

A Comprehensive Survey on Emerging Trends in Networking and Communication : From IoT to Edge Computing

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Abstract: The advancement of networking and communication technologies has escalated the IoT and edge computing integration by leaps and bounds. This paper provides a review of the current trends, technologies and issues concerning IoT and edge computing. Looking at the key application areas of smart cities, healthcare, industrial IoT and smart grids this paper demonstrates how edge computing solves the problems of cloud computing such as latency, bandwidth and privacy. The survey also reveals present day constraints such as the lack of standards for scalability, integration problems, and lack of strong data protection measures. This work can be considered as a reference source for researchers and practitioners since it reveals the relationship between IoT and edge computing and gives an idea of further advancements.

Keywords: IoT, Edge Computing, Smart Cities, Healthcare Iot, Scalability

1. INTRODUCTION

The technologies in networking and communication have received a drastic change in the last few decades. Starting from the centralized ones and passing through the highly distributed, scalable networks, these technologies have emerged as a driver for changing industries, economies and people's lives. The advancement in the use of the Internet has been instrumental in the change, since communication can now be done at faster and more reliable rates over large distances. Today, we find ourselves at the cusp of a new era driven by the convergence of two groundbreaking technologies: The two emerging technologies are the Internet of Things (IoT) and edge computing. Internet of Things or IoT is a system of interconnected objects which can collect, processing and sharing information. This IoT environment includes smart home and wearable devices, IoT that automate various industries, and many others.

With the growth of IoT, the need for time-sensitive data, integration of artificial intelligence into IoT, and enhanced network competency increases as well. On the other hand, edge computing seeks to solve these challenges by processing data nearer to where it is produced the edge of the network. Unlike centralized cloud computing models which have centralized computation workload, edge computing pushes the computation closer to the devices and the operations are performed near the data source and in real time. This combination of IoT and edge computing will be the next big thing for handling, transmitting, and acting on data in real-time.

Study Significance

The combination of IoT and edge computing is revolutionizing today's networks as they become more flexible, optimized, and elastic. Previously, the concept of central cloud computing was the only approach towards data storage and computation. However, as more IoT devices are being connected to the internet and as more request for response are being made, traditional cloud platforms are becoming insufficient. The inherent nature of cloud-based systems to have longer latency and limited bandwidth explain why edge computing is crucial as it can help to minimize latency and enhance response times to near real-time. In healthcare and transportation, smart cities, and many other fields, real-time analytics and decision-making are more necessary than ever. IoT devices collect enormous volumes of data and when this data is sent to distant data centres, it takes a long time before the information can be used, a problem that is solved by edge computing.

As the data is processed locally at the edge of the network, these technologies enable quicker and more efficient decision-making across sectors. Due to these numerous changes that IoT and edge computing has introduced, there is need to have a survey that captures the state of the technologies. A detailed review of the current state allows for knowing the situation and existing solutions, as well as for revealing voids and forecasting tendencies. Therefore, this paper seeks to present such a survey, whereby the current developments in IoT and edge computing will be integrated and analysed for the comprehension of their synergy in transforming today's networks.

Study Objectives

The paper's goal is to present a review of the current trends in networking and communication with a special emphasis on IoT and edge computing. The specific objectives of the paper are as follows:

- To understand the basic ideas and innovations of IoT and edge computing, technologies, structures, and protocols.
- To discuss the most popular trends in IoT and edge computing to determine the most effective applications and cases in different industries.
- To summarize the work of previous researchers and comparing the existing solutions, pointing out their merits, issues, and drawbacks.
- To discuss the current remaining issues, including scalability, security, and interoperability, and to suggest possible solutions.

• To provide a vision on what the future of IoT and edge computing may look like and to outline directions for further research and development.

Paper Organization

The paper is organized into five sections. Section 1 is the introduction which outlines the background and significance of this survey. Section 2 discusses the evolution of networking systems and major IoT and edge computing concepts. Section 3 delves into a comprehensive summary of diverse papers in the field of IoT and edge computing. Section 4 addresses the current challenges of IoT and edge computing. Section 5 concludes with overall analysis and future directions in this advancing field.

2. FOUNDATIONS OF NETWORKING AND COMMUNICATION TECHNOLOGIES Evolution of Networking technologies

When networking began to develop, communications systems were centralized and usually based on mainframe or early computers. These networks were normally intended for a limited number of devices such as those used in research or military. The first generation of the network was mainly concerned with the link-up of mainframe computers and offered little more than data transmission capabilities. When PCs started to proliferate in the 1980s and 1990s, there was a demand for a more extensive and intricate communication system. LANs were invented to bring computers in each locality especially within an office or a building. These networks used such technologies as Ethernet that encouraged higher transfer of data over coaxial or twisted-pair cable. In the early 1990s, the Internet changed networking by using TCP/IP to interconnect various types of networks for world-wide communication. In the late 1990s and early 2000s, Internet communication infrastructure emerged as the leading global system.

The advancement of cloud computing in the middle of the 2000s as a key development was the change in networking. With cloud computing the businesses and individuals did not have to depend on local hardware for storage or computational resources; they could get data and applications from remote servers. Among several benefits associated with the transition to centralized and cloud-based solutions, flexibility, scalability, and cost control were the most significant. However, with cloud computing being the revolution it was, it came with new problems. Although networks were getting more dependent on the centralized data centres, problems like latency, bandwidth issues and the rising amount of data from the IoT devices began to put pressure on the traditional cloud models. Centralized approach of cloud computing led to problems of bottleneck especially when real time processing was involved.

The expansion of IoT starting from the year 2010 changed the course of networking fundamentally. IoT is the connection of physical objects, including sensors, wearables, and smart devices that interact over networks. IoT generates a large amount of data from the surroundings and from the users and hence there is need to manage the data produced. Previous cloud computing models failed to address the real-time data processing of the large data produced by IoT devices. This led to the development of the edge computing model that deploys computation closer to the source of the data. Edge computing helps in exploiting data at the edge to minimize delay and to offload cloud traffic.

Due to the processing of data at the edge, closer to the source, edge computing offers faster, more responsive systems and real-time decision making. Due to the integration of IoT and edge computing, contemporary distributed systems that not only link devices but also process data locally have emerged. When more and more IoT devices are used in different fields, including healthcare and smart cities, effective, large-scale, and real-time communication is required. Edge computing solves many of the challenges experienced with cloud architectures and opens a new generation of networking solutions.

Key Concepts in IoT

IoT is a system of devices that are connected, can exchange data with one another through the internet or any other network. The IoT devices are equipped with sensors, software, and other technologies that help to gather and exchange data to control & enhance the efficiency of the autonomous process in different fields, including healthcare, smart homes, and industries. It is crucial to have a clear understanding of what IoT really means, how devices are connected and how data is transmitted and how it communicates to fully appreciate this technology.

Device connectivity

Device connectivity refers to the various technologies and methods used to connect IoT devices to a network. These devices, which can range from simple sensors to complex machinery, need reliable and secure connection to exchange data efficiently. The following are some of its types:

Short-Range Connectivity: This means communication between devices that is done within a limited range of distance and often within a limited space. Some of these technologies include Blue Tooth, Zigbee and Near Field Communications technology (NFC). These are applied in smart accessories such as watches, home automation and health monitoring systems.

Wide-Range Connectivity: For devices that require transmission over larger distances there are technologies like Wi-Fi, LoRaWAN, and cellular technologies like 4G/5G. These technologies are critical for application where there is need for large coverage such as agricultural IoT or smart city.

Low-Power Wide-Area Networks (LPWAN): LPWAN technologies such as LoRa, Sigfox, and NB-IoT are intended to operate on low power for long ranges, therefore, allowing the devices to send small payloads over large distances using limited power. These networks are well suited for application such as monitoring of environment, tracking of assets and metering.

Data Transmission

Data transmission is IoT refers to the process of sending data between IoT devices and their corresponding data processing systems, such as cloud platforms or edge devices. Efficient data transmission is critical for ensuring that IoT applications perform well under different network conditions. IoT devices often transmit data in the form of sensor readings or events, which need to be conveyed to central systems for analysis or action [8]. The following are some methods:

Wired Transmission: As for the IoT connectivity, the wireless transmission is currently more popular, but the wired connection like Ethernet is also suitable for delivering high-speed and secure data transfer in the dynamic environment where the power supply and reliability are critical, like the industrial or enterprise IoT.

Wireless Transmission: This is perhaps the most widely used means of information exchange in IoT where devices use RF, WiFi or cellular channels. Zigbee and Bluetooth Low Energy (BLE) are also utilized for the wireless connection especially in the low power systems.

Communication Protocols

IoT devices rely on communication protocols to facilitate interaction with other devices networks, and cloud platforms. The most used protocols include:

MQTT (Message Queuing Transport): A lightweight messaging protocol intended for use in low bandwidth high latency networks such as the publish-subscribe model. It is widely used in communication dominant IoT applications like smart home automation and industrial IoT.

HTTP/HTTPS: HTTP is used in IoT applications as well, although it is more common for traditional web communication; it is used where an IoT device needs to communicate over the Internet. HTTPS allows secure transmission of the data since the information is encrypted. Bluetooth and Zigbee: These are short range communication protocols commonly used in smart home systems for enabling different IoT devices to interface in the nearby environment.

Edge Computing Fundamentals

Edge computing is defined as distributed computing model that allows for the data to be processed, analysed, and acted upon closer to the point of the generation, such as IoT devices, sensors, or user devices, instead of sending all the data to centralized cloud servers. This paradigm is essential for time-sensitive applications that require fast decision-making, such as autonomous vehicles, industrial automation, and remote healthcare monitoring. By processing data at the edge, unnecessary delays in transmitting data to distant data centres are avoided, ensuring low-latency responses and reducing the strain on central cloud resources.

Architecture of Edge Computing

The architecture is composed of three layers:

Device Layer: This comprises of the IoT devices, sensors and actuators that provide data in the internet of things. Such devices are usually low power devices, and while they might have some form of computation ability, they may only be capable of doing a little bit of preprocessing or even no preprocessing at all before they send the data on the network.

Edge Layer: consists of edge nodes or gateways which are in the network's periphery and implement basic computational operations on collected data. They may be routers, servers or micro data centres located closer to the source of the data, and they have a critical role of sorting and filtering the data before forwarding it to the cloud. These nodes may perform learning algorithms, data analysis and local decision-making tasks including running machine learning models and analysing data from various sensors.

Cloud Layer: The cloud layer relates to the classical cloud computing systems in which data is stored, processed and analysed at a large scale. Although, edge computation distributes and decentralizes most of the computations, the cloud layer is also an important component of the architecture as it is responsible for long term data storage and heavy computations as well as data fusion from different sources.

Key Characteristics of Edge Computing

Low Latency: Edge computing allows decisions to be made at almost the speed of light which is fundamental for the implementation of self-driving cars, live video broadcasting, and industrial automation.

Scalability: Edge computing enables the IoT device and sensors' mass deployment through decentralizing computational tasks on the edge devices. This makes it easier to scale networks without putting too much load on the central cloud servers in terms of data.

Bandwidth Efficiency: This leads to optimization of the bandwidth used since edge computing allows some data processing to be done at the site where it is captured. This is particularly necessary for the applications that produce a high volume of data, like video surveillance.

Enhanced Security and Privacy: Edge computing increases data protection since the data collected is stored at the network's edge and not sent to the internet for storage at centralized data centres. This puts the risk of data leakage under control.

3. SURVEY OF RELATED WORK

Research into networking and communication technologies has seen significant advances, particularly in IoT and edge computing. This section provides a detailed overview of past research, highlighting key contributions, methodologies, findings and limitations of existing studies.

Overview of Past Research

Many research works are devoted to the Internet of Things (IoT) empowered edge computing in smart city environments. Wang et al. put forward a trust management mechanism that employs dynamic black-and-white lists; the authors also show that IoT devices interact better with one another and are highly resistant to malicious attacks. Zhang et al. follow this up by demonstrating an actual real time object tracking system over the Xilinx SoC platform that has high accuracy with low memory footprint hence the benefits of edge computing for efficient usage of resources in smart city environments. Further, Lv et al. design efficient algorithms for task scheduling where they obtain high convergence rates in the distributed systems for efficient resource allocation.

The evaluation of healthcare applications shows that edge computing can be integrated successfully. Oueida et al. applies simulation modelling to improve emergency department resource utilization, thus decreasing patient wait times while improving service quality. CNNs are employed by Shahbazi et al. for-fault diagnosis in IoT smart manufacturing systems, which decrease the network load and enhance the performance through edge computing Subhranshu et al. discuss the performance of the mist layer in the HealthMist framework, which shows better training accuracy and resource utilization as more nodes in the mist layer are added

Thus, Mehmood et al. pay much attention to the application of edge computing in smart grid systems, providing less latency and bi-directional energy exchange, as well as rational data management. Shahbazi et al. solve industrial IoT issues with cooperative edge computing, decreasing diagnosis time and enhancing system efficiency The proposed integration of edge A Comprehensive Survey on Emerging Trends in Networking and Communication : From IoT to Edge Computing

layers as discussed by Sittón-Candanedo et al. minimizes cloud traffic and energy consumption, which are cost implications. Finally, Le et al. BrainyEdge framework delivers high accuracy with private data at the edge, a prime example of optimized edge AI.

Research Summary

The following table 1 summarizes the methodology, results, and limitations of all the past research studies in the field of IoT and edge computing.

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[2]	Nebula:	Mathew	2014	Location and	Enabling edge	Implemented	Not tolerant
	Distributed	Ryden, et al.		context-aware	volunteers to	distributed	to compute
	Edge			edge	contribute for	data intensive	node failure
	Cloud for			cloud for	distributed	application	and data
	Data			data-	MapReduce apps	such as	node failure
	Intensive			intensive		MapReduce	
	Computing			computing			
[3]	Femto	Karim Habak,	2015	Sharing idle	It is a group of	Mobile device	Not possible
	Clouds:	et al.		resources	mobile devices	applications	because
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	Cloud					theatre.	dynamic,
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A Comprehensive Survey on Emerging Trends in Networking and Communication : From IoT to Edge Computing

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[7]	An Edge	Soraia Oueida	2018	Emergency	Simulation	An analysis of	A key
	Computing	et al.		department	modelling	simulation	feature of
	Based			resource	included	outcomes	these models
	Smart			allocation and	determination of	shows	is the
	Healthcare			performance	objectives,	potential	reliance on
	Framewor			with edge	accumulation of	benefits of	proper data
	k for			computing	system data and	enhanced	for data
	Resource				creating a	resource	gathering
	Manageme				validated model.	utilization by	and real
	nt					decreasing	system
						patient wait	participation
						while	for better
						preserving the	model
						quality of	calibration.
						services.	
[8]	Using	Hong-Linh	2021	Examines	Performance data	Client-	The
	IoTCloudS	Truong		performance	is obtained by	provider	framework is
	amples as			monitoring	instrumentation	location and	not intended
	a software			and	of the code and	network	for low level
	framework			simulation for	the use of	conditions	analysis such
	for			edge	monitoring tools.	affect	as network
	simulation			computing	Simulations.	performance	or power
	s of edge			frameworks		differentially,	consumption
	computing					depending on	, thus it
	scenarios					the chosen	doesn't offer
						deployment	a
						configurations	comparison
							with
							conventional
							simulation
							tools.
L				I	I	1	

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[9]	Edge	M. Yasir	2021	Focuses on	An EC gets	EC enhances	The
	Computing	Mehmood et	-	the integration	through data at	real time	limitations
	for IoT-	al.		of edge	the edge of IoT	interaction,	include the
	Enabled			computing to	systems, thus	decreases	decentralised
	Smart Grid			enable smart	minimizing the	response time	security
	Shinir onu			grid systems	amount of traffic	and facilitates	approach,
				gild systems	that needs to be	bidirectional	and the
					carried on the	energy and	possibility of
					network, and the	information	encountering
					time it takes to	interchange in	bottlenecks
					process data.	SG systems.	when
					process data.	SO systems.	
							processing
							huge data from the SG
F10		L=4. 0'#/	2010	E	True 4. 4	Th. F 1	sensors.
[10	Edge	Inés Sittón-	2019	Evaluates	Two tests were	The Edge	Additional
]	Computing	Candanedo et		Global Edge	conducted, the	layer reduced	Edge-to-
	, IoT and	al.		computing	first without	the number of	Cloud traffic
	Social			Architecture	adding the Edge	requests going	saving can
	Computing			(GECA) to	layer and the	to Cloud;	be made if
	in Smart			optimize data	second one	thus, lowering	the location
	Energy			traffic	adding the Edge	Cloud costs,	engine is
	Scenarios				layer to the	traffic, and	deployed on
					proposed	energy usage.	the Edge.
					architecture.		
[11	Improving	Zeinab	2021	Edge	Implemented	Shorter	Edge
]	Transactio	Shahbazi et al.		computing in	CNNs for fault	diagnosis time	intelligence
	nal Data			IoT for smart	diagnosis, data	of the fault,	is applicable
	System			manufacturing	preprocessing	decreased	only to
	Based on				performed in	network	lightweight
	an Edge				edge and cloud	traffic,	tasks, issues
	Computing				system where	increased	with data
	-				edge has MIPS	efficiency of	offloading or
	Blockchain				10 and cloud	data	load
	-Machine				MIPS 1000.	processing	balancing in
	Learning					with edge	big IoT
	Integrated					servers.	networks,
	Framewor						and security
	k						issues in
							real-time
		l				l	

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							data
							exchange.
[12	A Reliable	BO WANG et	2020	IoT enabled	Held tests in	Managed trust	The
]	IoT Edge	al.		edge	areas of self-care	successfully	accuracy of
	Computing			computing for	and air quality	to ensure	results is
	Trust			smart cities	sensors.	better	dependent
	Manageme				Suggested a trust	cooperation of	on these
	nt				management	IoT devices	results. More
	Mechanis				approach using	and security	verification
	m for				black-and-white	against	needs to be
	Smart				dynamic lists and	malicious	done on
	Cities				evaluated the	attacks.	other IoT
					strategies of the		applications
					trust		to determine
					management		its reliability
					approach using		and
					Game Theory		applicability
					and Lyapunov		across
					Stability Theory.		different
							domains.
[13	Object	Hong Zhang	2019	IoT enabled	This system has	Obtained high	Designed
]	Tracking	et al.		edge	been	accuracy of	and
	for a Smart			computing for	implemented on	top	optimized
	City Using			smart cities	Xilinx SoC	performance	mainly for
	IoT and				platform Zynq-	with	certain
	Edge				7000 which has	minimum	selected
	Computing				ARM Cortex-A9	memory	metrics and
					and FPGA.	utilization at	configuratio
						157 kilobytes	ns.
						and real-time	
						tracking on	
						the dual-core	
						1 Ghz CPU.	

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I ED: al. algorithms ADM and convergence limitation of Intelligent edge al. algorithms Stackelberg rate of the collaborative edge computing using edge for task distributed systems is based on computing scheduling in a ADMM scalability machine computing scheduling in a ADMM scalability ilearning computing scheduling in a ADMM scalability for smart city staff and IoT distributed algorithm was and privacy. convergence generalizatio rate of the requires conditions; conditions; conditions; convergence generalizatio rate of the requires algorithms use 600 - 800 iterations.	[14	RETRACT	Zhihan Lv et	2021	Centralized	Proposed an	The	Another
Intelligent edge and task Stackelberg rate of the collaborative edge computing scheduling game algorithm proposed MEC based on machine and IoT scheduling in a ADMM scalability learning for smart and IoT distributed algorithm was and privacy. learning for smart city iterations for different city iterations for different experiments with while the conditions; city iterations for different experiments with while the conditions; city iterations convergence convergence generalizatio analysis and rate of the n requires cumulative distribution lagorithms distribution testing with was 600 – 800 iterations. iterations. iterations. [15 ANovel Subhranshu et 2023 Performance Assessed the More number The 1 Edge- al. and accuracy of the enhanced	-	ED:	al.		algorithms	-	convergence	limitation of
edge computing based on machine scheduling using edge game algorithm for task proposed MEC isad on machine and IoT distributed algorithm was and privacy. learning for smart and IoT distributed algorithm was and privacy. environment. less than 150 Studies vary city ierations for different eity experiments with while the conditions; convergence convergence convergence generalizatio analysis and rate of the n requires cumulative distribution algorithms was 600 – 800 iterations iterations iterations. iterations. [15 A Novel Subbranshu et 2023 Performance Assessed the More number The [15 A Novel Subbranshu et 2023 Performance Assessed the More number The [16] A Novel Subbranshu et 2023 Performance Assessed the More number The [16] A Novel Subbra		Intelligent			and task	Stackelberg	rate of the	collaborative
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		System in				various mist		configuratio
Cities		Smart				topologies.		n.
		Cities						

Paper Limitations

Results presented by Wang et al. are scenario-based, which means that the trust management mechanism should be verified in a wider context of IoT applications. Zhang et al. tracking system, while being accurate in tracking, is tuned for configurations, and thus not versatile. Lv et al. highlight scalability and privacy as two of the key open issues in collaborative MEC systems The simulations of resource models in Oueida, et al. are only based

on the real data for calibration purposes. According to Shahbazi et al, edge intelligence is only suitable for lightweight tasks, while data offloading and load balancing are challenging in large IoT networks. Subhranshu et al. concentrate on the fact that increases in performance depend on certain configurations of the mist node and that there is a requirement for dynamic adjustment.

Mehmood et al. point out that the processing of large datasets generated by smart grid sensors may be a bottleneck and that decentralized security cannot be easily implemented. Shahbazi et al. note that collaborative computing is not very scalable and maintaining privacy during sharing of data is quite a challenge. In their work, Sittón-Candanedo et al. find other optimization zones in the traffic between edge and cloud. Le et al. admit that the computational resources of edge devices are still quite limited in terms of imposing large models.

4. TECHNOLOGICAL ADVANCEMENTS AND FUTURE CHALLENGES

Edge Computing Architectures

The changes in the edge computing architectures are a great breakthrough in networking and communication. Today's edge computing architectures like hierarchical and hybrid allow for dividing the computational loads and tasks among the layers, from the devices up to the nodes and servers. These architectures improve the system performance because of low latency and effective utilization of resources. For instance, BrainyEdge and HealthMist show how edge nodes can handle complex processing tasks, including real-time monitoring and fault diagnosis, with only limited interactions with the cloud servers As future architectures are likely to become more distributed and dynamic, edge systems should also be able to adjust their operational modes to changing processing and networking loads. However, this is not easily achievable now, and improvements in the orchestration tools and standardization protocols are needed to guarantee good operation across the different environments.

Scalability issues

The problem of scalability is still an issue when the number of connected IoT devices is increasing rapidly. Existing solutions including smart city and healthcare solutions are designed for static configurations that cannot effectively support dynamic and large-scale environments. Scalability is also a problem given by interoperability as most devices are incompatible with each other due to the use of different protocols from different manufacturers. The two issues of contention that require future work are scalability, which requires solutions for dynamic resource allocation and decentralized coordination. For example, some of the collaborative edge computing frameworks such as those proposed for industrial IoT are potential solutions because they allow the devices to share resources and divide workloads among themselves. Issues of compatibility are easily solvable when there is a need to standardize practices, including the use of communication languages and data protocols. Also, the implementation of the management systems based on artificial intelligence can also contribute to the identification of workload patterns and, therefore, resource allocation in real time.

Data Privacy and Security concerns

There are two main issues of data privacy and security in edge computing since private information is processed near the origin. Decentralized security mechanisms, such as those used in smart grids and healthcare systems, minimize the risks occasioned by centralized vulnerabilities, but complicate the management of distributed security policies. For instance, the trust management frameworks, including that of smart cities, do away with threats of malicious attacks and yet need extensive testing across various applications Emerging threats like data leakage and unauthorized access necessitate enhanced encryption and more secure authentication. Blockchain technology and the privacy-preserving machine learning models are likely to help improve data security in edge settings. However, the problem of deploying these solutions at scale has not been solved because of the limited resources of edge devices and the difficulties of orchestrating distributed systems.

5. CONCLUSION AND FUTURE WORK

The combination of IoT and edge computing is changing the trends in the modern networking and communication systems and providing great opportunities in different fields of activity, such as smart cities, healthcare, and the industrial Internet. This work is a comprehensive review of the state-of-the-art solutions with emphasis on their effectiveness in meeting important hurdles in the field including low latency, higher bandwidth, and enhanced data privacy. For example, BrainyEdge and HealthMist are edge computing frameworks that show better performance as they work with data more locally instead of depending on the cloud systems.

Further, the trust management mechanisms and collaborative computing models have been identified to enhance the device cooperation and system reliability in IoT networks in large scale. However, there are some difficulties that still exist in the context of the present work. The problem of scalability and interoperability increase as IoT networks grow, since more dynamic control over resources and common communication protocols are needed. Moreover, the problem of data protection and confidentiality is not yet solved in decentralized structures, especially as the amount of information increases.

Solving these problems is going to involve the use of complex encryption methods accompanied by lightweight security, and privacy-preserving AI. As for the future work in this domain, the researchers should develop the adaptive and intelligent edge computing structures to manage the resources and workloads flexibly. The application of blockchain technology to promote data sharing and Machine learning to forecast the demand for resources is some of the promising research areas.

Besides, further real-world case and big scale demonstrations are required for the performance evaluation and system optimization of edge computing systems in various applications. If IoT and edge computing address these challenges, these technologies can revolutionize industries and improve the existence of people in smart cities and other smart environments. This paper has been prepared as a base for the further study, the authors' intent is to encourage the development of the new ideas and cooperation in the field.

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