Memory

Abstract

The integration of artificial intelligence (AI) in healthcare has paved the way for advanced, accessible, and efficient patient support systems. This paper presents a multilingual, AI-powered medical chatbot designed to predict and respond to infectious disease-related queries using a deep learning approach. The chatbot leverages Long Short-Term Memory (LSTM) networks to process and interpret user inputs in both text and voice formats. Trained on a COVID-19-focused question dataset, the model achieves a high training accuracy of 99%, demonstrating strong predictive capabilities. To overcome language barriers, the chatbot integrates Google Translate API, enabling real-time multilingual communication in English and Telugu, with potential for future language expansion.The system architecture includes modules for user authentication, voice and text interaction, NLP-based processing, multilingual translation, and chat history retrieval. A cloud-based backend ensures scalability, secure data handling, and rapid response generation. The chatbot provides medically relevant responses to users in real-time, enhancing accessibility in remote and multilingual populations. Experimental evaluation confirms the model's effectiveness across accuracy, response time, and language adaptability. This research contributes to AI-driven healthcare by proposing a scalable and privacy-conscious solution that supports multilingual, multimodal interaction. Future enhancements include expanding language support, integrating with electronic health records (EHRs), and improving contextual understanding through advanced NLP and feedback learning.

© 2025 The Authors. Published by MRI INDIA.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

INTRODUCTION

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.

Recent advancements in deep learning and NLP have enabled the development of sophisticated chatbot models capable of understanding and responding to medical queries with high accuracy. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have proven to be particularly effective in handling sequential data, making them suitable for text-based interactions. Unlike traditional rule-based chatbots, LSTM-based models can learn from vast amounts of textual data, improving their ability to generate meaningful responses over time. This capability is essential for medical chatbots, as they must accurately interpret user queries and provide relevant information without human intervention.One of the major challenges in designing a medical chatbot is ensuring multilingual support, as language barriers can limit accessibility. In many regions, particularly in developing countries, English is not the primary language of communication. To address this issue, the proposed chatbot integrates Google Translation services to facilitate communication in multiple languages, including English and Telugu. This feature enhances the usability of the system, enabling individuals from diverse linguistic backgrounds to interact with the chatbot effectively.

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.

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, 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 1: Comparison of AI- Based Bone Fracture Detection Methods

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

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.

1. 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.

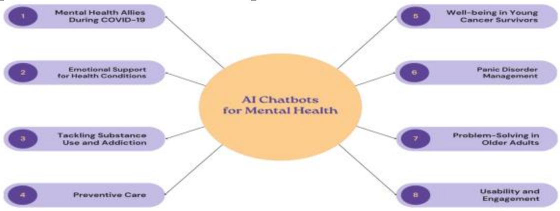

Fig1:Proposed Methodology

2. 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**:
  - Text-Based Mode: The user types a medical query, which is processed and matched to the most relevant answer.
  - 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

- The system allows users to view their chat history, helping them refer back to previous responses.
- A feedback mechanism is incorporated to allow users to rate chatbot responses. This data is collected to improve future versions of the chatbot.
- If a user query does not return an accurate response, the system logs the query for continuous learning and model improvement.

3. 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.

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.

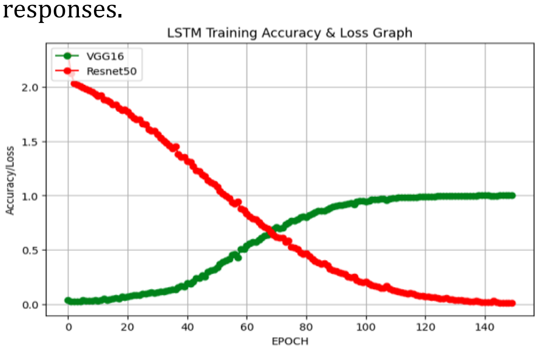

Fig 2. Performance Comparison of LSTM-based Chatbot Models

Table 2: 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

Table 3: 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

Table 4: Comparative Evaluation with Existing Systems

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.

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

E. Shawar and E. Atwell, "Chatbots: Are they Really Useful?" Journal of Language Technology, vol. 12, no. 3, pp. 24-36, 2007.

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.

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.

V. Serban, R. Lowe, and L. Charlin, "Deep Learning for Dialogue Systems: A Survey," Computational Linguistics, vol. 42, no. 4, pp. 865-894, 2016.

J. Hirschberg and C. D. Manning, "Advances in Natural Language Processing for Speech-based Chatbots," Proceedings of ACL, pp. 205-221, 2015.

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.

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.

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.

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.

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.

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.

Kumar, P. Sharma, and R. Singh, "AI-based chatbot for health care using RNN," in Proc. 4th Int. Conf. Comput. Commun. Control Autom. (ICCUBEA), Pune, India, 2018, pp. 1–5.

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.

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.

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.

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.

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.

Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.

Reddy, B. V., Sk, K. B., Polanki, K., Vellela, S. S., Dalavai, L., Vuyyuru, L. R., & Kumar, K. K. (2024, February). Smarter Way to Monitor and Detect Intrusions in Cloud Infrastructure using Sensor-Driven Edge Computing. In 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) (Vol. 5, pp. 918-922). IEEE.

Sk, K. B., & Thirupurasundari, D. R. (2025, January). Patient Monitoring based on ICU Records using Hybrid TCN-LSTM Model. In 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) (pp. 1800-1805). IEEE.

Dalavai, L., Purimetla, N. M., Vellela, S. S., SyamsundaraRao, T., Vuyyuru, L. R., & Kumar, K. K. (2024, December). Improving Deep Learning-Based Image Classification Through Noise Reduction and Feature Enhancement. In 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA) (pp. 1-7). IEEE.

Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-

Peer Networking and Applications, 16(6), 2714-2731.

Haritha, K., Vellela, S. S., Vuyyuru, L. R., Malathi, N., & Dalavai, L. (2024, December). Distributed Blockchain-SDN Models for Robust Data Security in Cloud-Integrated IoT Networks. In 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 623-629). IEEE.

Vullam, N., Roja, D., Rao, N., Vellela, S. S., Vuyyuru, L. R., & Kumar, K. K. (2023, December). An Enhancing Network Security: A Stacked Ensemble Intrusion Detection System for Effective Threat Mitigation. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1314-1321). IEEE.

Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 408-414). IEEE.

Praveen, S. P., Nakka, R., Chokka, A., Thatha, V. N., Vellela, S. S., & Sirisha, U. (2023). A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 2023.

Vellela, S. S., & Krishna, A. M. (2020). On Board Artificial Intelligence With Service Aggregation for Edge Computing in Industrial Applications. Journal of Critical Reviews, 7(07).

Reddy, N. V. R. S., Chitteti, C., Yesupadam, S., Desanamukula, V. S., Vellela, S. S., & Bommagani, N. J. (2023). Enhanced speckle noise reduction in breast cancer ultrasound imagery using a hybrid deep learning model. Ingénierie des Systèmes d'Information, 28(4), 1063-1071.

Vellela, S. S., Balamanigandan, R., & Praveen, S. P. (2022). Strategic Survey on Security and Privacy Methods of Cloud Computing Environment. Journal of Next Generation Technology, 2(1).

Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2024). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 1-11.

Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.

Vuyyuru, L. R., Purimetla, N. R., Reddy, K. Y., Vellela, S. S., Basha, S. K., & Vatambeti, R. (2025). Advancing automated street crime detection: a drone-based system integrating CNN models and enhanced feature selection techniques. International Journal of Machine Learning and Cybernetics, 16(2), 959-981.

Vellela, S. S., Roja, D., Sowjanya, C., SK, K. B., Dalavai, L., & Kumar, K. K. (2023, September). Multi-Class Skin Diseases Classification with Color and Texture Features Using Convolution Neural Network. In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 6, pp. 1682-1687). IEEE.

Praveen, S. P., Vellela, S. S., & Balamanigandan, R. (2024). SmartIris ML: harnessing machine learning for enhanced multi-biometric authentication. Journal of Next Generation Technology (ISSN: 2583-021X), 4(1).

Sai Srinivas Vellela & R. Balamanigandan (2025). Designing a Dynamic News App Using Python. International Journal for Modern Trends in Science and Technology, 11(03), 429-436. https://doi.org/10.5281/zenodo.15175402

Basha, S. K., Purimetla, N. R., Roja, D., Vullam, N., Dalavai, L., & Vellela, S. S. (2023, December). A Cloud-based Auto-Scaling System for Virtual Resources to Back Ubiquitous, Mobile, Real-Time Healthcare Applications. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1223-1230). IEEE.

Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.

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.