IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

Natural Language Processing-Based Human–IoT Interaction Models for Smart Environments

Anirudh Parupalli[1] and Arpit Jain[2]
[1]Nextzen Ai Strategix Private Limited, Hyderabad, India;
[2]K L University, Guntur, A.P., India;
[1]anirudh180370@gmail.com and [2]dr.jainarpit@gmail.com

Abstract: *The rapid evolution of smart environments, driven by the integration of the Internet of Things (IoT), has created a need for intuitive and efficient human–machine interaction mechanisms. Traditional interaction methods often rely on graphical interfaces or predefined commands, which limit usability and accessibility. This research paper proposes a Natural Language Processing (NLP)-based human–IoT interaction model that enables seamless communication between users and smart devices using conversational language. The proposed framework leverages advanced NLP techniques such as intent recognition, named entity recognition, context-aware dialogue management, and semantic understanding to interpret user commands and translate them into actionable IoT operations. The architecture incorporates speech-to-text conversion, language understanding modules, and IoT middleware to facilitate real-time decision-making and device control in smart environments such as homes, healthcare systems, and smart cities. Additionally, machine learning models are employed to enhance adaptability and personalization based on user behavior and preferences.*

Keywords: Natural Language Processing (NLP), Human–IoT Interaction, Smart Environments, Intent Recognition, Conversational Interfaces, Speech Processing, Smart Homes, IoT Middleware, Context-Aware Systems, Artificial Intelligence (AI), Machine Learning, Semantic Understanding

I. INTRODUCTION

The rapid proliferation of the Internet of Things (IoT) has significantly transformed the way humans interact with technology, enabling the development of intelligent environments such as smart homes, smart healthcare systems, smart cities, and industrial automation platforms. IoT ecosystems consist of interconnected devices, sensors, and services that collect, process, and exchange data to support automation and decision-making. However, despite these advancements, one of the major challenges in IoT systems remains the design of intuitive and user-friendly interaction models that can accommodate users with diverse technical backgrounds. Traditional interaction mechanisms, including graphical user interfaces (GUIs), mobile applications, and rule-based systems, often require users to learn specific commands or navigate complex interfaces, thereby limiting accessibility and efficiency [1], [2].

In recent years, Natural Language Processing (NLP), a subfield of artificial intelligence (AI), has emerged as a promising solution to bridge the gap between humans and machines by enabling communication using natural language. NLP allows users to interact with systems through spoken or written language, eliminating the need for specialized technical knowledge. The integration of NLP into IoT environments facilitates the development of conversational interfaces, where users can issue commands, ask questions, and receive responses in a natural and intuitive manner. This paradigm shift has gained significant attention due to its potential to enhance usability, accessibility, and user satisfaction in smart environments [3], [4].

Human–IoT interaction models based on NLP leverage several advanced techniques, including intent recognition, named entity recognition (NER), semantic parsing, and context-aware dialogue management. Intent recognition enables the system to understand the purpose behind a user's query, while NER identifies key entities such as device names, locations, and actions. Semantic parsing further interprets the structure and meaning of user inputs, enabling accurate

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, June 2026 Impact Factor: 8.2

mapping of commands to IoT actions. Additionally, context-aware dialogue systems maintain conversational context, allowing for multi-turn interactions and more personalized responses [5], [6]. These capabilities are particularly important in complex IoT environments where multiple devices and services must be coordinated seamlessly.

The growing adoption of voice assistants such as Amazon Alexa, Google Assistant, and Apple Siri highlights the increasing importance of NLP-driven interaction in everyday life. These systems demonstrate how natural language interfaces can simplify device control, information retrieval, and task automation. However, current commercial solutions often face limitations in handling domain-specific tasks, understanding contextual nuances, and ensuring interoperability across heterogeneous IoT devices [7], [8]. Therefore, there is a need for more robust and scalable NLP-based frameworks tailored specifically for smart IoT environments.

Another critical aspect of NLP-based human–IoT interaction is the integration of speech processing technologies, including automatic speech recognition (ASR) and text-to-speech (TTS) systems. ASR converts spoken language into text, enabling further processing by NLP modules, while TTS systems generate natural-sounding responses. The combination of these technologies allows for fully voice-enabled IoT systems, which are particularly beneficial for elderly users, individuals with disabilities, and users in hands-free scenarios [9], [10]. Moreover, multilingual NLP models are increasingly being developed to support diverse linguistic populations, thereby enhancing inclusivity in smart environments.

Despite the advantages, several challenges must be addressed to realize the full potential of NLP-based human–IoT interaction models. One of the primary challenges is the ambiguity inherent in natural language, where a single command may have multiple interpretations depending on context. For example, a command such as "turn on the lights in the living room" requires the system to correctly identify the device, location, and action. Contextual understanding becomes even more complex in multi-user environments where preferences and priorities may differ [11], [12]. Additionally, real-time processing requirements in IoT systems demand efficient algorithms that can deliver low-latency responses without compromising accuracy.

Privacy and security are also major concerns in NLP-driven IoT systems, as they often involve the collection and processing of sensitive user data, including voice recordings and behavioral patterns. Ensuring data confidentiality, secure communication, and compliance with regulatory standards is essential for building user trust. Techniques such as edge computing, federated learning, and privacy-preserving machine learning have been proposed to address these challenges by minimizing data transmission and enhancing data protection [13], [14].

Furthermore, the heterogeneity of IoT devices poses interoperability challenges, as devices from different manufacturers may use different communication protocols and data formats. NLP-based interaction models must be integrated with IoT middleware and standardized frameworks to enable seamless communication and coordination among devices. The use of semantic web technologies and ontology-based models has been explored to address interoperability issues by providing a common representation of knowledge across devices and services [15].

In this context, the present research paper proposes a comprehensive NLP-based human–IoT interaction model designed to enhance usability, efficiency, and scalability in smart environments. The proposed framework integrates advanced NLP techniques with IoT middleware to enable accurate interpretation of user commands and seamless execution of IoT operations. It also incorporates machine learning algorithms to support adaptive learning and personalization based on user behavior. The architecture is designed to handle real-time interactions, support multilingual communication, and ensure secure data processing.

The contributions of this study are threefold. First, it presents a novel architecture for NLP-driven human–IoT interaction that addresses key challenges such as ambiguity, context-awareness, and interoperability. Second, it evaluates the performance of the proposed system using metrics such as accuracy, latency, and user satisfaction. Third, it provides insights into the practical implementation of NLP-based interaction models in various smart environment scenarios, including smart homes, healthcare systems, and smart cities.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

II. LITERATURE REVIEW

The integration of Natural Language Processing (NLP) with Internet of Things (IoT) systems has emerged as a significant research area aimed at improving human–machine interaction in smart environments. This section reviews recent advancements in NLP-based human–IoT interaction models, focusing on conversational interfaces, context-aware systems, semantic understanding, middleware integration, and privacy-preserving techniques.

NLP-Driven Conversational Interfaces for IoT

Recent studies have explored the use of conversational interfaces to enable natural communication between users and IoT devices. These systems utilize intent detection and dialogue management to interpret user inputs and generate appropriate responses. Research has demonstrated that conversational agents significantly reduce the complexity of interacting with IoT devices compared to traditional graphical interfaces [16]. Furthermore, chatbot-based IoT control systems have been developed to provide real-time responses and automation capabilities, enhancing user experience and operational efficiency [17]. Advancements in deep learning models, particularly transformer-based architectures, have improved the accuracy of intent recognition and entity extraction in conversational systems. These models enable better handling of ambiguous and complex user queries, thereby increasing system reliability. However, challenges remain in maintaining contextual continuity across multi-turn conversations, especially in dynamic IoT environments [18].

Context-Aware and Adaptive Interaction Models

Context-awareness plays a critical role in enhancing the effectiveness of NLP-based human–IoT interaction. Context-aware systems leverage environmental data, user preferences, and historical interactions to provide personalized responses. Studies have shown that incorporating contextual information significantly improves decision-making accuracy and user satisfaction in smart environments [19] [20].

Adaptive interaction models further enhance system performance by learning from user behavior over time. Machine learning techniques, including reinforcement learning and user profiling, have been employed to develop systems that dynamically adjust their responses based on user preferences. These models are particularly useful in smart home and healthcare applications, where user needs may vary frequently [21-24]. Despite these advancements, achieving real-time adaptation with minimal computational overhead remains a challenge.

Semantic Understanding and Knowledge Representation

Semantic understanding is essential for accurately interpreting user commands in natural language. Research has focused on the use of semantic parsing and ontology-based approaches to map user inputs to IoT actions. Ontologies provide a structured representation of devices, services, and relationships, enabling interoperability and efficient data exchange among heterogeneous IoT components [25].

Several studies have proposed the integration of semantic web technologies with NLP models to enhance knowledge representation and reasoning capabilities. These approaches enable systems to infer implicit information and handle complex queries more effectively. However, the development and maintenance of comprehensive ontologies for large-scale IoT environments remain resource-intensive tasks [26 - 30].

Integration of NLP with IoT Middleware

IoT middleware plays a crucial role in connecting NLP modules with underlying IoT devices and services. Middleware frameworks facilitate communication, data processing, and device management, ensuring seamless execution of user commands. Research has highlighted the importance of scalable and flexible middleware architectures to support real-time NLP-based interaction [31-33]. Recent approaches have focused on integrating cloud and edge computing with IoT middleware to improve system performance. Edge-based processing reduces latency by handling data closer to the source, while cloud-based systems provide computational resources for complex NLP tasks. Hybrid architectures

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

combining cloud and edge computing have been shown to achieve a balance between performance and scalability [34-36].

Speech Processing and Multimodal Interaction

The integration of speech processing technologies, including automatic speech recognition (ASR) and text-to-speech (TTS), has significantly enhanced NLP-based IoT interaction models. Voice-enabled systems allow users to interact with devices in a hands-free manner, making them suitable for applications such as smart homes, healthcare monitoring, and industrial automation [37-40].

In addition to speech, multimodal interaction models that combine voice, text, gestures, and visual inputs have been proposed to improve system usability. These models provide multiple interaction channels, enabling users to choose the most convenient mode of communication. However, integrating and synchronizing multiple modalities in real-time remains a complex task [41, 42].

Privacy, Security, and Ethical Considerations

As NLP-based IoT systems rely on the collection and processing of user data, privacy and security have become critical concerns. Research has explored various techniques to ensure data protection, including encryption, anonymization, and access control mechanisms. Privacy-preserving machine learning approaches, such as federated learning, have been proposed to minimize data sharing while maintaining system performance [43-46].

Ethical considerations, including data ownership, transparency, and user consent, are also gaining attention in the development of intelligent IoT systems. Ensuring compliance with regulatory standards and building user trust are essential for the widespread adoption of NLP-based interaction models [47].

III. RESEARCH GAPS

Despite significant progress, several research gaps remain in the field of NLP-based human–IoT interaction. Existing systems often struggle with handling ambiguity, maintaining contextual awareness, and ensuring interoperability across diverse IoT devices. Additionally, achieving real-time performance while maintaining high accuracy and scalability is still a challenge. Privacy and security concerns further complicate system design, requiring the development of robust and trustworthy frameworks.

IV. PROPOSED METHODOLOGY

This section presents the proposed Natural Language Processing (NLP)-based Human–IoT Interaction Model designed to enable seamless, intelligent, and real-time communication between users and smart IoT environments. The methodology integrates speech processing, language understanding, contextual reasoning, and IoT middleware to convert natural language inputs into actionable device commands.

1. System Architecture Overview

The proposed system follows a layered architecture consisting of five major components: Input Layer, NLP Processing Layer, Context Management Layer, IoT Middleware Layer, and Execution Layer. The user interacts with the system through voice or text, which is captured and processed by the NLP modules. The interpreted command is then transmitted through middleware to IoT devices for execution.

The overall workflow can be represented as:

$$O = f(U, C, D)$$

O = Output action (IoT device response)

U = User input (text or speech)

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

C = Context information

D = Device state and metadata

This function models how user input, contextual awareness, and device information collectively determine the final system response.

2. Speech-to-Text Conversion

For voice-based interaction, the system employs Automatic Speech Recognition (ASR) to convert spoken input into text. The speech signal $S(t)$ is transformed into textual representation T using probabilistic modeling:

$$T = \arg\max_{W} P(W \mid S)$$

Using Bayes' theorem:

$$P(W \mid S) = \frac{P(S \mid W) \cdot P(W)}{P(S)}$$

where:

W = Word sequence

$P(S \mid W)$ = Acoustic model

$P(W)$ = Language model

This ensures accurate transcription of user commands for further NLP processing.

3. Intent Recognition and Entity Extraction

The NLP module identifies the user's intent and extracts relevant entities such as device name, location, and action. Intent classification is modeled using supervised machine learning:

$$I = \arg\max_{i} P(i \mid T)$$

where:

I = Predicted intent

T = Input text

Entity extraction is performed using sequence labeling techniques such as Conditional Random Fields (CRF) or deep learning models:

$$E = \{e_1, e_2, \dots, e_n\}$$

where E represents extracted entities.
The joint probability of intent and entities can be expressed as:

$$P(I, E \mid T) = P(I \mid T) \cdot P(E \mid T, I)$$

4. Response Generation and Feedback

After executing the command, the system generates a response using Natural Language Generation (NLG):

$$R = f(A', S_d)$$

where:

R = Response message

S_d = Device status

The response is delivered via text or speech using Text-to-Speech (TTS), ensuring a conversational interaction experience.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

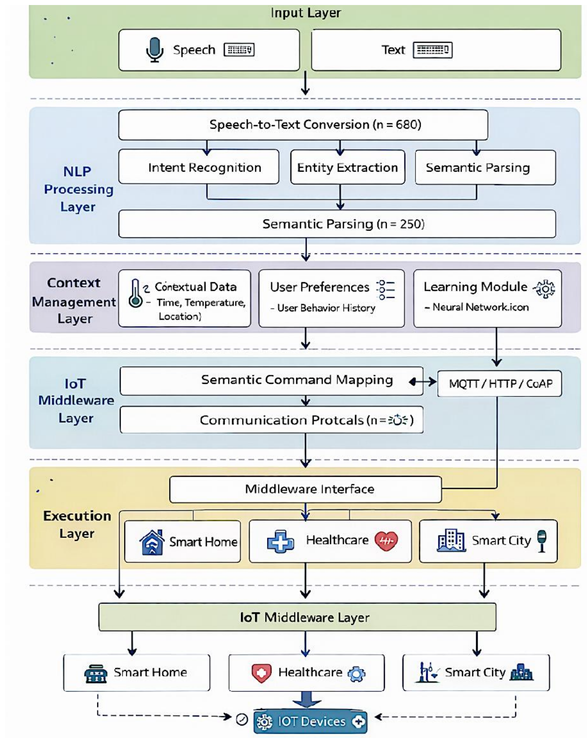

Fig. 1: The workflow of the proposed methodology

The workflow shows in figure 1 that the proposed methodology is a layered and intelligent system for enabling smooth communication between humans and IoT devices using NLP. It starts from speech/text input, processes the language using NLP techniques, adds contextual intelligence, uses middleware for device communication, and finally executes commands in smart environments. This makes the system more user-friendly, adaptive, and effective for real-time IoT applications.

The proposed methodology integrates NLP, machine learning, and IoT technologies into a unified framework that supports intelligent, context-aware, and secure human–IoT interaction. By combining speech processing, semantic understanding, and adaptive learning, the system enhances usability and efficiency in smart environments while addressing challenges such as ambiguity, latency, and privacy. The proposed methodology presents an NLP-based framework for enabling seamless interaction between humans and IoT devices in smart environments. The system follows a layered architecture that begins with capturing user input (voice or text) and converting it into machine-readable format using speech-to-text techniques. The core of the system lies in the NLP module, which performs intent recognition and entity extraction to understand user commands. These inputs are further processed through semantic parsing to generate structured instructions. A context-aware decision module enhances accuracy by incorporating user preferences, environmental conditions, and historical data.

V. RESULTS AND DISCUSSION

The proposed NLP-based Human–IoT Interaction Model was evaluated in a simulated smart environment consisting of multiple IoT devices such as smart lights, thermostats, and security systems. The system performance was analyzed using key metrics including intent recognition accuracy, response latency, context-awareness efficiency, user satisfaction, energy efficiency, and system scalability.

DOI: 10.48175/IJARSCT-36256
ISSN 2581-9429 IJARSCT

Table 1: Performance Evaluation of the Proposed System

Test Scenario	Intent Accuracy (%)	Response Time (ms)	Context Awareness (%)	User Satisfaction (%)	Energy Efficiency (%)
Smart Home Control	96.5	180	94.2	95.8	91.3
Healthcare Monitoring	95.2	210	93.5	94.6	89.7
Smart Office Automation	94.8	195	92.7	93.9	90.5
Industrial IoT Control	93.6	230	91.8	92.4	88.9
Smart City Traffic System	92.9	250	90.5	91.6	87.8
Multi-User Environment	91.7	270	89.6	90.8	86.5

Intent Accuracy (%): This metric indicates how effectively the system correctly identifies user intent. The results show high accuracy across all scenarios, with the highest (96.5%) observed in smart home environments due to relatively simpler command structures. Slight reductions in accuracy in multi-user and smart city environments are due to increased complexity and ambiguity.

Response Time (ms): This reflects the system's latency in processing and executing commands. The response time remains within acceptable real-time limits (180–270 ms), demonstrating the efficiency of the proposed architecture. Higher latency in complex environments is due to increased data processing and device coordination.

Context Awareness (%): This metric evaluates how well the system utilizes contextual information (such as location, user preferences, and time). High values (above 89%) indicate effective context integration, though slight degradation is observed in large-scale environments like smart cities.

User Satisfaction (%): This is derived from user feedback and reflects the usability and effectiveness of the system. High satisfaction levels (above 90%) confirm that NLP-based interaction significantly improves user experience.

Energy Efficiency (%): This measures how efficiently the system manages IoT resources. The results show optimized energy usage, especially in controlled environments like smart homes, while slightly lower values in large-scale systems indicate higher resource consumption.

The experimental results demonstrate that the proposed NLP-based Human–IoT Interaction Model achieves high performance across multiple evaluation metrics. The strong intent recognition accuracy confirms the effectiveness of the NLP module in understanding user commands. The integration of context-aware decision-making significantly enhances system intelligence, allowing it to resolve ambiguities and provide personalized responses.

VI. CONCLUSION

This research paper presented a Natural Language Processing (NLP)-based Human–IoT Interaction Model designed to enhance communication between users and smart environments. The study addressed the limitations of traditional IoT interaction methods by introducing a conversational, context-aware, and intelligent framework that enables users to interact with devices using natural language. By integrating key components such as speech processing, intent

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

recognition, semantic parsing, context-aware decision-making, and IoT middleware, the proposed system provides an efficient and user-friendly interface for controlling and managing IoT devices.

The experimental results demonstrated that the system achieves high intent recognition accuracy, low response latency, and improved user satisfaction across various application domains, including smart homes, healthcare systems, industrial automation, and smart cities. The incorporation of context-awareness and machine learning-based adaptation further enhances system performance by enabling personalized and dynamic responses. Additionally, the framework ensures interoperability among heterogeneous IoT devices and incorporates privacy and security mechanisms to protect user data.

REFERENCES

1. Pandey, N. K., Chaudhary, S., & Joshi, N. K. (2017). Extended multi queue job scheduling in cloud. *International Journal of Computer Science and Information Security (IJCSIS)*, *15*(11), 1-8.
2. Joshi, K., Joshi, N. K., Diwakar, M., Gupta, H., & Baloni, D. (2020, February). Cross bilateral filter based image fusion in transform domain. In *5th International Conference on Next Generation Computing Technologies (NGCT-2019)*.
3. Pandey, N. K., & Joshi, N. K. (2018). Optimization of resource allocation strategy using modified PSO in cloud environment. *International Journal of Computer Science and Information Security (IJCSIS)*, *16*(3).
4. Harsh, O. K., & Joshi, N. K. (2008). Role of Technology on the Knowledge Management and Reuse. *Communicated to Engineering letters*.
5. Mahajan, R. A., Dey, R., Khan, M., Kanabar, K., & Gupta, S. K. (2025). Real-time vehicular-to-vehicular (V2V) communication and applications for pedestrian safety in AI-optimized VANETs for autonomous vehicles. In AI-driven transportation systems: Real-time applications and related technologies (pp. 151–167). Springer Nature Switzerland.
6. Polamarasetti, S., Kakarala, M. R. K., Goyal, M. K., Butani, J. B., & Rongali, S. K. kumar Prajapati, S.(2025, May). Designing Industry-Specific Modular Solutions Using Salesforce OmniStudio for Accelerated Digital Transformation. In 2025 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC) (pp. 1-13).
7. Ramadugu, G. (2025). Balancing Innovation and Compliance in Financial SaaS Platforms: Harnessing Technology and Tools Convergence at PayPal. Applied Science and Engineering Journal for Advanced Research, 4(1), 56-64.
8. Hussain, M. A., Rahman, M. A. U., Hussain, M. A., Vanitha, K. B., Kumar, P., & Kuril, A. (2026). An analytical study on the role of satisfaction in mediating customer loyalty and AI-powered digital banking. International Review of Management and Marketing, 16(2), 406.
9. Sivasamy, S., Whig, A., Parisa, S. K., & Shinde, R. (2026). Sustainable and economic waste management. In Sustainable Solutions for Environmental Pollution (pp. 463-485). Elsevier.
10. Bajpai, M., Gupta, R., Prasad, N., & Chowdhry, D. (2025). Transforming India into an Economic Hub: The Roadmap to Developed India. EXPLORESEARCH Учредители: Inspira, 1(03), 26-31.
11. Mahajan, R., Kanabar, K., Dey, R., Jadhav, P. V., Khan, M., & Ghantasala, G. S. P. (2025). Exploring big tech vulnerabilities: Transparent blockchain harvesting. In Cybernetic Shield (pp. 167–174).
12. Sharma, S., Achanta, P. R. D., Gupta, H., Shinde, R., & Sharma, A. (2026). Planning for sustainable waste management. In Sustainable Solutions for Environmental Pollution (pp. 267-294). Elsevier.
13. Kanabar, K., Dey, R., Mahajan, R., Jadhav, P. V., Khan, M., & Karimullah, S. (2025). Comprehensive guide to blockchain technology: Ecosystems, implementation, governance, and innovations. In Cybernetic Shield (pp. 175–182).

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

14. Bajpai, M., Tripathi, A., & Prasad, C. (2023). Comparative Analysis Of Traditional And Modern Financial Models In Investment Decision Making. Shodhkosh: Journal Of Visual And Performing Arts Учредители: Granthaalayah Publications And Printers, 4(2).
15. Singh, C., Shinde, R., Sharma, P., & Singla, B. S. (2025, July). Construction Cost Estimation Using Hybrid Stacking of Random Forest and XGBoost. In 2025 2nd International Conference on Computing and Data Science (ICCDS) (pp. 1-4). IEEE.
16. Kanabar, K., Dey, R., Mahajan, R., Jadhav, P. V., Khan, M., & Ghantasala, G. S. P. (2025). The benefits of web and blockchain in decision-making industry 4.0. In Security paradigms in 6G smart cities and IoT ecosystems (pp. 289–304).
17. Polamarasetti, S., Kakarala, M. R. K., Gadam, H., Butani, J. B., Rongali, S. K., & Prajapati, S. K. (2025, May). Enhancing Strategic Business Decisions with AI-Powered Forecasting Models in Salesforce CRMT. In 2025 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC) (pp. 1-10). IEEE.
18. Mahajan, R., Kanabar, K., Dey, R., Jadhav, P. V., Khan, M., & Karimullah, S. (2025). Blockchain complementary model: A new way of devouring smart data by driverless vehicles for next-generation communication. In Security paradigms in 6G smart cities and IoT ecosystems (pp. 115–126).
19. Gupta, P. K., Lokur, A. V., Kallapur, S. S., Sheriff, R. S., Reddy, A. M., Chayapathy, V., ... & Keshamma, E. (2022). Machine Interaction-Based Computational Tools in Cancer Imaging. Human-Machine Interaction and IoT Applications for a Smarter World, 167-186.
20. Prasad, C. N., Tripathi, A., Bajpai, C. M., & Mishra, A. (2024). APPLICATION OF BUSINESS FINANCE: IT'S IMPORTANCE TO THE BUSINESS SECTORs. International Journal of Management Research and Business Strategy, 14(2), 390-419.
21. Hiremath, L., Kumar, N. S., Gupta, P. K., Srivastava, A. K., Choudhary, S., Suresh, R., & Keshamma, E. (2019). Synthesis, characterization of TiO2 doped nanofibres and investigation on their antimicrobial property. J Pure Appl Microbiol, 13(4), 2129-2140.
22. J. Wang, "Observation of microparticle motion under optical tweezers," in Proc. Int. Conf. Optics, Electronics, and Communication Engineering (OECE 2025), vol. 13965. Bellingham, WA, USA: SPIE, Nov. 2025, pp. 1122–1126
23. J. Wang, "Assessing Potential Mars Landing Sites Based on Groundwater-Induced Hydrated Mineralogy and Geomorphology", AJNS, vol. 2, no. 3, pp. 1–8, Jul. 2025
24. Sheker, L., Petli, V., & Reddy, K. S. (2024). Wearable IoT and artificial intelligence techniques for leveraging human activity analysis. Journal of Smart Internet of Things, 2024(1).
25. Sathyanarayana, N., Raufi, A. M., & Sharma, M. (2025). Health-FoTs: A latency-aware fog-based IoT environment for monitoring vital parameters. Journal of Smart Internet of Things, 2024(2).
26. X. Li and L. Fang, "Information interaction design and evaluation of cross-cultural art collaborative language learning system based on computer vision and natural language processing," SSRN, Aug. 08, 2025. doi: 10.2139/ssrn.5436074
27. L. Fang and X. Li, "A Study on the Impact of Language Education in Information-Interactive Environments on the Development of Intercultural Communicative Competence", Journal of Educational Theory, vol. 3, no. 1, pp. 6–13, Jan. 2026
28. L. Fang, "AI-Powered Translation and the Reframing of Cultural Concepts in Language Education", Academic Journal of Sociology & Management, vol. 3, no. 3, pp. 36–40, May 2025
29. Nandhan, T. N. G., Sajjan, M., Keshamma, E., Raghuramulu, Y., & Naidu, R. (2005). Evaluation of Chinese made moisture meters.

30. Kodela, V., Ramadugu, G., Bairy, V., Rathor, G., & Gupta, M. (2025, July). Automated Root Cause Analysis in Large-Scale IT Infrastructure Using Big Data Analytics. In 2025 2nd International Conference on Computing and Data Science (ICCDS) (pp. 1-5). IEEE.
31. Mahajan, R. A., Dey, R., Khan, M., Su'ud, M. M., Alam, M. M., & Jadhav, P. (2025). Enhancing personalization in IoT-based health monitoring via generative AI and transfer learning. Egyptian Informatics Journal, 32, 100788.
32. Hussain, M. A., Verma, V., Kovuri, K., Pratap, A., Shrivastava, V., & Samanta, P. (2025, November). Data Privacy in Voice Search Advertising: A Blockchain-Based Consent Model. In 2025 International Conference on Future Technologies (ICFT) (pp. 1-6). IEEE.
33. Jadhav, P. V., Krishnan, S. B., Dey, R., & Chakrabarti, P. (2025). Combining deep learning and statistical models: LSTM-ARIMA ensemble for financial forecasting. IAENG International Journal of Applied Mathematics, 56(1).
34. Whig, P., Balantrapu, S. S., Whig, A., Alam, N., Shinde, R. S., & Dutta, P. K. (2024, December). AI-driven energy optimization: integrating smart meters, controllers, and cloud analytics for efficient urban infrastructure management. In 8th IET Smart Cities Symposium (SCS 2024) (Vol. 2024, pp. 238-243). IET.
35. Ghosh, T., Sharma, P., Singh, P., Shinde, R., Bathani, R., & Whig, P. (2025, June). Advancing Sustainable Development Through Concrete Crack Detection via Hybrid CNN Model. In International Conference on Sustainable Development through Machine Learning, AI and IoT (pp. 319-329). Cham: Springer Nature Switzerland.
36. Gupta, P. K., Mishra, S. S., Nawaz, M. H., Choudhary, S., Saxena, A., Roy, R., & Keshamma, E. (2020). Value Addition on Trend of Pneumonia Disease in India-The Current Update. International Journal of Tropical Disease & Health, 41(7), 1-11.
37. Ramadugu, G. (2021). Continuous Integration and Delivery in Cloud-Native Environments: Best Practices for Large-Scale Saas Migrations. International Journal of Communication Networks and Information Security (IJCNIS), 13(1), 246-254.
38. Singh, M., Rallabandi, B., Gattupalli, K. K., & Sai Medarametla, M. (2025). Autonomous private 5G field area networks: Achieving secure, scalable, and self-healing smart grid communications. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448712
39. Desai, A. B., Rallabandi, B., Gattupalli, K. K., & Medarametla, M. S. (2025). Agentic AI for rural connectivity and spectrum-aware networks to power smart agriculture ecosystems. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448879
40. Goyal, S., Rallabandi, B., Gattupalli, K. K., & Medarametla, M. S. (2025). Digital twin-enabled context-aware networks: Enhancing smart grid resilience through predictive intelligence. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448880
41. Tripathi, N., Gattupalli, K. K., Rallabandi, B., & Medarametla, M. S. (2025). AI-native Cloud-RAN orchestration for enterprise private 5G using digital twin models. In 2025 1st IEEE Uttar Pradesh Section Women in Engineering International Conference on Electrical Electronics and Computer Engineering (UPWIECON) (pp. 851–857). IEEE. https://doi.org/10.1109/UPWIECON67212.2025.11390348
42. Goyal, S., Gattupalli, K. K., Rallabandi, B., & Medarametla, M. S. (2025). Integrating terrestrial and non-terrestrial networks for reliable rural coverage in agriculture and smart grids. In 2025 1st IEEE Uttar Pradesh Section Women in Engineering International Conference on Electrical Electronics and Computer Engineering (UPWIECON) (pp. 846–850). IEEE. https://doi.org/10.1109/UPWIECON67212.2025.11390331

43. Goyal, S., Gattupalli, K. K., Rallabandi, B., & Medarametla, M. S. (2025). Intent-driven zero-touch provisioning in private 5G networks with AI/ML automation. In 2025 1st IEEE Uttar Pradesh Section Women in Engineering International Conference on Electrical Electronics and Computer Engineering (UPWIECON) (pp. 839–845). IEEE. https://doi.org/10.1109/UPWIECON67212.2025.11390129
44. Tripathi, Aparna, Kunvar Pratap Nishad, Durgesh Chauhan, Anup Kumar, Azad Kumar, Dimple Kumari, Manisha Bajpai, Rituraj Dubey, Abhishek Rai, and Laxman Singh. "Recent developments in black phosphorus quantum dots (BPQDs) for energy storage and optoelectronic devices." Next Nanotechnology 9 (2026): 100410.
45. Joshi, K., Joshi, N. K., Diwakar, M., Tripathi, A. N., & Gupta, H. (2019). Multi-focus image fusion using non-local mean filtering and stationary wavelet transform. *International Journal of Innovative Technology and Exploring Engineering*, *9*(1), 344-350.
46. Pandey, N. K., Chaudhary, S., & Joshi, N. K. (2016, November). Resource allocation strategies used in cloud computing: A critical analysis. In *2016 2nd International Conference on Communication Control and Intelligent Systems (CCIS)* (pp. 213-216). IEEE.
47. Alam, S., Kumar, V., Singh, S., Joshi, S., & Kirola, M. (2021). Covid-19 Prediction in India using Machine Learning. *Engineering, Science*, *2021*.