International Journal of Sustainable Studies, Technologies, and Assessments

IJSSTA

Review

Generative AI Empowerment in IoT Ecosystems: Review of Real-Time Processing Challenges and Solution

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Received: 20 November 2024 / Revised: 05 January 2025 / Accepted: 14 January 2025 / Published online: 30 January 2025

Abstract: Generative artificial intelligence (GAI) is revolutionizing data processing, interpretation, and use in real-time scenarios as rising changing agents on the Internet of Things (IoT) ecosystem. Traditional processing systems are seriously challenged by the fast rise in volume, speed, and diversity of data resulting from the explosion of IoT devices. IoT presents exciting opportunities for improving system efficiency and intelligence by including generative artificial intelligence, generative adversary networks (GAN), and variable automated encoders (VAEs). However, including generative artificial intelligence in the IoT environment brings particular difficulties and restrictions. Given limited resources, generative artificial intelligence models can need more processing resources than IoT devices can handle. Efficient compression and model optimization techniques make real-time processing possible and help maintain speed. Many of the driven devices of IoT systems have an energy source dependency, so sustaining power efficiency is essential. Real-time feedback and optimization of AI-generated algorithms will be helpful in decreasing energy usage. This paper discusses how to add generative AI to an IoT system. It's a review paper that clarifies these challenges while setting out the added complexity of Generator AI in the real-time operation in the IoT system. Overcoming these challenges shall enhance the intelligentsia, effectiveness, and responsiveness of IoT systems towards unlocking the total potential of generative artificial intelligence in many applications.

Keywords: AI Empowerment, Generative artificial intelligence (AI), IoT system, Real time processing, ecosystem.

1. Introduction

Generative artificial intelligence models in IoT applications suffer significantly in performance dependent on real-time processing. Local data processing on IoT devices lowers dependency on remote cloud services for processing, improving privacy, access, and cost-effectiveness. Moreover, real-time restrictions in the time-series data processing of IoT applications demand particular hardware accelerators to run ML operations efficiently without a high-performance CPU. Using specialized hardware accelerators and distributed model architectures, real-time processing in IoT applications is essential in optimizing generative AI models' performance.

The LMMs (large language model) are more resource-intensive since extra data modalities need more significant memory and computational capacity to maintain [3]. By aggregating data across several data kinds, LMMs can manage ever-challenging jobs at the sacrifice of processing speed [4]. Between generative artificial intelligence and IoT sensors, the following table highlights the fundamental difficulties of real-time processing.

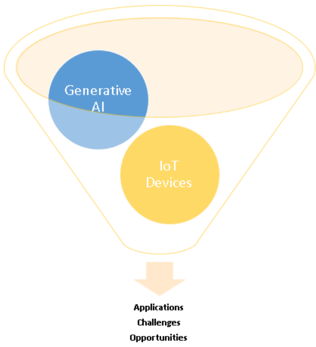

Figure 1. IoT in era of generative AI.

TABLE 1: The fundamental difficulties and challenges of IoT device real time processing

Reference	Category	Challenges	Description
[2]	Latency	Network Latency	The network latency reduces the performance of the network as well as application.
[3]	Limitations	Storage Limitations	Limited storage in IoT device required Clever data processing, and maintenance
[4]	Bandwidth	Limited Bandwidth	It is difficult to immediately broadcast significant volumes of data when IoT devices use the limited bandwidth
[52]	Computational Power	Limited Processing Power	IoT devices' computational power is constrained compared to centralized servers or cloud-based solutions.
[6]	Data Volume	High Data Generation	IoT devices constantly create massive amounts of data, which makes real-time analysis and processing challenging.
[7]	Energy Efficiency	Power Consumption	The IoT device uses the battery for transfer of data and processing.
[8]	Integration	Seamless Integration	Seamless integration reduces data quality and scalability.
[9]	Interoperability	Diverse Protocols and Standards	IoT device uses diverse connection protocols and standards and challenges the integration and real-time data processing of generative artificial intelligence systems
[10]	Latency	Low Latency Requirements	Real-time applications demand low latency, which network and processing delays might make it challenging to reach.
[11]	Model Complexity	Computationally Intensive Models	Deep learning networks and other generative artificial intelligence models can be computationally demanding and require tuning to operate on constrained IoT devices.
[12]	Privacy	Data Privacy	In real-time processing situations involving generative artificial intelligence, privacy issues, especially personal data, must be addressed immediately.
[10]	Reliability	Fault Tolerance	Continuous real-time processing depends on system dependability and fault tolerance in case of a device or network breakdown.
[13]	Response Time	Real-Time Decision Making	Generative artificial intelligence systems need help in the demand for quick decisions based on real-time data collected from IoT devices.
[14]	Scalability	Handling Scale	As the number of IoT devices increases, the system must expand to meet the mounting data load and processing need.
[15]	Security	Data Security	These issues can lead to privacy breaches, tampering, unauthorized access, data leaks, physical attacks, and user ignorance of basic security practices.
[16]	Updating Models	Updating and Continuous Learning	IoT devices have some limited processing capabilities so, it may pose challenges in maintaining generative AI models and enabling real-time learning from new data.
[17]	Vulnerability	Vulnerability of Device	IoT devices are at risk of necessitating the implementation of robust security systems to prevent access and cyberattacks.

The rest of the paper covers the applications, security issues and real time processing challenges of IoT with generative AI. In the section 2 explore the background and context as well as application of IoT and AI. In section 3 explains the generative AI and echo system. Section 4 and 5 explore the various challenges and solutions of IoT system and IoT in terms of real time processing and finally in section 6 and Section 7 explore the future direction as well as Challenges and Ethical Considerations.

2. Background and context

Artificial intelligence's ability to generate data, make predictions, and form decisions improves Internet of Things applications. Among the critical applications are:

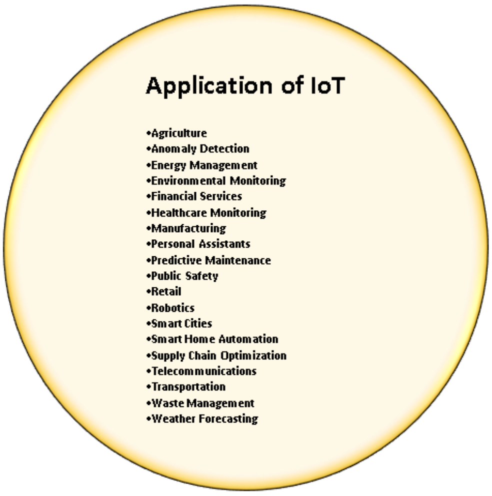

Figure 2. Application of IoT

TABLE 2: Applications of IoT

Application	Description	Examples
Agriculture [18]	Boosting yields using IoT sensors and generative artificial intelligence improves agricultural techniques.	To project agricultural diseases, maximize irrigation schemes, and improve resource allocation.
Anomaly Detection [19]	Real-time IoT data stream potential security threats identification and unusual trend identification.	The strange network activity suggests a potential cyberattack.
Energy Management [20]	The industrial facilities utilize the Optimizing energy	The sensor-based real-time data is utilized to develop projects that optimize utilization and energy savings.
Environmental Monitoring [21]	Implemented systems for monitoring and controlling environmental conditions, offering valuable insights and predictions.	The task involves monitoring animal habitats, identifying pollution sources and assessing air quality projects.
Financial Services [22]	IoT data from many sources makes Monitoring and trend-predicting financial activities and market development possible.	I find false activity and project stock market fluctuations.
Healthcare Monitoring [23]	generating predictions and knowledge from IoT health data produced by devices.	Monitoring important indicators helps one project health problems and provide early warning.
Manufacturing [24]	Using predictive and productive models helps us to enhance manufacturing methods and quality control.	The design custom manufacturing schedules and spot product defects

Personal Assistants [25]	improving IoT-enabled flexible and contextual interactions for personal assistants.	More exact and appropriate answers and actions are required depending on user activity.
Predictive Maintenance [10]	We are using generative artificial intelligence to predict equipment faults and organize maintenance before breakdowns.	Using prevention and forecasting industrial machine part failures helps to avoid downtime.
Public Safety [26]	Using real-time surveillance and predictive analytics helps public safety policies to be improved.	We predict major crime hotspots, simplify emergency response, and monitor public spaces for events.
Retail [27]	The individual is enhancing inventory control and enhancing the overall buying experience.	The creating personalized recommendations system for estimating inventory demand and customers.
Robotics [28]	The objective is to enhance the generative artificial intelligence capabilities for IoT-connected robots and monitor the adaptive behavior and decision-making.	Technology is used to enhance the work performance of robots independently by learning from their interactions.
Smart Cities [29]	Real-time data analysis and prediction modeling help to improve urban infrastructure and services.	Control traffic, garbage collecting, and emergency services more effectively.
Smart Home Automation [6]	improving home automation systems by using adaptive and customized control plans.	Heating, changing security systems. and lighting depends on user tastes and behavior.
Supply Chain Optimization [30]	Improved logistics and supply chain management through optimization and predictive analytics.	levels of inventory and Forecasting demand, along with distribution channel optimization.
Telecommunications [19]	forecasting maintenance and maximizing network performance for infrastructure supporting communication.	Network packet forecasting and best-allocating bandwidth.
Transportation [29]	The goal is to enhance the efficiency and safety of mobility methods.	The focus is on improving traffic control, predictive vehicle maintenance, and route design.
Waste Management [31]	The study aims to optimize garbage pickup and processing by utilizing real-time data from IoT sensors.	The goal is to predict waste generation patterns and streamline the collection and scheduling processes.
Weather Forecasting [32]	The integration of IoT data and generative models enhances the speed and precision of weather forecasts.	The focus is on creating localized temperature forecasts and predicting extreme weather events.

TABLE 3: Application and functionality of IoT in many fields

Concept	Description	Components
Analytics and ML [9]	The process involves acquiring knowledge and creating forecasts based on IoT data.	There are various data analytics tools available like Power BI and Tableau, ML (Machine Learning) platforms like PyTorch,, TensorFlow, AWS SageMaker, and AI algorithms are essential for effective data analysis.
Cloud Computing [17]	The system involves centralized processing and storage at remote data centres.	The platform offers cloud storage, cloud computing services like AWS Lambda and Google Cloud Functions, and big data analytics like Hadoop and Spark.
Connectivity [25]	The communication infrastructure system enables devices to transmit data.	The wireless protocols like Wi-Fi, Bluetooth, ZigBee, LoRaWAN, and NB-IoT utilizes through the system as well as wired protocols like PLC and Ethernet and operates on various frequencies.
Data Management [4]	The task involves effectively managing the vast amount of data generated by IoT devices.	The list includes databases such as MySQL, PostgreSQL, MongoDB, Cassandra, data lakes, and data warehouses like AWS Redshift and Google Big Query.

Devices/Sensors [31]	physical things with environmental data collecting capability.	Some devices are used to monitor various aspects of a system like Sensors, actuators, and embedded systems, such as smart thermostats and fitness trackers.
Edge Computing [33]	Data processing nearer the source helps to lower bandwidth use and delay.	Edge devices (local servers, gateways) edge analytics.
Integration [8]	guaranteeing flawless running between several systems and components.	API, middleware, interoperability standards (MQTT, COAP, OPC UA).
Maintenance & Management [34]	Constant efforts will be made to maintain the IoT ecosystem in perfect functioning.	Device management platform, remote management, performance monitoring.
Security [12]	The data protection from illegal access and attacks.	The device security (firmware update, secure boot, intrusion detection) Encryption (SSL / TLS) authentication (OAuth, JWT)

IoT applications improve decision-making, responsiveness, and efficiency for real-time processing. They offer rapid feedback, resource optimization, personalization, and practical insights. They also forecast maintenance and enhance safety and security, including environmental Monitoring, smart cities, industrial IoT, and intelligent healthcare. Real-time processing improves dependability and utility in many disciplines.

3. Generative AI in IoT Ecosystems

The table shows how generative artificial intelligence enhances IoT systems' usability, intelligence, and efficiency through data production, anomaly detection, predictive analytics, and security enhancement.

TABLE 4: Aspect of IoT and role of generative AI

Aspect of IoT Systems	Role of Generative AI
Adaptive Control [35]	The IoT system dynamically adjusts settings based on environment and user preferences.
Anomaly Detection [31]	Identifying anomalies and unusual patterns in IoT data streams can provide early warnings of potential threats or issues.
Behavior Prediction [29]	preferences, thereby enhancing the customization capabilities of IoT devices and Historical data analysis aids in predicting user behavior.
Data Augmentation [7]	The machine learning model is enhanced by generating additional data samples to supplement the limited collection.
Data Generation [36]	The IoT system generates synthetic data to supplement real-world data for expanding the scope and quantity of training sets.
Fault Diagnosis [24]	The process involves enabling the need for preventative maintenance and repairs and analyzing IoT data to identify system issues
Personalization [37]	Customized recommendations and responses tailored to specific interests enhance the user experience.
Predictive Analytics [34]	The system uses real-time IoT data and past performance to predict future trends and results using generative models.
Real-time Decision Making [28]	The Internet of Things (IoT) utilizes real-time sensor data based on generative artificial intelligence algorithms to make swift decisions.
Resource Optimization [38]	The Internet of Things (IoT) enhances efficiency by optimizing system resource allocation and consumption.
Security Enhancement [24]	The Internet of Things (IoT) generates adversarial cases, which expose vulnerabilities and enhance system security.

TABLE 5: Benefits and challenges of using generative AI in IoT (Internet of Things)

Aspect	Benefits	Challenges
Data Generation [39]	Generative models can create synthetic data while augmenting restricted datasets for better training and improving data protection. Synthetic data avoids including private information, preserving privacy.	The data generated determines the effectiveness of the artificial intelligence model; hence, more real-world precision is necessary. The statistics may unintentionally present an unrealistic or biased representation.
Predictive Maintenance [34]	Artificial intelligence aids in forecasting equipment failures, reducing downtime and maintenance costs, thereby extending IoT device lifetime and reducing replacement demand.	The relief relies on reliable and timely data predictive maintenance, but its interoperability with various protocols and IoT devices.
Resource Efficiency [34]	Generative AI can be used to optimize resource allocation in Internet of Things systems, reducing pricing and energy consumption, enabling efficient scalability through AI-driven resource management.	Generative AI requires robust hardware, ground-based processing, and integrating it into current IoT systems can be time-consuming and labor-intensive.

TABLE 6: Types of data generated by Generative AI in different IoT application domain

AI Generated Data	Application domains of IoT				
	Mobile Networks	Autonomous Vehicles	Robotics	Health Care	Cybersecurity
Text				√	
Image				√	
Video			√		
Network traffic Data	√		√		√
Vehicular Traffic Data	√	√	√		
Code	√		√	√	
Time-series Sensor Data	√	√	√	√	√
Audio			√		

4. Real-Time Processing Challenges

Latency, data volumes, resource constraints, and scalability are concerns of genAI in IoT. Latency issues can originate due to complex computational requirements for some functions, which makes these applications not real time. Edge computing reduces round-trip latency and latency [34].Real-time systems can handle data volumes with stream processing systems. Scalability and performance are affected by limited resources. Resource-limited conditions can be overcome using lightweight architecture, quantization methods, or optimizing AI models. Poor performance or system failures occur when IoT systems cannot accommodate several devices or control data volume. Using lightweight architectures, quantization methods, or optimizing AI models for resource-limited conditions can help overcome resource constraints. Poor performance or system failures occur when IoT systems cannot accommodate several devices or control data volume. Distributed processing systems allow horizontal growth and artificial intelligence models created with scalability help improve scalability. Dealing with these challenges requires a mix of system design issues, algorithmic enhancements, and deployment strategies customized to the unique needs of generative artificial intelligence in IoT environments.

TABLE 7: Challenges and solutions of IoT System

Challenge	Solution
Data Volume Management [33]	Stream Processing Systems is used to process data in real time.
Fault Tolerance and Reliability [2]	Redundancy and Replication Mechanisms is used improve performance and reliability
Integration of Heterogeneous Data Sources [14]	Protocols and Standardized Data Formats
Low Latency Requirements [14]	Edge Computing can reduce latency by processing data closer to the source
Scalability [26]	Distributed Processing Systems can enhance the scalability
Security and Privacy [12]	Encryption and Access Control used for security and privacy

5. Existing Solutions and Technologies

The techniques to overcome real-time processing problems in IoT systems are perimeter computing, flow processing, and optimization algorithms. Optimizing algorithms are the computer techniques for finding the optimal solution to a problem with given restrictions within a certain limit. They help in maximizing the use of networks, energy efficiency, and resource allocation. These methods enable firms to extract information relevant to the task and produce outcomes that are amenable to processing.

TABLE 8: Approaches and technologies are used for data processing

Approach/Technology	Description	Article Reference
Edge Computing	Local data analysis helps process data closer to the source, reducing bandwidth usage and delay.	[40]
Stream Processing	There is no need to create a whole new tool for Fog; stream processing engines like Apache Storm and Spark Streaming can run on Fog servers.	[41]
In-Memory Computing	The dataflow in MVM and a dense 2D array of bit cells are structurally aligned, which can be used in in-memory computing (IMC) to solve issues with computational energy and throughput. Data storage and processing low-latency, high-throughput IoT data processing is made possible by RAM.	[42]
Complex Event Processing (CEP)	Real-time pattern and trend detection enables swift judgments and event reactions in streaming data.	[43]
Fog Computing	extending cloud computing to the edge of the network of IoT environments to get beyond bandwidth limits and latency.	[44]

This table represents a picture of the advantages and disadvantages of each technique. However, technological advancement, particular use cases, and implementation technique also may have an effect on the actual effectiveness and constraints.

TABLE 9: Technologies effectiveness and limitations

Technique	Effectiveness	Limitations
Edge Computing [44]	Data processing nearer the source reduces delays.	Edge devices require higher network dependability and bandwidths, but they have limited processing and storage capacities.
Stream Processing [45]	Decision-making and real-time data analysis allows ongoing data processing free from storing vast volumes of data	Design and maintenance of a stream processing pipeline can be challenging and resource-intensive, requiring large memory and computational capability. Real-time processing issue debugging and troubleshooting challenges

Optimization Algorithms [46]	Raising the effectiveness and performance of several procedures. Turning on decision-making and automation in dynamic surroundings.	Initial condition and parameter sensitivity; complexity in choosing and fixing suitable algorithms. Particularly for complex optimization issues, computationally intense restricted relevance to specific categories of problems

6. Future Directions and Opportunities

Generative artificial intelligence combined with real-time processing capabilities in IoT systems create enormous opportunities for the transformation of sectors such as manufacturing and health care. The synthetic data generation capabilities may prove to be impressive in generative artificial intelligence modes like VAE and GAN to mimic real-world data quite closely. This enables the synthesis of extensive volumes of real-life data to complement restricted or incomplete real-time flows of data [47]. Combining generative models with real-time IoT data processing helps to find abnormalities and supports predictive maintenance in significant systems [48]. Furthermore, adaptive learning and self-optimization are being developed to enable IoT devices to maximize their behavior through independent adjustment. Privacy concerns take the front stage in IoT systems; generative artificial intelligence can address these problems by generating synthetic data and hiding sensitive information while preserving the statistical properties of the original data [36]. Perimeter artificial intelligence and federated learning are being investigated to enable cooperative training of generative models on distributed periphery devices while maintaining data privacy. Virtual environments and simulated data created by generative artificial intelligence can also be utilized to teach and test Internet of Things systems[49].Combining generative artificial intelligence with real-time processing in IoT systems has exciting possibilities for improving data-based decision-making, raising system efficiency, and enabling new applications in many fields[29].Manufacturing and healthcare are only two industries where generative artificial intelligence with real-time processing on IoT networks has significant potential to transform. Real-time data generating, anomaly detection, predictive maintenance, adaptive learning and self-optimization, data-preserving generation, cutting-edge artificial intelligence and federated learning, human-machine interaction and simulation, blockchain and IoT integration, bio-inspired artificial intelligence and ethical and regulatory frameworks define advances and research directions in this field [50].

Synthetic data generated by Generative Adversarial Networks (GAN) and Variational Autoencoders (VAE) approximates real-world occurrences, allowing for real-time data generation. Combining generative models with real-time IoT data processing improves predictive maintenance in essential systems and helps to discover anomalies. Developing generative models suited for specific IoT applications and more muscular anomaly detection systems is a research process in progress. IoT systems can independently change and maximize their behavior using adaptive learning and self-optimization [36]. The researchers want to develop adaptive learning algorithms and self-optimizing methods to operate in dynamic and uncertain situations. Privacy concerns take the front stage in IoT systems, as sensitive data is sometimes collected and distributed.

Generative AI can alleviate privacy concerns because it will create synthetic data, and the perimeter computing over IoT systems helps in real-time decision-making by processing data near its source, hence reducing latency. The deployment of 5G networks will allow for faster data transfer, lower latency, and easier seamless integration of IoT devices. Such conditions will fuel the growth of generative artificial intelligence algorithms at the edge of the network [51]. Explainable AI techniques help create confidence in AI models by consumers; therefore, the responsible implementation of AI-driven IoT systems [52].

7. Challenges and Ethical Considerations

Algorithms that are biased result in inequality in access to opportunities, thus contributing to social inequality and algorithmic bias. AI models' complexity raises issues with responsibility and openness in judgments from machines. Privacy issues arise from the analysis of personal and sensitive data, such as location information, medical records, as well as behavior patterns, and data collecting. Data transmission between IoT devices and cloud servers may be intercepted or managed, threatening the integrity and privacy of the data. Training biased artificial intelligence systems on unrepresentative input can lead to algorithmic biases, which maintain feedback loops and generate discriminatory outputs. Dealing with these issues requires a holistic approach, including ethical issues, technical safeguards, and legislative activities. Although generative artificial intelligence analysis is possible, privacy-protection methods, security-by-design ideas, justice and responsibility, and legal systems help protect personal IoT data. By addressing these problems, stakeholders could safeguard consumer data privacy, security, and justice, promoting generative artificial intelligence's ethical and responsible use.

8. Conclusions

The impact of Generative Artificial Intelligence with Internet of Things (IoT) ecosystems also deals with the processing of real-time data, automation, and decision-making processes. Other forms of Generative AI technologies are GANs and VAEs. These are synthetic data generation, predictive analytics, and anomaly detection for improving IoT systems. They optimize resource utilization, predictive maintenance, and adaptive learning, which means they make a pretty significantly different difference in many IoT applications in health care, manufacturing, agriculture, or smart cities, among others. Still, all the benefits that generative AI has to bring are met by challenges that affect the IoT system in embracing these changes, particularly in latency management, data volumes, energy, computational power constraints, and concern over privacy. Advanced solutions include edge computing, stream processing, and distributed architectures to meet real-time processing requirements. Strong policies on cybersecurity as well as robust ethical frameworks regarding data privacy are also crucial. The future of IoT systems is based on synthetic data generation, federated learning, and adaptive self-optimization toward scalability and intelligence. Technologies that are emerging, including 5G networks and explainable AI, will ensure seamlessness and trust from the users, which could open up wide adoption of IoT. Generative AI can thus simplify various technical, ethical, and infrastructural challenges to fully unlock the potential of IoT systems in transforming industries into real-time intelligent decision-making and automation.

Abbreviations

GAI	Generative artificial intelligence
IoT	Internet of Things
GAN	Generative Adversary Networks
VAE	variable automated encoders
LLM	large language model
API	Application Programming Interface

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