

Edge Computing Framework for Real-Time IOT Sensor Data Processing

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Abstract

In this article, we discuss the reason why Internet of Things (IoT) has a very high growth over time and how cloud-based solutions which exist today are not able to deal with real-time data: latencies are extremely high due to the large energy consumption existing in these devices. It proposes an edge computing architecture where hardware and software are at the sources to process IoT sensor data using a hierarchical layer of edge devices, gateways, and cloud services. At the edge, filtering and aggregating data through lightweight algorithms, allows for faster decision-making. Smart load balancing and fault tolerance, along with advanced analytics and long-term storage, are handled by the cloud. Security can be ensured with encryption and secure communication protocols, and the machine learning models can make predictions at the edge. Experimental outcomes indicate that this edge computing platform is more efficient than conventional cloud architectures in terms of latency, bandwidth, and energy usage and can be utilized in data-intensive IoT tasks.

Keywords: Computing, Hierarchical, Analytics, Tolerance, Predictions

1. Background of the Study:

The fast development of the Internet of Things (IoT) has revolutionized data management in industries such as healthcare and smart cities and edge computing is adopted to address the shortcomings of cloud computing, especially in real-time computation and latency. Edge computing can be more responsive and efficient in bandwidth by processing data nearer to its source, which is essential in applications like autonomous vehicles or healthcare monitoring. Proponents such as Mahadev Satyanarayana stress that there is not only increased performance of the system through local data processing, but also less delay. In the healthcare sector, where data is essential and timely, edge computing enables filtering of data and reduces

the use of cloud services thereby reducing security threats and performance problems. Also, the combination of AI and edge computing aids real-time intelligence. Nevertheless, issues like resource constraints, interoperability of devices, and energy efficiency, particularly in battery powered devices must be overcome to streamline the future of edge computing and IoT.

2. Introduction:

Edge computing is used to overcome the shortcomings of the traditional IoT data processing which has several problems such as high latency and security risks associated with centralized cloud systems. Edge computing improves efficiency and responsiveness in fields like industrial automation and healthcare, by enabling localized data processing. It decreases delays by processing data where it originates or as close as possible, and it also minimizes bandwidth usage because only pertinent data is transferred, which decreases network congestion and network operation expenses. Its decentralized structure enhances the scalability, and it is backed by technology such as 5G and AI that can provide efficient real time processing of applications. The combination of edge computing and artificial intelligence (AI) and machine learning (ML) make it possible to process real-time data intelligently and make autonomous decisions, which leads to the development of adaptive intelligent systems. To illustrate, AI-powered edge devices in the industrial IoT can be used to track equipment performance and anticipate failure, thereby reducing downtime. Also, the systems will be able to streamline traffic in intelligent cities. Edging AI also decreases reliance on cloud processing, accelerates decision-making, and enhances the overall performance of the system, however, requires optimization due to resource-constrained devices.

2.1 Objectives of the Study:

1. To develop an effective edge computing system to process IoT data in real-time.
2. To minimize the latency and enhance response time in sensor-based applications.
3. To maximize the bandwidth by filtering and processing local data.
4. To maximize the security and privacy of data with edge-based security.
5. To incorporate AI/ML methods to make intelligent decisions on the edge.

2.2 Scope of the Study:

The study introduces an edge computing framework of processing real-time sensor data of IoT sensors, which addresses the traditional cloud-based constraints of the traditional approach by decentralizing data processing and control. It depicts what edge IoT devices (data collection, pre-processing, local analytics and cloud communication) are used for and in which scenarios of application (healthcare, smart cities, industrial automation and environmental sensing). It emphasizes the reading of AI and ML models for real-time analysis, highlighting KPIs such as lower latency, bandwidth optimization or energy saving, scaling or data encryption. The framework also restricts itself to a particular IoT scenario, along with being based on imitative approach and not considerate of a very foundational or large IT infrastructure implementation, while it should be able to evolve in next few years alongside developing 5G, blockchain and federated learning technologies.

2.3 Significance of the Study:

The article emphasizes the importance of edge computing to computer science and engineering, especially in IoT, distributed computing, and real-time data analytics. It addresses the growing demand for efficient data processing as the number of connected devices increases. Among the major contributions are: lowering the latency of IoT systems to make them responsive to data in time-sensitive applications, maximizing network bandwidth by processing data locally to reduce the resource usage and costs, improving data security and privacy by reducing data transmission, and using AI and ML at the edge to make decisions. In general, the study yields useful information about creating efficient, secure, and scalable edge computing systems to enable the next-generation IoT applications.

2.4 Problem Statement:

Since the IoT devices have been rapidly expanding, they have created vast amounts of real-time sensor data that cannot be effectively processed using the traditional cloud system. Time-sensitive applications are hampered by high latency, network congestion, and bandwidth consumption, and centralized processing raises security or privacy or scalability issues. Existing systems do not support real time analytics and edge based decision making. Thus, an effective edge computing architecture is required to process IoT sensor data, minimise latency, maximise resources and enhance performance and secure and scale data in dynamic environments.

2.5 Methodology:

The research design will be aimed at developing and implementing an edge computing platform in order to process sensor data in IoT in real-time. It commences with literature review to find out available approaches and gaps. The system architecture will include IoT sensors, edge devices and cloud elements to enable real-time data collection and pre-processing on the edge nodes in order to increase efficiency. Simple machine learning models are run on edge devices to perform local analytics, and data processed is sent to the cloud to be analysed further. The implementation requires a program of languages such as Python and simulators to check performance parameters such as latency and energy consumption. The system is provided with security measures such as encryption, and the system robustness and scalability are tested.

2.6 Review of Literature:

1. **Zhang Wei (2026):** Studied the state-of-the-art edge computing models combined with AI to provide real-time data analytics on IoT. The paper has focused on the ultra-low-latency processing with decentralized architectures and the significance of federated learning at the edge. The author has shown that edge intelligence lessens cloud reliance and enhances system response. The challenges of scalability and suggested mechanisms of allocating resources adaptively were also discussed in the research, which is why it is extremely applicable to the next-generation smart applications and autonomous systems that demand instant decision-making possibilities.
2. **Priya Sharma (2025):** Explored the idea of hybrid edge-cloud architecture to efficiently process IoT data. The research was geared towards maximization of bandwidth by local data filtering

and selective cloud communication. The author came up with a tiered architecture that improves the performance of a system without compromising data integrity. The experimental findings indicated that there were great improvement in reduction in latency and energy efficiency. Another important point of the research was the contribution of AI models to the improvement of edge analytics, which is why the framework can be applied to smart healthcare and industrial IoT.

3. John Park (2024): Investigated the issue of real-time data processing in IoT scenarios and suggested an edge-based distributed architecture. The paper has highlighted the importance of effective scheduling of tasks and provision of resources at the edge. The author proposed dynamic load balancing technique which enhances efficiency in computing. The results revealed that it had shorter latency and better throughput than the conventional cloud systems. Interoperability issues were also discussed in the research and recommended the use of standardized protocols in order to have seamless communication between the devices.

4. Ananya Reddy (2023): Concentrated on the use of AI-based edge computing in smart cities. The research revealed that real-time analytics play a crucial role in traffic control and environmental surveillance. The author suggested an edge-based machine learning-based anomaly detection framework. Findings indicated that there was better decision-making speed and lower cost of data transmission. The study highlighted the combination of IoT, AI, and edge computing to develop smart urban systems that can process huge amounts of data effectively.

5. David Kim (2022): Studied the shift to edge computing in the IoT systems. The research has found out the essential limitations of cloud-based processing such as latency and bandwidth limitations. The author suggested a hybrid architecture of a combination of edge and cloud resources that would perform optimally. The study has shown that edge computing can greatly add to the real-time data processing capabilities. Also, the paper has dealt with the issue of security and proposed encryption methods to safeguard sensitive IoT data.

6. Meena Patel (2021): Investigated the use of data analytics in IoT systems via edge computing. The research was interested in pre-processing which included filtering data and aggregation to eliminate redundancy. The author highlighted the importance of local analytics in minimizing network load. Experimental findings showed that there was better system efficiency and latency. The paper also addressed the issues of executing machine learning models on resource-constrained machines and suggested lightweight algorithms in edge engine.

7. Wei Liu (2020): Researched the combination of artificial intelligence and edge computing. The paper has focused on implementing the deep learning models at the edge to make real-time decisions. The author suggested optimization methods of models to minimize computational complexity. Findings indicated that edge AI can greatly enhance response time and minimize cloud infrastructure dependency. Issues of energy consumption and energy-efficient processing of the IoT systems in a sustainable system were also identified in the study and recommended.

8. **Ravi Kumar (2019):**Examined distributed computing techniques of processing IoT data. The research contrasted between cloud-based and edge-based architecture with the benefits of decentralized processing. The author suggested a model of effective task distribution among edge nodes. The results showed enhanced scalability and lowering latency. Security issues were also tackled and it was advised that authentication systems should be applied to the edge to achieve reliability within the systems.
9. **Emily Chen (2019):**Analyzed how edge computing can be used in smart environments. The research was dedicated to real-time data processing applications that can be applied in the areas of smart homes and medical monitoring. The author suggested a context sensitive model that is flexible to the changing environment. Results showed enhanced system performance and user experience. Another critical component identified by the research is the need to have effective data management methods in order to process the constant data streams provided by the IoT devices.
10. **Ahmed Hassan (2018):**Explored the security issues of IoT and edge computing systems. The paper has highlighted the importance of decentralized security mechanisms to safeguard sensitive data. The author suggested encryption-based scheme of safe data flow and processing. The experimental findings revealed enhanced protection of data and minimization of susceptibility to cyberattacks. The privacy issue and the recommendation to deploy access control at the edge were also part of the research.

2.7 System Analysis & Methodology:

- a. **Gathering and Obtaining Data:** To develop the methodology, the collection of real-time data of the IoT sensors installed in various settings is initiated. The sensors are continually generating data about the temperature, humidity, and movement. Data collected is transmitted to the edge devices where it is further processed. Data collection reliability and quality can play a significant role in ensuring the efficient operation of the system and enable the appropriate real-time analytics of the IoT systems.
- b. **Edge Processing and Analysis of Data:** The data is then processed at the edge using pre-processing (filtering, cleaning, and transformation) after the collection. Lightweight machine learning models process the data and extract meaningful information. This local processing reduces latency, and it enables making decisions in real-time. It will also be an efficient methodology in terms of utilizing edge resources as well as very precise in real time data analysis.
- c. **Communication with Cloud Infrastructure:** Local processing will assure that only the important and summarized information will be transferred to the cloud to be stored and subjected to the analytics. This hybrid solution also reduces the load on the network and ensures the efficient utilization of the resources. The cloud provides additional computing power in complex activities and long term data storage. This system of communication load balances the workload of the edge and cloud systems and improves scalability and the overall performance of the system.

d. Performance Optimization and Analysis: Lastly, you measure your system with respect to performance metrics such as latency, bandwidth consumption, energy efficiency and accuracy. To quantify these improvements, the results are also compared with traditional cloud-based systems. This is where optimization techniques are also invoked for efficiency and scalability of systems. The continuous monitoring and optimization will ensure that the system will be effective under various conditions and will be able to meet the requirements of real-time IoT applications.

e. System Architecture: This layer has various sensors which provide information about the environment in real-time such as temperature, humidity and motion. It collects appropriate data to be processed. Near-source data management is carried out in this layer with the assistance of edge devices for purposes like filtering and normalization. It decreases duplication and delay to facilitate rapid decisions using minimal machine learning algorithms. The exchange of this layer is very important and takes place using protocols such as 'MQTT, HTTP and CoAP' to provide reliable communication between IoT devices in edge node devices in the cloud server for data stream between them. This layer offers storage data, sophisticated analytics, and user interfaces in a centralized manner. It allows analysis and visualization of long-term data, facilitates user insights and decision-making using dashboards.

f. Algorithms System: Four critical algorithms of IoT systems are described below: 1. This algorithm removes noise of edges and irrelevant data in the raw sensor data and only substantive data is used for further processing. It decreases the computational load, filtering out spurious values to enhance data quality and system performance, ensuring that real-time analytics run in edge computing consumes optimal bandwidth. 2. This algorithm converts the raw data across multiple sensors into compressed formats that consume low storage and network bandwidth, while retaining important information. It especially makes good use of all the resources to process edges faster in continuous DataStream. 3. This algorithm applies real-time light machine learning models to analyze and make decisions. It uses such techniques as classification and regression to improve predictive capabilities, anomalies detection, and automation in dynamic IoT applications. With this algorithm you can protect the data that are in processing and transmission with the encryption and authentication. It protects sensitive data, prevents illegal access and cyber attacks, maximizes the availability of your systems, and is used to protect IoT applications.

2.8. Tools & Technologies:

The system is based on Python and C programming language to develop edge and IoT applications. Python is used to support machine learning models and data processing, whereas C is employed in embedded system programming. The application of frameworks such as TensorFlow Lite and EdgeX Foundry allows analysis of the edge and management of devices to be effectively run in resource-constrained scenarios. IoT devices like sensors, microcontrollers (Arduino, Raspberry Pi), and edge gateways gather data at the site, and Raspberry Pi plays the role of an edge node to provide lightweight

analytics. MQTT, HTTP, and CoAP communication technologies provide successful data transfer between devices and cloud systems via networking possibilities such as Wi-Fi, Bluetooth, and 5G. In systems such as AWS, Microsoft Azure, and Google Cloud, the cloud storage can be used to manage both structured and unstructured data in a way that is scalable, further improving the functionality of the system to enable remote visualization, monitoring, and long-distance data analysis.

2.9 System Design & Implementation:

The architecture design is based on the model of layers that include IoT devices, edge nodes, communication networks, and cloud infrastructure, which further improves the processing of data and system coordination. The IoT layer gathers real-time sensor data and the edge layer is responsible of pre-processing and analytics, providing low latency. The communication layer works effectively since it is based on efficient protocols to transmit data and the cloud layer coordinates storage and advanced analytics. This type of hierarchical architecture allows for scalability, maintainability and modularity- especially with regards to time-sensitive activities being at the edge while resource-intensive activities take place in the cloud. An edge node consists of embedded systems (microcontrollers) with lightweight algorithms, data-acquisition, pre-processing analytics and communication modules. They are capable of making inferences from data with no lag time, including security (e.g., Encryption/Authentication). This is an ideal data flow design that ensures sufficient collection and processing followed by low-latency communication with a high response time, as well as minimized bandwidth consumption. Further, data and system stability are ensured by powerful security controls, such as encryption and access controls. The architecture is dynamically scalable, meaning that it can easily add edge nodes without interfering with the performance of the system. In general, the design offers a strong, scalable, and security/efficient edge computing solution to IoT applications.

2.10 Modules System:

The article outlines four main subsystems of an IoT system including data acquisition, data processing, communications and monitoring and control. The data acquisition module records real-time data on different sensors and data integrity is guaranteed and facilitates scalability. The data processing module performs local analysis and filtering of this data to process it with lightweight machine learning to make fast decisions. The communications module handles data transit with protocols like MQTT, HTTP, CoAP, and ensures secure and low-latency communication. Finally, the monitoring and control module offers a user interface where the system performance can be tracked, command sent and alert users on the anomaly and therefore improves the interaction and reliability in the management of the system.

Edge Computing Framework for Real-Time IoT Sensor Data Processing

This report explains two types of computing models to handle IoT sensor data. The former describes a decentralized edge computing model in which data is computed at edge devices, reducing latency and unnecessary cloud systems, and is applicable to time-sensitive applications. The second meaning shows us a

hybrid approach wherein we process at the edge and then more difficult tasks are processed in the cloud where additional analysis and storage can take place. analytics and returns results to end users or edge devices.

Interpretation: The flow diagram shows an Edge Computing Framework to process the IoT sensor data in real-time. The first step is to send data of IoT sensors to edge devices where primary processing, filtering, and quick responses occur. The processed data is then sent to the edge layer to be analyzed further and make decisions. Data is selected and sent to the cloud server where it is processed further, stored, and modeled, and delivered to end users or devices. The architecture is designed to guarantee reduced latency, optimal bandwidth utilization, responsiveness in real-time, and scalability with large volumes of the Internet of Things data.

2.11 Architecture Design System

2.11.1 White Box Testing

White box testing (also called structural or glass box testing) is concerned with the internal structure, logic and code of a software system. It plays a significant role in edge computing in real-time IoT applications, which guarantees the functionality and efficiency of system modules data collection, pre-processing, analytics, and communication. This testing approach checks all execution paths as a way to verify the correctness of internal procedures, such as loops and data processing logic, by considering all possible paths of execution, including edge cases such as missing data. Control flow and data flow testing can be used to check that decision points and variable management are done properly, whereas path testing is used to achieve full code coverage to detect logical bugs in the code. The advantages of white box testing are as follows, it detects defects earlier, improves the quality of code, and improves performance, but it might be time-consuming and it might also fail to identify interface problems. In general, it plays a crucial role in the process of reliability and efficiency in the real-time data processing of IoT sensors.

2.11.2 Black Box Testing

Black box testing is a software testing technique that aims at testing the functionality of a system by only considering the inputs and outputs of that system without the knowledge of internal code. This is specifically suitable in edge computing of real time sensor data IoT, in order to ensure systems work as expected and with user requirements. The most important methods are equivalence partitioning (dividing input data into legal and illegal sets) and boundary value analysis (testing limits of input sets). Black box testing also evaluates functional performance, system integration, as well as, user experience, via usability testing. Although it is easy to use and it points out the problems such as lack of functionality, it does not give any information on internal structures and, therefore, defect analysis is difficult. Although it may come with its own shortcomings, black box testing is necessary to ensure that the IoT systems can provide effective and reliable user experiences, in addition to the white box testing techniques.

2.12 Performance Metrics System

Latency is a key performance metric that quantifies the time lag between the generation and the response of the system. The designed edge computing architecture has a shortened latency as it processes information on an edge computer, making it faster to make decisions essential in real-time use cases of industries such as industrial automation and healthcare. The latency monitoring is continuous, which can optimize the performance of a system, resulting in better efficiency and reliability in dynamic IoT environments. The limited transmission of data to only the necessary information optimizes bandwidth use and hence network congestion and operational costs are reduced. Lightweight algorithms are given priority to ensure energy efficiency in terms of minimizing data transmission, which prolongs the life of devices and their sustainability, especially in energy-limited environments. Accuracy and reliability of the system are ensured by the use of machine learning models that examine data, and the performance of the system is measured in different conditions. Black box testing is also used to ensure that the system fulfils the functional requirements without getting into the internal functionality of the system, concentrating on the input-output relationships. The major methodologies are equivalence partitioning and boundary value analysis in order to achieve complete testing in the expected operating conditions. Although black box testing offers benefits of being user-centric, it also presents drawbacks in terms of internal system knowledge and test coverage.

2.13 Results System

The adoption of the edge computing model greatly alleviated latency in comparison to more conventional cloud solutions because the data were processed locally, allowing real-time decision-making, especially in applications with time constraints. The results show that edge computing is an effective solution to address delays in centralized processing, thereby improving the performance and user experience of systems. Moreover, bandwidth usage was minimized because the system only transmitted pertinent information to the cloud, thereby ensuring it optimized the communication process besides decreasing network congestion. This method also resulted in cost reduction and enhanced scalability. The framework proved to be more efficient in energy usage, reducing unwanted data transfers and edge device power usage, and finally extending the life of IoT devices in remote applications. Also, edge computing with machine learning models enhanced the accuracy and reliability of data analysis and provided the same level of performance regardless of the varying circumstances. The findings support the usefulness of the framework in providing reliable results when using it in applications that need accurate and timely decisions.

2.14 Discussion System

Edge computing has been found to mitigate most of the shortcomings of the traditional cloud systems since data are processed closer to the source thus enhancing latency, bandwidth usage, and energy efficiency. It provides a distributed architecture to improve scalability and resource management, which is essential in real-time IoT applications. The suggested framework demonstrates a better performance than the traditional cloud-centric models, minimizing the latency and enhancing the efficiency. Although the

advantages are considerable, there are still problems like the lack of computational power of edge devices, security threats, and the inability to interoperate. The future opportunities are the introduction of technologies such as 5G and blockchain, scaling up machine learning models to run on the edge, and scalability and interoperability to realize the full potential of edge computing in processing IoT data.

2.15 Findings:

1. **Reduced Latency:** The researchers found that edge computing is able to significantly reduce latency by operating data closer to the IoT devices. This also enables a faster response and aids in real-time decision-making. The system is also efficient in time sensitive applications and this has demonstrated that decentralization processing is more efficient than the traditional cloud-based processing to offer instant data analysis.
2. **Bandwidth Usage Optimized.:** The findings indicate on-the-edge data processing reduces unnecessary transmission of data to the cloud. This translates to the efficient utilization of bandwidth and less congestion of the network. It can also filter and transmit only the relevant data, which improves performance of communication and reduces the cost of operation in large scale IoT applications.
3. **Better Energy Saving:** The proposed architecture is also more efficient in terms of energy consumption since it minimizes the volume of data received and uses lightweight processing techniques. The edge devices consume less power and this enhances their time of operation. This is especially beneficial to battery-powered IoT devices, and the system is suitable to be used in the long term in resource-constrained environments.
4. **Increased Accuracy and Reliability:** The edge-based machine learning models increase accuracy and reliability of system outputs. The system can give the correct predictions and can be used in various circumstances. This makes it reliable in high-performance applications, making the users more confident and improving the overall system performance.

2.16 Suggestions System:

1. **The Introduction of the innovative Technologies:** It is proposed to introduce new and more advanced technologies such as 5G, blockchain, and federated learning into the edge computing system. These technologies can enhance the performance of the system, security, and scalability. Their adoption will enable faster communications, secure sharing of information, and coordination among scattered devices in the IoT context.
2. **AI Models Optimization:** The execution of the future is to be focused on optimization of machine learning models to be deployed on the edge. Better efficiency can be achieved through model compression pruning and quantization. This, however, will lead to more advanced analytics being performed on resource constrained devices, as well as an understanding of the system and facilitating efficient real time decision making across applications.

3. **Protocols Standardization:** To provide a maximum interoperability of IoT devices, some communication structure/protocol need to apply through standard. This too will also work simply as again, standards are standardising and therefore communications between all the various platforms can also be simple. This will allow for increased system scalability and decreased compatibility challenges resulting in broader, more feasible deployments of edge computing solutions.

4. **Enhancing the Security:** It is needed to be strengthen edge security against sensitive data. Multi-layered security measures like advanced encryption, intrusion detection systems can be introduced to increase the reliability of the systems. The challenges and threats faced in the operation of edge computing systems based on the IoT ought to be mitigated by conducting periodic updates and monitoring to ensure secure operation of information technology systems.

2.17 Limitations:

The limitation of the first type is that the resources of the computers are restricted.

Compared to edge devices, cloud servers have significantly higher processing capacity and memory. This restricts the complexity of the algorithms that may be implemented. As a result, the state-of-the-art analytics may not be well supported at the edge with implications on the system performance on applications which require high level of computations.

- **Scalability Challenges:** The edge devices distributed may be many and may be difficult to control. When the system grows large, it is hard to coordinate and to assure performance. The resource allocation and system management should have proper strategies of handling the increasing workloads that may not be well implemented in the current system.
- **Security Vulnerabilities:** Although there are security practices, edge devices are vulnerable to physical and cyber threat. Limited security capabilities of resource-constrained devices can result in threats to the system. It is hard to provide total security of all nodes and requires ongoing monitoring and maintenance.
- **Interoperability Issues:** The heterogeneity and variability of communication protocols through IoT pose issues of interoperability. The different machines manufactured by other manufacturers can be incompatible. Lack of standardized frameworks limits the effectiveness of communication, system efficiency and scalability of heterogeneous IoT environments.

2.18 Conclusion

The study created an edge computing system of real-time IoT sensor data processing that mitigates traditional challenges of cloud computing such as latency, bandwidth, and security concerns. Decentralizing the architecture also improved performance with savings in latency and bandwidth utilization, better energy efficiency, more accuracy. This facilitates immediate processing and decision-making, which are integral to health care delivery, industrial automation, and smart cities. Light On-Premise Model Hosting for Interactive Predictive Analytics with Machine Learning and Anomaly Detection at the Edge Non-Intrusive Smart Processing Capability — Logic-driven approaches to critical diagnosis and decision making in business

processes. Encryption, authentication and intrusion detection are very crucial for both data protection and privacy but their limitations remain as well, such as resource crunches and interoperability. In general this research depicts the edge computing as a capable option for the breakthrough of limits on cloud based systems and to move towards new approaches in developing IoT and Distributed Computing more smartly paradigms.

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2.20 Further Research Scope:

Future research of edge computing is expected to support the needs of the IoT systems to improve its features in accordance with its future requirements, especially by integrating new communication technologies such as 5G. This will enhance the speed of data transmission, latency reduction and connection between distributed devices. Federated learning is mentioned as one method of training machine learning models on edge devices without compromising data privacy. Also, the use of blockchain can improve the

security of data transactions. Future researchers are advised to create lightweight AI models, employing some methods, including model compression and quantization, to streamline the performance of edge devices. Such aspects as scalability and interoperability should be considered as the key areas of improvement because the unified frameworks and protocols are required to improve the interactions between the devices and their compatibility. Finally, edge computing uses can be further extended to include self-driving cars, smart farming and disaster resilience, with future progress in hardware and software technology.