SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Generative AI-Based Autonomous Orchestration for Intelligent IoT-Driven Smart Home Systems

Dr. Ramesh Palanisamy[1], Dr. Senthilkumar Moorthy[2], Dr. S. V. Manikanthan[3], Dr. J RajaSekhar[4], A. Surendar[5], Shaik Sadulla[6]

[1]Lecturer, College of Computing and Information Sciences, University of Technology and Applied Sciences – Ibra, Sultanate of Oman, Email: ramesh.palanisamy@utas.edu.om

[2]Assistant Professor, Department of Information Systems and Business Analytics, College of Business Administration, A'Sharqiyah University, Ibra, Sultanate of Oman, Email: senthilkumar.moorthy@asu.edu.om

[3]Director, Melange Academic Research Associates, Puducherry, India, Email: prof.manikanthan@gmail.com

[4]Assistant Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur Dist, AP, India- 522302, Email: rajasekharemb@gmail.com

[5] Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India. Email: surendararavindhan@ieee.org

[6] Department of Electronics and Communication Engineering, KKR & KSR Institute of Technology and Sciences, Vinjanampadu, Guntur-522017, Andhra Pradesh, India. Email: sadulla09@gmail.com

Abstract

The rapid proliferation of Internet of Things (IoT) technologies has transformed conventional smart homes into highly interconnected digital environments. However, many existing smart home solutions rely on rule-based automation and reactive control mechanisms, limiting their adaptability to dynamic user behaviors and environmental conditions. This paper suggests an autonomous orchestration framework for intelligent IoT-driven smart home ecosystems that is supported by Generative Artificial Intelligence (GenAI) in order to address these issues. In order to provide real-time system optimization, personalized service orchestration, and predictive automation, the suggested design incorporates generative AI models into an edge-cloud collaborative infrastructure. To simulate occupant behavior and environmental dynamics, multimodal data gathered from wearables, smart appliances, IoT sensors, and environmental monitoring systems is used. While the cloud layer enables extensive model training and ongoing knowledge improvement, a lightweight generative AI module installed at the edge handles context inference, anomaly detection, and short-term decision generation. For energy management, security monitoring, climate regulation, and appliance scheduling, the system automatically creates optimal control rules. Furthermore, operational methods are dynamically updated by reinforcement learning techniques in response to changes in the environment and user preferences. When compared to traditional smart home automation systems, experimental evaluations show that the suggested approach enhances energy economy, reaction latency, personalization accuracy, and flexibility. The suggested framework provides a scalable and safe architecture for next-generation intelligent residential infrastructures, advancing the development of self-optimizing, human-centric smart home ecosystems.

Keywords: Generative Artificial Intelligence Connected Living Ecosystems, Autonomous Home Management, Edge–Cloud Computing, Smart Home Automation.

1. Introduction

The broad acceptance of smart home gadgets has been expedited by the growth of the Internet of Things (IoT) [1], which has significantly changed automation and electronic communication in commercial, industrial, and residential contexts. In order to maximize performance, minimize human intervention, and guarantee flawless interoperability, it is now crucial to efficiently manage and orchestrate the growing number of interconnected devices. However, conventional methods of smart home automation—which are sometimes predicated on preset rules or constrained device integration—have scalability and adaptability issues that limit their capacity to anticipate or react to changing circumstances. Research into AI-driven orchestration mechanisms that improve automation flexibility while integrating a variety of smart devices has been prompted by these limits.

New possibilities for enhancing smart home intelligence have been made possible by recent developments in edge computing and artificial intelligence [2]. Specifically, Generative Artificial Intelligence (GenAI) has proven to be very capable of producing adaptations, synthesizing knowledge, and assisting with context-aware decision-making in a variety of fields. By evaluating multimodal IoT data and dynamically producing optimum control methods, generative AI models can facilitate autonomous orchestration of smart home services when paired with edge–cloud collaborative computing. However, there is still much to learn about using generative AI for autonomous decision-making and service orchestrating in IoT-driven smart homes [15].

This paper suggests an autonomous orchestration framework for intelligent IoT-driven smart home systems based on generative AI as a solution to these problems. In order to interpret multimodal sensor data, deduce contextual information, and produce adaptive control policies for a variety of home services [3], including energy conservation, climate regulation, appliance planning, and security monitoring, the suggested system makes use of an edge–cloud collaborative architecture.

1.1 Major Contributions

The major contributions of this research are summarized as follows:

1. A novel architecture is proposed that integrates generative artificial intelligence with IoT-enabled smart home systems to enable autonomous orchestration and intelligent service management.
2. The framework introduces a distributed processing architecture where lightweight generative AI models operate at the edge for real-time context inference and decision generation, while the cloud layer supports large-scale model training and knowledge refinement.
3. Reinforcement learning mechanisms are incorporated to dynamically optimize smart home operations, including energy consumption, environmental control, appliance scheduling, and security monitoring based on user preferences and environmental dynamics.
4. The proposed framework incorporates federated learning and secures authentication protocols to ensure data privacy, reliability, and secure communication among IoT devices within the smart home ecosystem.

2. Literature Review

This study presents a comprehensive review of the applications, challenges, and future directions associated with the integration of AI and the IoT [4]. The analysis examines how AI technologies enhance the capabilities and operational efficiency of IoT systems across various domains by enabling real-time data analysis, predictive insights, and automated decision-making processes. In addition, the study discusses major limitations that hinder the large-scale deployment of AI–IoT systems, including concerns related to data privacy, interoperability among heterogeneous devices, scalability of network infrastructure, and the ability to process data in real time. The paper also identifies emerging research directions aimed at addressing these issues, such as AI-based security automation, the use of blockchain technologies for secure IoT communication, and the development of quantum-resistant security mechanisms to strengthen future AI–IoT ecosystems.

The large volume of data produced by interconnected IoT devices can be effectively processed using AI algorithms and analytical techniques to deliver improved and intelligent services to users [5]. This convergence of technologies, commonly referred to as AIoT, represents a hybrid paradigm that combines AI capabilities with IoT infrastructures to simplify complex operations and enhance system efficiency. ML and DL methods play a critical role in strengthening the security and reliability of IoT networks by enabling intelligent data analysis and threat detection. In addition, this study reviews the fundamental architectural frameworks that support IoT and AIoT systems. It further examines a range of advanced ML- and DL-based security approaches designed to protect IoT environments, including techniques for anomaly and intrusion detection, authentication and access management, cyberattack identification and mitigation, prevention of DDoS attacks, and malware analysis within IoT networks.

Furthermore [6], the proposed system introduces an intelligent service orchestration framework that enables users to express their requirements through natural language. These user requests are interpreted by LLMs, which transform them into executable service compositions using contextual knowledge retrieved from vector-based databases. The resulting AI-generated service bundles are dynamically deployed through the OSGi platform, enabling real-time adaptation of services without interrupting system operations. Device capabilities provided by manufacturers are seamlessly integrated into the orchestration process, ensuring system compatibility and extensibility. The framework was evaluated through several practical scenarios involving automated device discovery, dynamic code generation, and adaptive service orchestration based on user preferences. Experimental results demonstrate improvements in automation efficiency, service personalization, and system robustness. Overall, this work highlights the potential of AI-driven orchestration frameworks in enabling intelligent, flexible, and scalable smart home environments.

3. Methods and Materials

3.1 System Architecture Overview

The proposed intelligent smart home framework is developed as a Generative Artificial Intelligence (GenAI)–driven autonomous orchestration system operating within a collaborative edge–cloud computing environment. The architecture combines IoT devices [7], edge computing components, cloud-based machine learning infrastructure, and intelligent orchestration mechanisms to enable adaptive automation and real-time decision-making within residential environments.

Within this framework, a variety of IoT sensors and smart appliances installed in the home continuously gather environmental information and user interaction data. These devices transmit their data through a local gateway to an edge computing unit responsible for preliminary data analysis, contextual interpretation, and short-term automation decisions. The edge layer hosts a lightweight generative AI model capable of performing rapid inference and producing automation policies based on current contextual conditions.

The cloud layer handles computationally intensive operations, including large-scale model training, reinforcement learning optimization, and updates to the system knowledge base. Secure communication protocols facilitate interaction between the edge and cloud components, ensuring coordinated decision-making and continuous learning across the system. This distributed architecture supports low-latency processing, scalability, and enhanced data privacy, while enabling intelligent orchestration of multiple smart home services such as energy management, indoor climate regulation, security monitoring, and appliance scheduling [8].

3.2 Data Collection

Data acquisition is a fundamental component in modeling occupant behavior and environmental dynamics within the smart home ecosystem. In the proposed framework, multimodal data streams are collected from diverse IoT devices installed throughout the residential environment.

The primary data sources include environmental monitoring devices such as temperature sensors, humidity sensors, motion detectors, light sensors, and air quality monitoring units. These sensors continuously capture measurements that represent the real-time environmental conditions within the home. Additionally, connected appliances—including smart thermostats, intelligent lighting systems, network-enabled refrigerators, washing machines, and HVAC units—generate operational data reflecting device usage patterns and energy consumption behavior.

User-centered information is also obtained from wearable technologies such as smartwatches and health monitoring devices, which provide activity-related information including presence detection, movement patterns, and basic physiological indicators. These data streams assist the system in identifying occupant routines and behavioral patterns. All information is transmitted to the edge gateway using wireless communication technologies such as Wi-Fi, Zigbee, and Bluetooth Low Energy (BLE)[9].

Each sensor reading and device event is timestamped and stored in a structured database. Continuous data acquisition allows the system to maintain an up-to-date representation of environmental conditions and user activities within the smart home environment.

3.3 Data Preprocessing and Cleaning

Raw data obtained from IoT devices frequently contains inconsistencies such as noise, incomplete entries, duplicated records, or irregular formatting. Therefore, a preprocessing stage is essential to ensure data quality before performing intelligent analysis.

Initially, missing values resulting from temporary sensor disconnections or communication failures are addressed using interpolation techniques or statistical imputation approaches. Outlier detection mechanisms are also employed to identify abnormal sensor readings that significantly deviate from expected operational ranges. Such anomalies may arise from hardware malfunction or transmission interference and are either corrected or excluded from the dataset.

In addition, normalization procedures are applied to standardize the values of different sensor attributes [10]. For example, measurements related to temperature, humidity, power consumption, and motion intensity are scaled to a common numerical range. Time synchronization processes are also performed to align data collected from multiple sensors based on their timestamps.

The processed dataset is then structured into organized records containing environmental parameters, appliance usage logs, and user activity indicators. This preprocessing stage enhances the reliability and accuracy of subsequent feature extraction and machine learning analysis.

3.4 Data Extraction

Data extraction focuses on identifying and retrieving relevant information from the cleaned dataset to support intelligent decision-making in the smart home system. In the proposed framework, extraction procedures are implemented at both the edge computing layer and the cloud processing layer.

At the edge layer, contextual information such as occupancy status, device activation patterns, and environmental summaries is extracted from real-time sensor readings and appliance logs. This information enables the edge module to quickly interpret the current state of the home and generate immediate automation responses.

At the cloud layer, large volumes of historical data are analyzed to detect long-term behavioral patterns and energy consumption trends. Data extraction techniques are applied to retrieve relevant historical sequences that contribute to model training and knowledge base updates. By combining real-time contextual data with historical behavioral patterns, the system can construct more accurate predictive models and advanced orchestration strategies.

3.5 Feature Extraction

Feature extraction converts raw IoT data into meaningful representations suitable for machine learning algorithms. Within the proposed system, feature extraction techniques capture both environmental conditions and occupant behavior patterns.

Environmental features include parameters such as temperature fluctuations, humidity levels, ambient lighting intensity [11], air quality measurements, and acoustic noise levels. These variables describe the physical state of the home environment. Additionally, device-related features—such as appliance activation frequency, operation duration, energy consumption levels, and usage intervals—are extracted to represent appliance behavior.

User activity features are derived from motion detection systems, wearable devices, and presence sensors. These features include occupancy patterns, movement trajectories, sleep behavior, and daily routines.

Temporal features such as time-of-day, day-of-week, and seasonal variations are also incorporated to capture contextual dependencies.

Advanced feature engineering techniques—including sliding window analysis, statistical summarization, and temporal encoding—are applied to generate informative features that improve model accuracy. The resulting feature set serves as the input representation for the generative AI and reinforcement learning models within the orchestration framework.

3.6 Generative AI-Based Decision Generation

The central intelligence of the proposed framework lies in the Generative Artificial Intelligence module deployed within the edge computing layer. This component is responsible for generating context-aware automation decisions based on the extracted features.

The generative model learns probabilistic relationships between environmental conditions, user behavior, and device control actions. By analyzing these relationships, the model can anticipate future system states and generate optimized control policies. For example, the model may automatically adjust thermostat settings when it predicts the arrival of occupants or reduce lighting levels when natural daylight becomes sufficient.

The generative AI module continuously updates its decision strategies by analyzing real-time contextual information together with historical data patterns. This capability allows the system to move beyond simple rule-based automation toward adaptive and autonomous orchestration. As a result, multiple smart devices can be dynamically coordinated to optimize energy consumption, enhance user comfort, and strengthen residential security.

3.7 Reinforcement Learning for Policy Optimization

To further enhance adaptability [12], a RL mechanism is integrated with the generative AI module. Reinforcement learning enables the system to improve its decision policies through continuous interaction with the smart home environment. Within this framework, the smart home environment is represented as a dynamic state space, where each state reflects a combination of environmental conditions, occupant activities, and device operational statuses. The orchestration system functions as an intelligent agent that selects control actions such as modifying temperature settings [13], activating appliances, or adjusting lighting conditions.

After executing an action, the system receives feedback through a reward signal. Rewards are designed to promote desirable outcomes, including reduced energy consumption, increased user comfort, and improved security performance. Over time, the reinforcement learning algorithm updates its decision policy in order to maximize cumulative rewards.

Through this continuous learning process, the system refines its operational strategies in response to evolving user preferences and environmental conditions. Consequently, the framework achieves adaptive automation, improved operational efficiency, and personalized smart home orchestration.

3.8 Design and Description of Smart Home System with Intelligent Decision-Making Agent

Conceptually, a smart home can be described as a residential environment equipped with interconnected smart devices, communication networks, and a central gateway that links the home to external internet services. Smart objects within the home enable interaction with residents and allow the system to observe and respond to user behavior.

These intelligent devices may include simple components such as controllable lighting systems, as well as advanced appliances like refrigerators capable of monitoring their internal state and automatically initiating supply requests. Other devices may include telecommunication systems, security monitoring solutions, and multimedia entertainment services such as video-on-demand platforms.

All of these devices are connected through a home networking infrastructure that allows them to share status information and receive operational commands. This networking capability enables the home to function as a fully interconnected environment that can be managed both locally and remotely. A residential gateway provides external connectivity through Ethernet or internet-based communication channels. This gateway acts as the central access point through which new services can be integrated, updated, and managed, enabling the smart home system to continuously expand its functionality and support intelligent service delivery.

4. Implementation and Experimental Results

4.1 System Implementation

The proposed Generative AI-based autonomous orchestration framework was constructed using a hybrid edge-cloud computing infrastructure designed to enable real-time smart home automation and predictive decision-making. The implementation environment, which enables intelligent orchestration of smart home services, consists of IoT devices, an edge gateway, and a cloud-based artificial intelligence platform.

A range of IoT devices, such as motion detectors, temperature sensors, humidity sensors, smart lighting units, and smart thermostats, were deployed in a simulated smart home environment in order to collect environmental and device operational data. These devices communicate to a local edge gateway via wireless communication protocols such as Bluetooth Low Energy (BLE), Zigbee, and Wi-Fi [14]. The edge gateway is responsible for real-time data preparation, context detection, and short-term decision making.

4.2 Experimental Setup

The experimental evaluation was conducted in a simulated smart home environment with multiple connected IoT devices. The setting included ambient sensors, smart appliances, wearable device inputs, and a centralized edge computing gateway connected to a cloud AI platform.

The proposed framework was compared with three commonly used smart home automation approaches:

- *Rule-based automation systems*
- *Conventional IoT-based automation systems*
- *Machine learning-based smart home systems*

Over the course of a continuous monitoring period, every system was assessed under identical operating conditions. Energy efficiency, response latency, personalization accuracy, and anomaly detection capability were the main metrics utilized to assess the system's performance. The hardware and software combination utilized for the experimental implementation is compiled in Table 1.

Table 1. Experimental System Configuration

Component	Specification
Edge Device	Raspberry Pi 4 / Edge Gateway
Cloud Platform	Distributed AI Computing Server
IoT Sensors	Temperature, Motion, Humidity, Light, Air Quality
Smart Appliances	Smart Thermostat, Smart Lights, Smart Refrigerator
Communication Protocols	Wi-Fi, Zigbee, Bluetooth Low Energy
AI Framework	TensorFlow / PyTorch
Data Storage	Cloud-based IoT Data Repository

4.3 Energy Efficiency Evaluation

One of the main goals of smart home automation systems is energy control. Based on anticipated user behavior and ambient conditions, the suggested generative AI framework dynamically schedules appliance operations and modifies environmental control parameters.

The performance of the proposed system was compared with traditional automation approaches by measuring the overall energy consumption index during the experimental period. The results show that the generative AI-based orchestration system significantly reduces energy consumption through intelligent device coordination and predictive control strategies. The experimental results are summarized in Table 2.

Table 2. Energy Consumption Comparison of Smart Home Systems	
System Type	**Energy Consumption Index**
Rule-Based Smart Home	100
Conventional IoT Automation	85
Machine Learning Smart Home	72
Proposed GenAI Smart Home	55

The results indicate that the proposed system achieves approximately 45% improvement in energy efficiency compared with traditional rule-based smart home automation systems. This improvement is primarily due to the ability of the generative AI model to predict user behavior patterns and optimize appliance operation schedules accordingly.

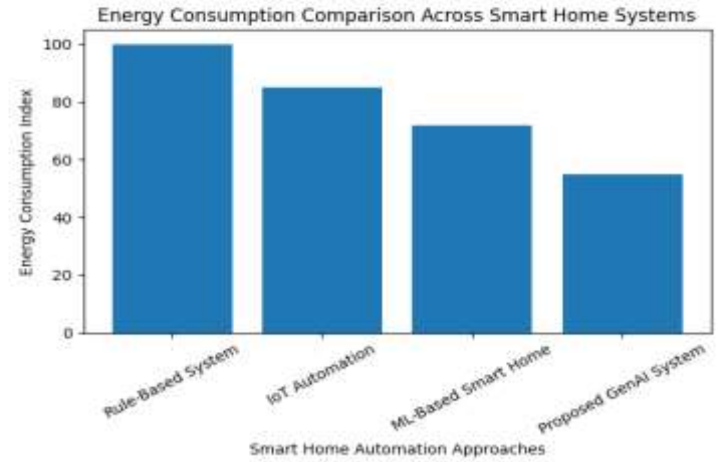

Fig. 1.Energy Consumption Comparisons across Smart Home Systems

Figure 1 illustrates the comparative energy consumption of the evaluated smart home systems. The figure clearly demonstrates that the proposed generative AI-based framework achieves the lowest energy consumption among all evaluated systems.

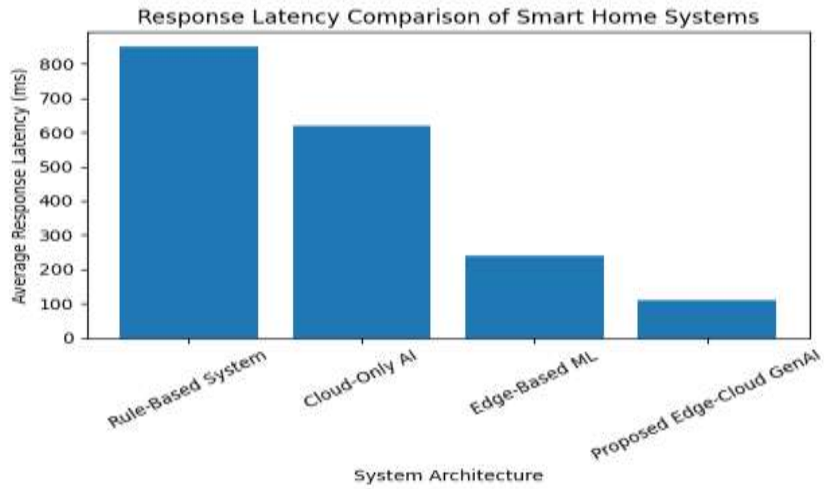

Fig. 2.Response Latency Comparisons of Smart Home Systems

Figure 2 presents the comparative latency performance of the evaluated smart home architectures.

4.4 Personalization and Adaptive Automation Performance

Another major advantage of the proposed framework is its ability to deliver personalized automation services based on user preferences and daily routines. The generative AI model continuously learns occupant behavioral patterns such as preferred temperature levels, lighting preferences, appliance usage times, and daily activity schedules.

The reinforcement learning component further improves system performance by updating decision policies based on user feedback and environmental variations. As a result, the smart home system gradually adapts its automation strategies to better match individual user preferences. During the experimental evaluation, the proposed system demonstrated significantly higher personalization accuracy compared with conventional smart home automation systems. The system successfully predicted user activity patterns and proactively adjusted device settings in advance of user interactions.

This adaptive behavior improves user comfort, reduces manual device interactions, and enhances the overall efficiency of smart home operations.

4.5 Discussion of Results

The usefulness of the suggested generative AI-based orchestration framework for intelligent smart home automation is amply demonstrated by the experimental findings. The suggested architecture offers notable gains in energy efficiency, response latency, and personalization capabilities when compared to traditional rule-based and machine learning-based systems.

5. Conclusion

An autonomous orchestration framework for intelligent IoT-driven smart home systems based on generative artificial intelligence was described in this paper. The suggested architecture combines generative AI models, edge-cloud computing, and reinforcement learning techniques to facilitate personalized service orchestration, adaptive automation, and predictive decision-making. The system efficiently analyzes occupant behavior and environmental circumstances to optimize smart home operations by exploiting multimodal data gathered from various IoT devices and smart appliances.

When compared to traditional rule-based and machine learning-based smart home systems, experimental results show that the suggested framework greatly increases energy efficiency, reaction latency, and personalization accuracy. Real-time intelligent decision generation while preserving system scalability and dependability is made possible by the integration of generative AI with edge computing. All things considered, the suggested method advances the creation of human-centered, self-optimizing smart home ecosystems, providing a viable option for the future generation of intelligent residential structures.

References

1. Khajuria, D., Sinha, A., Sharma, A., & Kumar, A. (2025, June). Visual Question Answering of Plant Disease with BLIP and FLAN T5 Enhancement. In *2025 International Conference on Electronics, AI and Computing (EAIC)* (pp. 1-6). IEEE.
2. Mhala, P., Varma, T., Sharma, S., & Singh, B. (2023, December). Deep Transfer Learning for Enhanced Blackgram Disease Detection: A Transfer Learning-Driven Approach. In *International Conference on Advanced Network Technologies and Intelligent Computing* (pp. 195-213). Cham: Springer Nature Switzerland.
3. Raman, P. (2025). Early Detection and Classification of Black Gram Plant Leaf Diseases Using ITL-CHB Method. *IETE Journal of Research*, *71*(2).
4. Randive, M. L., Sapkal, S., &Bornare, D. (2025). Exploring deep learning approaches for detecting nutritional deficiencies in crop leaves: A comprehensive overview. *International Journal of Agriculture and Environmental Research*, *11*(1), 33-59.
5. Bappi, M. I., Richter, D. J., & Kim, K. (2024). MAE-fViT: Fine-tuned Masked Autoencoder Vision Trans for Potato Leaf Disease Classification. In *The 13th International Conference on Smart Media and Applications*.
6. Paul, N. (2025). *Deep Learning Application in Plant Stress Detection* (Doctoral dissertation, North Dakota State University).

7. Srinivasan, S., Somasundharam, L., Rajendran, S., Singh, V. P., Mathivanan, S. K., &Moorthy, U. (2025). DBA-ViNet: an effective deep learning framework for fruit disease detection and classification using explainable AI. *BMC Plant Biology*, *25*(1), 965.
8. Sharma, P. (2025). Green and Intelligent Signal Processing: Deep Learning Approaches for Energy-Efficient MIMO Systems. *Journal of Wireless Networks and Communication Systems*, *1*(3), 62-73.
9. Cakmak, Y., &Zeynalov, J. (2025). HIGH-PERFORMANCE CLASSIFICATION OF CUCUMBER DISEASES: A COMPARATIVE DEEP LEARNING APPROACH WITH CNN AND TRAN
10. Nnamdi, U. V., &Abolghasemi, V. (2025). Optimised MobileNet for very lightweight and accurate plant leaf disease detection. *Scientific Reports*, *15*(1), 43690.
11. Wang, X., Yan, F., Li, B., Yu, B., Zhou, X., Tang, X., ...&Lv, C. (2025). A multimodal data fusion and embedding attention mechanism-based method for eggplant disease detection. *Plants*, *14*(5), 786.
12. Yani, N. A. N. A., Fauzi, S. S. M., Zaki, N. A. M., & Ismail, M. H. (2024). A systematic literature review on leaf disease recognition using computer vision and deep learning approach. *Journal of Information Systems Engineering and Business Intelligence*, *10*(2), 232-249.
13. Shafik, W., Tufail, A., De Silva, L. C., Haji MohdApong, R. A. A., & Kim, K. H. (2025). Deep learning technique for plant disease classification and pest detection and model explainability elevating agricultural sustainability. *BMC Plant Biology*, *25*(1), 1491.
14. Chaiwuttisak, P., & Gilal, A. R. (2025). T-Tracking: An Energy-Aware Distributed Approach for Face-Based Target Monitoring. *Journal of Computer Applications and Information Technology*, *1*(2), 61-72.
15. Sangeetha, M., & Sujin, B. (2025). Deep Learning-Based Intrusion Detection Framework for Securing IoT-Enabled Smart Homes. *International Innovative Research Journal of Engineering and Technology*, *10*(3), 20-29.