

ARTIFICIAL INTELLIGENCE BASED CHATBOT FOR SOLAR PANELS QUALITY ASSURANCE

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Abstract

The paper addresses the need for improved solar panel quality assurance by developing an AI-based chatbot system tailored for installers and manufacturers. Traditional quality assurance is often slow, resource-intensive, and subject to human error. Leveraging advances in large language models, the chatbot provides automated support for performance testing, failure detection, and maintenance guidance. Implemented using Promptly and Flowise AI platforms, the system incorporates domain-specific knowledge through Retrieval-Augmented Generation. It delivers technical recommendations, identifies frequent failure points, and offers actionable advice to enhance diagnostic efficiency and maintenance effectiveness. Performance comparisons between platforms show distinct operational characteristics, underscoring the impact of system choice on user experience. Overall, the chatbot demonstrates promising potential to streamline solar panel testing, maintenance, and decision-making processes for industry professionals.

Keywords: Solar panels, chatbot system, artificial intelligence, large language models, quality assurance

Klepetalni robot na osnovi umetne inteligence za zagotavljanje kakovosti sončnih panelov

Izvleček

Članek obravnava potrebo po izboljšanjem zagotavljanju kakovosti sončnih panelov z razvojem sistema klepetalnih robotov, ki temelji na umetni inteligenci in je prilagojen monterjem in proizvajalcem. Tradicionalno zagotavljanje kakovosti je pogosto počasno, zahteva veliko virov in je podvrženo človeškim napakam. Klepetalni robot, ki izkorišča napredek v modelih velikih jezikov, zagotavlja avtomatizirano podporo za testiranje delovanja, odkrivanje napak in vodenje vzdrževanja. Sistem, ki je implementiran z uporabo platform umetne inteligence Promptly in Flowise, vključuje znanje, specifično za področje, prek generiranja z razširjenim iskanjem (Retrieval-Augmented Generation). Zagotavlja tehnična priporočila, prepozna pogoste točke napak in ponuja uporabne nasvete za izboljšanje diagnostične učinkovitosti in učinkovitosti vzdrževanja. Primerjave delovanja med platformami kažejo različne operativne značilnosti, kar poudarja vpliv izbire sistema na uporabniško izkušnjo. Na splošno klepetalni robot kaže obetaven potencial za poenostavitev procesov testiranja, vzdrževanja in odločanja sončnih panelov za strokovnjake v industriji.

Keywords: Sončne celice, sistem klepetalnih robotov, umetna inteligenca, veliki jezikovni modeli, zagotavljanje kakovosti

1 INTRODUCTION

Sustainability and the transition to renewable energy sources have become global priorities, with solar energy playing a significant role due to its availability, scalability, and minimal environmental impact. However, the efficiency and reliability of solar systems largely depend on the quality of solar panels and the consistency of their installation, testing, and maintenance processes. Traditional quality assurance methods are often time-consuming, costly, and prone to human error, which can reduce system performance and increase long-term operational costs.

Recent advances in artificial intelligence, particularly in large language models (LLMs), have opened new opportunities for automating and enhancing diagnostic and maintenance processes in technical systems. In the context of the solar industry, generative AI models can enable rapid data analysis, pattern recognition of failures, and tailored recommendations for installers and manufacturers. This reduces the need for manual data entry and expert consultation while improving accuracy and efficiency in maintenance and quality assurance workflows.

This paper presents the development of an AI-based chatbot system designed to support installers and manufacturers of solar panels. The system is implemented using the low code approaches **Promptly** and **Flowise AI** platforms and incorporates domain-specific knowledge through the **Retrieval-Augmented Generation (RAG)** approach. The chatbot contributes to automated performance testing, identifies common failure points, and delivers actionable technical recommendations to optimize maintenance processes. Performance comparisons between the two platforms highlight differences in user experience and operational characteristics. Overall, the findings demonstrate the promising potential of such AI-driven systems to enhance quality assurance. This paper is organized as follows. Section 2 gives overview of related work. Section 3 defines requirements for AI based system. Section 4 provides overview of system development using both, Flowise AI and Promptly. Section 5 evaluated the system. Section 6 concludes the paper and gives guidelines for future work.

2 RELATED WORK

The application of conversational AI systems in technical and specialized domains has evolved considerably in recent years, with particular growth in the renewable energy sector. This section reviews relevant research on chatbot architectures, natural language processing methodologies, and domain-specific implementations that inform the development of quality assurance systems for solar panel technology.

Chatbot Architectures and Frameworks

Earlier generations of chatbot systems were predominantly built on deterministic rule-based logic and pattern-matching techniques, often enhanced with compressed matching optimization [1], alongside early explorations of voice-based interaction models [2] and studies

on conversational agent behaviour in distributed environments [3]. Subsequent developments introduced more structured modelling approaches for general-purpose chatbot architecture [4], as well as applied dialogue systems designed for domain-specific information retrieval such as college enquiry assistants [5], forming the conceptual foundation on which modern modular and transformer-based systems were later developed.

The foundational work by Augello et al. (2011) introduced a modular framework for building versatile conversational agents, establishing principles for parallel and cooperative use of diverse techniques in conversational systems. This modular approach enables flexible performance tailored to specific domain attributes and user activities, a concept directly applicable to the specialized requirements of solar panel quality assurance [6]. Similarly, Ghose and Barua (2013) demonstrated the effectiveness of topic-specific dialogue-based chatbots through their implementation of a natural language chatbot designed specifically for university students. Their work emphasized the importance of domain-focused knowledge repositories that can be easily customized without requiring extensive code redesign, a principle that aligns with the need for specialized technical documentation integration in solar panel systems [7].

The advancement of chatbot knowledge acquisition methodologies has been significantly influenced by the research of Yu Wu et al. (2008), who proposed automatic knowledge acquisition from online forums using rough set and ensemble learning techniques. Their approach to indexing corpuses and selecting appropriate responses demonstrates the evolution toward more sophisticated information retrieval mechanisms, which forms the conceptual foundation for modern Retrieval-Augmented Generation approaches employed in contemporary chatbot systems [8].

Domain-Specific Applications in Energy Sector

Recent implementations of chatbots in the renewable energy domain reveal diverse approaches to addressing information accessibility and decision support challenges. The Solarbot system developed by Rahane et al. (2018) represents an early attempt to provide solar panel information to the general public in India through pattern matching and natural language processing [9]. While conceptual in nature, this work established the fundamental need for accessible solar energy information systems and demonstrated the viability of conversational interfaces for non-technical users seeking guidance on solar panel selection, installation, and maintenance.

More sophisticated implementations have emerged in recent years, as documented in comparative studies of renewable energy chatbots. Hulsmann et al. (2021) developed a natural language interface for energy system models covering the German energy transition, employing the RASA framework with Dual Intent and Entity Transformer (DIET) architecture based on transformer-based neural networks [10]. This system demonstrated the capability to make complex energy models accessible to non-expert decision makers including politicians and company managers, addressing the critical gap between technical expertise and practical decision-making needs. The work highlighted important limitations including lack of model agnosticism and challenges with diverse user inputs due to limited training data, insights that inform the design considerations for specialized quality assurance systems.

Patni et al. (2021) implemented a solar-specific chatbot for energy prediction and financial estimation in Mumbai, integrating multiple machine learning algorithms including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and regression models [11]. Their system achieved remarkable accuracy with SVM scores reaching 0.998 and relative errors of approximately 0.05%, demonstrating that focused solar energy applications can achieve high performance within well-defined operational boundaries. The integration of financial estimation capabilities alongside technical prediction represents a holistic approach to user support that extends beyond pure information provision.

The Cooee system developed by Gamage et al. (2022) represents the most advanced deployment in the energy domain, functioning as a real-time decision support tool within a multi-campus tertiary education institution [12]. Unlike previous systems targeting non-technical users, Cooee serves technical experts in energy management through conversational interaction with dynamic data spaces. The successful deployment of this system demonstrates the maturity of AI-powered chatbot technology for complex energy environments and validates the approach of integrating chatbots with real-world energy platforms.

Natural Language Processing and Information Retrieval

The technical foundations supporting conversational AI in specialized domains have been thoroughly explored through various NLP methodologies. Banchs and Kim (2014) evaluated information retrieval-based strategies for chat-oriented dialogue systems using vector space models, demonstrating how both current user input and conversation history can be strategically leveraged to improve response quality [13]. This work established important principles for context-aware conversational systems that maintain coherence across extended interactions.

Chen et al. (2011) contributed to the advancement of keyword-based search and exploration on databases, providing methodologies that improve knowledge access through intuitive query interfaces [14]. Their research on eliminating the need for complex query languages and intricate data schemas directly supports the accessibility goals of modern chatbot systems, particularly for users without technical database expertise. This approach is particularly relevant for quality assurance applications where installers and manufacturers require rapid access to specific technical information without navigating complex documentation structures.

The challenge of handling diverse user inputs and out-of-domain queries has been addressed through various innovative approaches. Ameixa et al. (2014) demonstrated techniques for managing out-of-domain requests by leveraging large text corpora, establishing methods for graceful degradation when chatbots encounter queries beyond their primary knowledge base [15]. This capability is essential for quality assurance systems that must acknowledge the boundaries of their expertise while maintaining user confidence and system credibility.

Research Gap and Contribution

Existing literature demonstrates substantial progress in chatbot technology and renewable energy applications, yet the specific area of quality assurance and technical diagnostics for solar panel systems has not been adequately addressed. The reviewed solar energy chatbots concentrate on consumer-oriented services. Solarbot provides informational guidance for potential adopters, Patni et al.'s system focuses on energy output prediction and investment feasibility, and Hulsmann et al.'s platform enables non-expert interaction with energy system models. Cooee, while more technically sophisticated, addresses broad energy management in institutional settings rather than the specialized diagnostic requirements of individual solar installation and manufacturing operations. Collectively, these systems address market information, financial estimation, general energy modeling, and administrative decision-making, but none specifically target the technical challenges inherent to solar panel quality validation. Critically, no existing AI-based chatbot system has been specifically designed for solar panel performance testing, fault diagnosis, or maintenance guidance which are the three core operational needs of solar panel manufacturers and installation professionals.

The absence of specialized quality assurance chatbots represents a significant gap in the renewable energy technology landscape. Unlike consumer information systems or energy market prediction platforms, quality assurance operations demand precise technical knowledge coordination, real-time diagnostic capabilities, systematic failure pattern recognition, and seamless integration with industry testing protocols and maintenance procedures. Performance testing requires detailed knowledge of standardized test methodologies; fault diagnosis demands pattern recognition across complex failure modes and operational contexts; maintenance guidance necessitates comprehensive understanding of degradation mechanisms and prevention strategies. These specialized requirements have not

been addressed by existing renewable energy chatbot systems and represent an unexplored opportunity for AI-supported technical operations.

The present work directly addresses this critical research gap by developing the first AI-based chatbot system specifically engineered for solar panel quality assurance across the complete lifecycle from manufacturing through installation to ongoing maintenance. Leveraging modern Retrieval-Augmented Generation technology and low-code AI platforms (Promptly and Flowise), this system uniquely integrates conversational interfaces with domain-specific technical knowledge encompassing performance testing protocols, systematic failure diagnostics, and evidence-based maintenance recommendations. By establishing this new application category within renewable energy chatbot systems, the work demonstrates how conversational AI can transform quality assurance workflows, enhance diagnostic efficiency, and improve maintenance effectiveness for industry professionals.

3 DOMAIN SPECIFICATION AND SYSTEM REQUIREMENTS

3.1 Domain Definition

The chatbot system operates within the specialized domain of solar panel technology, encompassing three primary areas of expertise: performance testing protocols for solar panel systems, identification and diagnosis of common solar panel failures, and comprehensive guidelines for extending system operational lifespan. The system addresses these technical domains from dual perspectives, serving both manufacturing professionals and installation specialists.

The primary purpose of the chatbot system is to provide comprehensive technical support throughout the solar panel production and installation lifecycle. The system's fundamental objectives include the automation of performance testing recommendations for solar panels and associated systems, systematic identification of common failure points, provision of evidence-based maintenance guidelines for proper system care and lifespan extension, and significant reduction of diagnostic time requirements while simultaneously enhancing maintenance operational efficiency.

The training dataset comprises comprehensive technical documentation sourced from industry-leading manufacturers including Shilden [16], Jingsung [17], [18], and DS Energy [19], [20], covering standardized testing protocols, destructive testing methodologies, safety performance verification procedures, and International Electrotechnical Commission (IEC) standard testing protocols. Additional resources encompass failure analysis documentation from solar power plant operators and comprehensive maintenance guidelines from various solar industry stakeholders [21]-[28].

The knowledge base architecture consists of four thematically organized document collections covering testing procedures, common failure modes, maintenance protocols, and a comprehensive operational guide for both installers and manufacturers. The knowledge base incorporates methodologies for thermal stress management, performance optimization recommendations, material degradation assessment protocols, and electrical load analysis under various operational conditions.

2.2 Functional Requirements

The chatbot system maintains an accessible and professional communication tone while ensuring technical accuracy in all provided information. System response times are constrained to a maximum of thirty seconds, ensuring efficient user interaction experiences. The system implements comprehensive user data security measures to protect sensitive technical and operational information. The chatbot maintains rigorous standards for technical information accuracy, ensuring all provided guidance reflects current industry best practices and regulatory requirements. The system continuously updates its knowledge base to reflect evolving industry standards and technological developments.

Furthermore, the chatbot supports specialized technical domains by providing accurate and reliable responses to inquiries related to solar panel performance testing protocols, common system faults, and best-practice guidelines for extending the operational lifespan of solar installations. It records interaction data to enhance personalization and tailors its responses based on previous user interactions, ensuring a more relevant and adaptive user experience. At the conclusion of each conversation, the chatbot proactively offers additional assistance to promote user satisfaction and maintain engagement.

4 DEVELOPMENT OF AI BASED SYSTEM

4.1 System Implementation in Promptly Platform

The chatbot implementation utilizing the Promptly platform incorporates four fundamental components: Workflow management, Datasource Search functionality, OpenAI ChatGPT processing, and Application Output delivery.

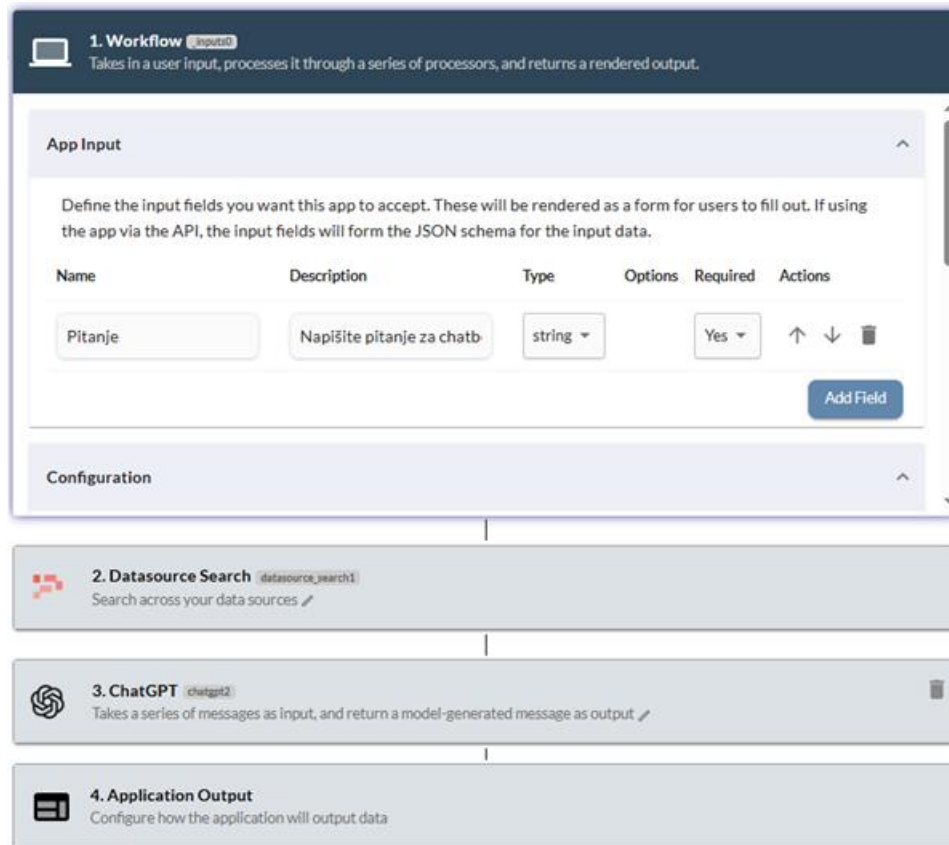


Figure 1 Promptly AI Components

Figure 1 shows the main components of the chatbot system on the Promptly platform, illustrating the flow from user input through data retrieval to the OpenAI ChatGPT engine generating responses based on a specialized knowledge base.

The Workflow component manages user input through a mandatory string-type input designated as "Question," facilitating direct user query submission to the chatbot system.

The Datasource Search component performs intelligent retrieval operations across the established knowledge base, consisting of four thematically organized Word document collections. The system utilizes user input as search queries while referencing the comprehensive datasource collection. Upon identifying relevant information through user query analysis, the Datasource Search component transmits retrieved data to the OpenAI ChatGPT processor.

The ChatGPT processor synthesizes user questions with retrieved data to generate comprehensive responses. The system operates with carefully configured parameters including GPT-4 model utilization for optimal performance, token allocation of 6,080 for input processing and 5,034 for response generation, creativity temperature setting of 0.4 for

balanced output quality, and conversation history retention for enhanced contextual understanding.

The system prompt instructs the chatbot to function as a specialized technical support assistant for solar panel installation and manufacturing processes, maintaining professional yet accessible communication while providing accurate technical information. The system consistently incorporates examples and step-by-step guidance where appropriate, concluding interactions with proactive assistance offers.

4.2 System Implementation in Flowise AI Platform

The Flowise AI implementation architecture comprises four essential elements: Conversational Retrieval QA Chain, ChatOllama processing, Document Store vector database, and Buffer Memory management. The Conversational Retrieval QA Chain enables comprehensive document interaction capabilities, serving as the central coordination component for all system elements [29].

The implementation utilizes ChatOllama for local model execution capabilities, specifically employing the Mistral 7b language model. ChatOllama was selected as the chat model node because it allows local execution of large language models via the Ollama runtime, which is well aligned with privacy and deployment requirements of an industrial quality-assurance scenario. ChatOllama acts as the interface between FlowiseAI and the Ollama runtime, exposing locally hosted large language models as a configurable chat node within the workflow. In this configuration, the node is bound to the Mistral 7B model, which offers a favourable balance between model size, response quality, and hardware requirements for on-premise deployment.

This selection provides cost-effective operation while maintaining multilingual support capabilities and straightforward implementation requirements. The model operates with a creativity temperature of 0.6, providing enhanced responsiveness for complex technical queries.

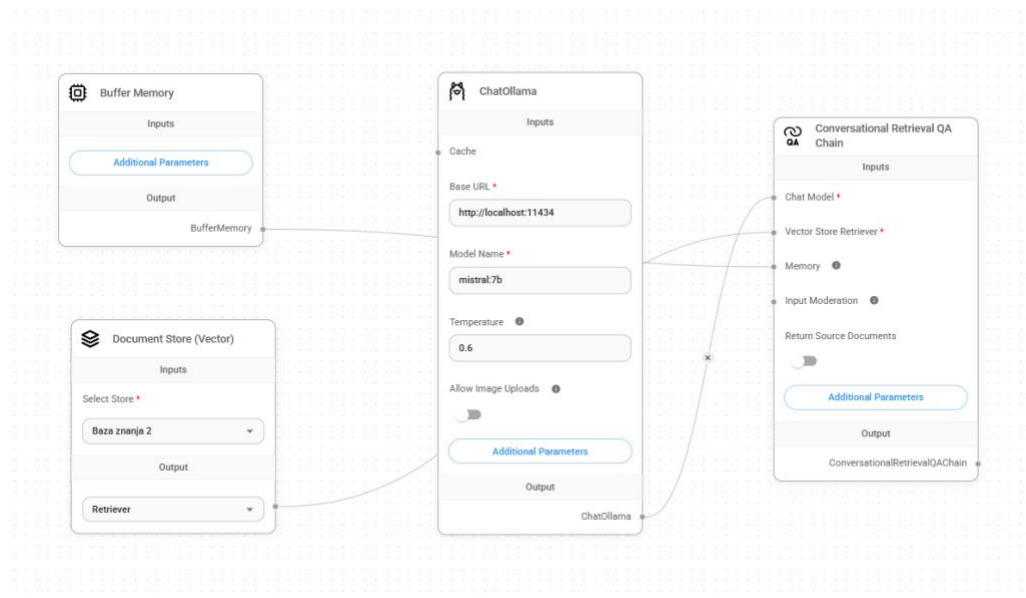


Figure 2 FlowiseAI components

The knowledge base resides within the Document Store vector database, utilizing Ollama Embeddings and Faiss for comprehensive text processing and similarity search capabilities. Ollama Embeddings transform each text chunk into a dense numerical vector that encodes the

semantic meaning of the content, allowing concept-level comparison rather than simple keyword matching. Faiss then indexes these vectors and performs efficient nearest-neighbour searches, so that for each user query the system can quickly retrieve the most similar document segments and pass them to the chatbot as grounded context for answer generation.

The system employs the "nomic-embed-text" embedding model for text vectorization, accommodating extended token sequences for enhanced contextual understanding. Document processing utilizes Recursive Character Splitter with standard parameters of 1,000-character chunks and 200-character overlap for optimal information retrieval.

The Buffer Memory component ensures conversation history retention, enabling the system to maintain contextual awareness throughout extended user interactions. This functionality supports the system's personalization capabilities while ensuring coherent multi-turn conversations.

5 SYSTEM EVALUATION AND PERFORMANCE ANALYSIS

The evaluation methodology employed domain-specific test questions drawn from each knowledge base component to assess system performance across all technical areas. Test scenarios included inquiries regarding common solar panel failures such as white trace identification, comprehensive operational verification procedures for solar panel systems, technical measurement procedures including voltage measurement protocols, and specialized maintenance approaches for polycrystalline panel preservation.

Performance analysis revealed distinct operational characteristics between the two implementation platforms. The Promptly implementation demonstrated superior keyword identification capabilities, providing direct responses that successfully located relevant information from the document repository. In contrast, the Flowise implementation tended to generate more generalized responses, indicating different information retrieval and processing approaches between the platforms.

This performance differential pattern remained consistent across multiple test scenarios, suggesting fundamental differences in information processing and response generation methodologies between the two platforms. The evaluation results indicate that platform selection significantly impacts system performance characteristics and user experience quality.

The fulfilment of the requirements is shown below in Table 1.

Requirement	Promptly	Flowise
The chatbot provides accurate and reliable responses to inquiries related to solar panel performance testing protocols	Requirement fulfilled	Requirement fulfilled
The chatbot provides accurate and reliable responses to common system faults	Requirement fulfilled	Requirement fulfilled
The chatbot provides guidelines and best-practices for extending the operational lifespan of solar installations	Requirement fulfilled	Requirement fulfilled
The chatbot records interaction data	Requirement fulfilled	Requirement fulfilled
The chatbot tailors its responses based on previous user interactions	Requirement fulfilled	Requirement fulfilled
At the conclusion of each conversation, the chatbot offers additional assistance	Requirement fulfilled	Requirement fulfilled
The chatbot maintains an accessible and professional communication tone	Requirement fulfilled	Requirement fulfilled

The chatbot response times are constrained to a maximum of thirty seconds	Requirement fulfilled	Requirement not fulfilled
The chatbot implements user data security measures to protect information	Requirement partially fulfilled	Requirement partially fulfilled
The chatbot must provide accurate and up-to-date technical information	Requirement partially fulfilled	Requirement partially fulfilled

6 CONCLUSION

The implementation of artificial intelligence-based chatbot technology within the solar energy industry demonstrates significant potential for enhancing manufacturer and installer capabilities in testing, maintenance, and quality assurance processes. The research findings indicate that intelligent conversational systems can serve as valuable operational tools for industry professionals in daily technical operations.

The comparative implementation across Promptly and Flowise AI platforms revealed distinct operational characteristics and performance profiles. Despite platform-specific limitations, both implementations successfully provided domain-specific technical guidance, demonstrating the viability of AI-supported decision-making systems in specialized technical domains.

Future research directions should explore enhanced integration capabilities with existing industry systems, expanded knowledge base coverage to encompass emerging solar technologies, and improved personalization algorithms for enhanced user experience delivery. The findings suggest that continued development of AI-supported technical assistance systems will provide increasingly valuable support for solar energy industry professionals.

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References

- [1] A. Augello, M. Scriminaci, S. Gaglio, and G. Pilato, 'A Modular Framework for Versatile Conversational Agent Building', 2011 International Conference on Complex, Intelligent, and Software Intensive Systems. IEEE, pp. 577–582, June 2011. doi: 10.1109/cisis.2011.95.
- [2] S. J. du Preez, M. Lall, and S. Sinha, 'An intelligent web-based voice chat bot', IEEE EUROCON 2009. IEEE, pp. 386–391, May 2009. doi: 10.1109/eurcon.2009.5167660.
- [3] Y. Wu, G. Wang, W. Li, and Z. Li, 'Automatic Chatbot Knowledge Acquisition from Online Forum via Rough Set and Ensemble Learning', 2008 IFIP International Conference on Network and Parallel Computing. IEEE, pp. 242–246, Oct. 2008. doi: 10.1109/npc.2008.24.
- [4] B. Setiaji and F. W. Wibowo, 'Chatbot Using a Knowledge in Database: Human-to-Machine Conversation Modeling', 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS). IEEE, Jan. 2016. doi: 10.1109/isms.2016.53.
- [5] P. Salve, V. Patil, V. Gaikwad, Prof. G. Wadhwa. "College Enquiry Chat Bot," International Journal on Recent and Innovation Trends in Computing and Communication, March 2017., doi: 10.17762/ijritcc.v5i3.330.
- [6] A. Patni, A. Prabhu, S. Singh, and S. Sankhe, 'Solar Chatbot and Energy Prediction using different Machine Learning Algorithms', 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). IEEE, pp. 1–9, Nov. 11, 2021. doi: 10.1109/i-smac52330.2021.9640817.
- [7] G. Gamage, N. Mills, P. Rathnayaka, A. Jennings, and D. Alahakoon, 'Cooee: An Artificial Intelligence Chatbot for Complex Energy Environments', 2022 15th International Conference on Human System Interaction (HSI). IEEE, pp. 1–5, July 28, 2022. doi: 10.1109/hsi55341.2022.9869464.
- [8] J. P. McIntire, L. K. McIntire, and P. R. Havig, 'Methods for chatbot detection in distributed text-based communications', 2010 International Symposium on Collaborative Technologies and Systems. IEEE, pp. 463–472, 2010. doi: 10.1109/cts.2010.5478478.
- [9] Y. Chen, W. Wang, and Z. Liu, 'Keyword-based search and exploration on databases', 2011 IEEE 27th International Conference on Data Engineering. IEEE, pp. 1380–1383, Apr. 2011. doi: 10.1109/icde.2011.5767958.
- [10] J. Hulsmann, L. J. Sieben, M. Mesgar, and F. Steinke, 'A Natural Language Interface for an Energy System Model', 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe). IEEE, pp. 1–5, Oct. 18, 2021. doi: 10.1109/isgteurope52324.2021.9640196.
- [11] C. Erdogan, H. Nusret Bulus, and B. Diri, 'Analyzing the performance differences between pattern matching and compressed pattern matching on texts', 2013 International Conference on Electronics, Computer and Computation (ICECCO). IEEE, pp. 135–138, Nov. 2013. doi: 10.1109/icecco.2013.6718247.
- [12] S. Ghose and J. J. Barua, 'Toward the implementation of a topic specific dialogue based natural language chatbot as an undergraduate advisor', 2013 International Conference on Informatics, Electronics and Vision (ICIEV). IEEE, pp. 1–5, May 2013. doi: 10.1109/iciev.2013.6572650.

- [13] R. E. Banchs and S. Kim, 'An empirical evaluation of an IR-based strategy for chat-oriented dialogue systems', Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific. IEEE, pp. 1–4, Dec. 2014. doi: 10.1109/apsipa.2014.7041736.
- [14] W. Rahane, S. Patil, K. Dhondkar, and T. Mate, 'Artificial Intelligence Based Solarbot', 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT). IEEE, pp. 601–605, Apr. 2018. doi: 10.1109/icicct.2018.8473172.
- [15] D. Ameixa, L. Coheur, P. Fialho, and P. Quaresma, 'Luke, I am Your Father: Dealing with Out-of-Domain Requests by Using Movies Subtitles', Lecture Notes in Computer Science. Springer International Publishing, pp. 13–21, 2014. doi: 10.1007/978-3-319-09767-1_2.
- [16] Shilden. (n.d.). How to Test Solar Panels? A Complete Guide. Retrieved from: <https://hr.shieldenchanel.com/blogs/solar-panels/test-solar-panels>
- [17] Jingsun. (n.d.). Verification Method of Solar Panel Safety Performance. Retrieved from: <https://hr.jingsun-power.com/info/verification-method-of-solar-panel-safety-perf-88179934.html>
- [18] Jingsun. (n.d.). Destructive Testing of Solar Panels and Performance Verification. Retrieved from: <https://hr.jingsun-power.com/info/destructive-testing-of-solar-panels-and-verifi-89141475.html>
- [19] DC Energy. (n.d.). Basic Understanding of IEC Standard Testing for Solar Photovoltaic Panels. Retrieved from: <https://hr.dsnsolar.com/info/basic-understanding-of-iec-standard-testing-fo-47051491.html>
- [20] DS Energy. (n.d.). Most Common Problems and Explanations Why. Retrieved from: <https://hr.dsnsolar.com/info/solar-pv-module-faults-and-failings-41926335.html>
- [21] Solarne-elektrane.shop. (n.d.). Failures in Solar Power Plants – A Detailed Analysis of Challenges and Solutions. Retrieved from: <https://www.solarne-elektrane.shop/l/kvarovi-u-solarnim-elektranama/>
- [22] Benny. (n.d.). Most Common Failures and How to Fix Them. Retrieved from: <https://www.beny.com/hr/four-most-common-pv-system-failures-and-how-to-fix/>
- [23] Joca. (n.d.). How to Test Solar Panels: Measuring Panel Output and Performance. Retrieved from: <https://joca-cable.com/hr/blog/how-to-test-solar-panel/#>
- [24] ZGRADOnačelnik.hr. (n.d.). You Can Sell Damaged Solar Panels, and Buy Refurbished Ones. Retrieved from: <https://www.zgradonacelnik.hr/savjeti/ostecene-solarne-panele-mozete-prodati-a-obnovljene-kupiti/1078>
- [25] Mobis Solar. (n.d.). Cleaning and Maintenance of Solar Panels: How and How Often Should You Clean Solar Panels? Retrieved from: <https://www.mobis-solar.hr/ciscenje-i-odrzavanje-solarnih-panela-donosimo-vam-odgovor-na-pitanje-kako-i-koliko-cesto-je-potrebno-o-cistiti-solarne-panele>
- [26] Raysol Solar. (n.d.). How Are Solar Panels Stored? Retrieved from: <https://ba.raysolsolar.com/info/how-are-solar-panels-stored--92323629.html>
- [27] Energy2Store. (n.d.). Lifespan and Degradation of Solar Panels. Retrieved from: <https://www.energy2store.hr/solarni-paneli-vijek-trajanja-i-degradacija/>

- [28] Markvart, T., & Castaner, L. (eds.). (2003). Practical Handbook of Photovoltaics: Fundamentals and Applications, Chapter 34: Testing Photovoltaic Systems. Retrieved from: <https://www.sciencedirect.com/science/article/abs/pii/B9781856173902500349>
- [29] FlowiseAI Documentation, "Conversational Retrieval QA Chain and System Architecture," November 2025, Retrieved from: <https://docs.flowiseai.com/integrations/langchain/chains/conversational-retrieval-qa-chain>

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