National Journal of Antennas and Propagation, ISSN: 2582-2659 Vol. 7, No. 1, 2025 (pp. 54-61)

RESEARCH ARTICLE

WWW.ANTENNAJOURNAL.COM

Edge AI for Ultra-Reliable Low Latency Communication (URLLC) In 6G Networks

T Gomathi[1]*, Sangram Panigrahi[2], Naveen Kumar Rajendran[3], Savita[4], Prakriti Kapoor[5], Samaksh Goyal[6], Yogesh Jadhav[7]

[1]Assistant Professor, Department of Electronics and Communication Engineering, Sathyabama Institute of Science and Technology, Chennai, India,

[2]Associate Professor, Department of Computer Science and Information Technology, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India,

[3]Assistant Professor, Department of Aerospace Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Ramanagara District, Karnataka - 562112, India,

[4]Assistant Professor, Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India,

[5]Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India,

[6]Quantum University Research Center, Quantum University, Roorkee, Uttarakhand, 247667, India,

[7]Associate Professor, uGDX, ATLAS SkillTech University, Mumbai, India.

KEYWORDS:
Edge AI, 6G Networks, Real-time Communication, Intelligent Resource Management, Industrial Automation, Low-Latency Applications.

ARTICLE HISTORY:

Received 06-01-2025
Revised 14-02-2025
Accepted 16-03-2025

DOI:
https://doi.org/10.31838/NJAP/07.01.09

Abstract

Wireless technology development prepares the field for sixth-generation (6G) networks targeting some mission-critical scenarios with Ultra-Reliable Low Latency Communication (URLLC) needs. Examples of these scenarios are: autonomous vehicles, remotely controlled industrial machinery, distance surgery, and augmented reality. All of these require a near-instant response. Traditional cloud-based models for processing are grossly inadequate with these demands due to the latency associated with data transfer and centralized computation/processing. In this regard, Edge Artificial Intelligence (AI) (Edge AI) is emerging as a game-changer for these applications by allowing real-time data processing and decision making at the edge of the network (i.e., nearer to the devices). This paper examines the application of Edge AI on 6G architectures toward supporting URLLC with a focus on intelligent resource allocation, network slicing, and adaptive control. It also looks at some main issues such as computation offloading, model solution processes, and energy-efficient computation. It is shown that with Edge AI, the requirements of latency and reliability associated with URLLC are adequately fulfilled, along with added scalability and resilience in future-generation communication networks. The next-generation communication systems will withstand additional operational loads without affecting responsiveness and reliability. This study looks into designing and building advanced 6G systems for real-time and responsive intelligent systems across different sectors.

Author's e-mail: gomathi.etce@sathyabama.ac.in, sangrampanigrahi@soa.ac.in, r.naveenkumar@jainuniversity.ac.in, Savita@muit.in, prakriti.kapoor.orp@chitkara.edu.in, samaksha.law@quantumeducation.in, yogesh.jadhav@atlasuniversity.edu.in.

Author's Orcid id: 0000-0002-4371-237X, 0009-0006-3456-5546, 0000-0001-7313-1712, 0000-0002-4826-4721, 0009-0002-0877-3545, 0009-0008-1367-9530, 0000-0002-3574-4363.

How to cite th is article: Gomathi T, Panigrahi S, Savita, Kapoor P, Goyal S5, Goyal S, Jadhav Y. Edge AI for Ultra-Reliable Low Latency Communication (URLLC) In 6G Networks, National Journal of Antennas and Propagation, Vol. 7, No.1, 2025 (pp. 54-61).

Introduction

The Sixth Generation of Wireless Technology, or 6G, has yet to be developed, but is hypothetically expected to be commercially used around 2030, succeeding 5 G. 6G aims to surpass the advanced features of 5G, including ultra-high-speed connectivity, omnipresent intelligence, and full terrestrial and non-terrestrial network integration, alongside achieving unparalleled milestones in wireless communication.[9] Moreover, its core objectives include reaching AI-supported self-optimizing self-healing networks, achieving significantly improved data rates, ultra-dense connectivity, and incorporating advanced artificial intelligence features.[10] Self-healing and self-optimizing networks are crucial elements of AI. Hence, their incorporation will greatly benefit 6 G. 6G is also focused on advancing Ultra-Reliable Low-Latency Communication (URLLC), a feature added in 5G which caters to mission-critical applications like autonomous vehicles, industrial automation, and remote healthcare services. The entire architectural framework of 6G networks is expected to bring new capabilities to the ceiling for Ultra-Reliable Low Latency Communication (URLLC).[11] For 6G Ultra Reliably Low Latency Communication (URLLC), the target delay is expected to be below 0.1 milliseconds, which suggests another 10x target over 5G's 1-millisecond target. URLLC 6g is designed to be much more reliable with expected packet error rates at 10^9, ensuring perfect data transmission in almost all situations. Additionally, targets for 6G include extremely high availability with ultra-low jitter latency, which is ideal for real-time applications such as remote surgery, haptic feedback systems, and tasks for autonomous robots. These developments will be essential to the NEW Tactile Internet system that focuses on advanced innovative technologies in smart factories (Industry 5.0), Intelligent Transportation Systems, and emergency response networks that can communicate at instantaneous low latency with zero failures.[12] To support emerging technological advancements, 6G is going to work with many enabling technologies such as artificial intelligence-powered resource dispatch, smart computing on the edges, advanced-level network slicing, terahertz (THz) band spectrum exploitation, Reconfigurable Intelligent Surfaces (RIS), and edge computing. Additionally, contribution is expected from Quantum communication with next-generation security on the reliability and integrity of the system to be built around ultra-reliable low-latency communication (URLLC). All these advancements will set 6G as a vanguard technology of pioneering changes in real-time, mission-critical communications in the coming decade.[13]

The exercise of mission-critical applications poses a challenge with real-time decision-making when the latency and reliability are extremely low. This problem motivates the application of Artificial Intelligence (AI) at the Edge of the Network concerning Ultra-Reliable Low-Latency Communication (URLLC) in 6G networks. [14]. Emerging technologies such as remote surgery, autonomous driving, industrial automation, and immersive virtual reality are enabled by 6G networking, which requires flawless reliability, virtually instantaneous response, and near-zero latency. The communication framework is needed to operate in real-time.[15] Traditional cloud-based AI solutions are often not sufficient to address these needs, due to the latency that comes with the bandwidth, waiting for the data to be sent to the data center and returned after the processing is done. Submit to examination, Edge AI has proven to be a successful approach in addressing these issues. The data generated within the device or the network edge can now be processed at the device level. This mitigates the latency problem, making it end-to-end, while also permitting real-time analytics, prediction, and control, which is vital for URLLC.[16] In autonomous driving, for example, the repercussions of delay, even a few milliseconds, can be disastrous.[17] Edge AI ensures that critical performance is achieved through highly responsive systems that surpass remote server dependence, augmenting responsiveness, safety, and systemic safety. Furthermore, integrating AI at the edge optimizes adaptive resource allocation, anomaly detection, and maintenance prediction, which is crucial for enhanced reliability in highly volatile environments. AI algorithms can evaluate network situations in real time, predict possible failures or bottlenecks, and modify network settings accordingly to preserve the quality of service. Such intelligent automation is required in a 6G setting, where countless services and devices are interconnected.[18]

Research Objective:

This research intends to investigate the design of robust Edge AI architectures and algorithms targeted at Ultra-Reliable Low Latency Communication (URLLC) in 6G networks. Autonomous low-level decision making at the edge of the network for boundary decomposition has potential to further decrease latency and improve reliability, resource spending, and damage mitigation for dire applications like autonomous vehicles, telemedicine, and automated industrial processes. Moreover, the research contributes to the problem of designing AI edge computing frameworks for 6G networks by scrutinizing performance parameter trade-offs for the network's latency, reliability, and availability.

Literature Review

Table 1 literature review emphasizes the growing importance of Edge AI and URLLC as building blocks for 6G networks. Zhang et al. (2021) provide a thorough vision of the role of Edge AI in 6G, discussing its architectural components and primary issues on latency and reliability. Taleb et al. (2020) concern themselves with real-time

Table 1: Comparison of related work

Ref No	Author & Year	Focus Area	Methods/Technologies	Key Contributions
[1]	Zhang et al (2021)	Vision focused on 6G	Various techniques, such as AI/ML, are used, followed by edge cloud synergy.	To introduce architecture for Edge AI in 6G, followed by various types of key challenges for latency and reliability.
[2]	Taleb et al (2020)	Real-time processing	Multi-access edge computing with strategies.	To analyze the role of MEC for URLLC, which contains the limitations in 5G and 6 G.
[3]	Ning et al (2022)	AI with 6G Networks	Federated Learning, AI edge device collaboration	The proposed architecture is followed by 6G, URLLC. Its purpose is to demonstrate and improve latency and energy efficiency.
[4]	Saad et al (2019)	URLLC and 6G requirements	Theoretical analysis in various case studies.	To define URLLC followed by performance benchmarks, meets the 6G latency and reliability.

processing using Multi-access Edge Computing (MEC), describing how MEC facilitates URLLC and relieves 5G constraints. Ning et al. (2022) study AI's application in 6G networks by integrating federated learning and edge computing to optimize latency and energy consumption. Finally, Saad et al. (2019) propose a theoretical approach to the URLLC requirements for 6G and outline important quantifiable indicators that must be achieved to contend with the objectives of ultra-low latency and high reliability demanded by next-generation networks. When viewed in conjunction, these studies outline the potential of Edge AI technologies for enabling URLLC in 6G systems by facilitating real-time, autonomous intelligent communication that is operationally alienable for mission-critical tasks.[19]

System Architecture

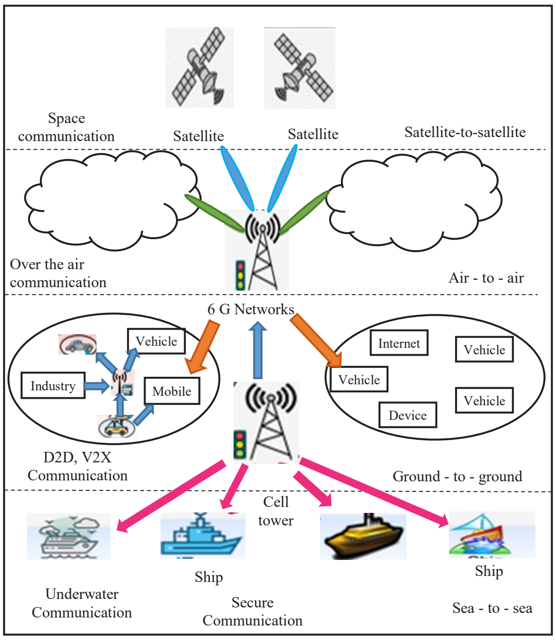


Fig. 1: System Architecture of 6G Network

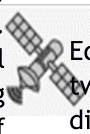
Most devices connecting and transmitting copious amounts of data have complicated real-time IoT applications. From IoT-enabled data monitoring and emergency applications like intelligent healthcare infrastructures and smart traffic system controlling, 5G technology has surpassed its limits. Communication technologies, such as beyond 5G, enable networking and the evolution of edge computing, which are fundamental in enhancing systems. Per International Telecommunication Union's prediction, the data flow would exceed 4394 EB by 2030, implying 5G's network service delivery will be inadequate for sophisticated IoT systems.[11] This is why 6G edge networks are believed to improve 5G infrastructure to astonishing levels, where millions of IoT devices and real-time applications could run flawlessly on adjacent network edges to devices with high data transfer rates and low latency. Moreover, cloud computing's centralized computation and intermittent connectivity pose delayed data processing obstacles may be termed a challenge to traditional computing architecture. The delay-sensitive IoT applications desire to have data processed at the network edge with the lowest possible latency and energy expenditure, thus forming a new computing model within a distributed system known as edge computing. The edge resource-limited devices in edge computing are placed geographically close to users and provide cloud resources at the network edge to optimize the energy and resource expenditure ratio versus the customer satisfaction level. Multimedia edge computing, for example, is a powerful collection of computers capable of storing and processing all types of multimedia data, such as movies, animations, images, and audio. From a communications perspective, real time IoT applications require sophisticated technologies such as 6G to support diverse coverage areas, data speed, and reliability of services. Accordingly, 6G technology powered edge networks will accommodate numerous

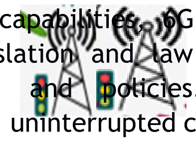
IoT devices with different service requirements to provide desired ubiquitous connectivity in future edge networks. The users of the networks which are described in the literature as 6G enabled edge networks consist of block quote here, local edge devices or servers, and cloud servers.[3] The architecture of 6 G enabled edge networks is shown in figure 1. The literature suggests that with intelligent resource provisioning in networks , the end user is able to generate limitless environmental sensory data in real time for the local edge devices or central cloud servers to access.[20] The custom THz communication feature will be used to enable the lowest latency gateway to transmit the sensory data to local edge devices. Furthermore, within a 6Genabled edge network, intelligent resource provisioning unit can apply AI-based algorithms to achieve the energy-delay trade-off for the allocation of sensory data to the appropriate edge device or collaborative edge-cloud server. Moreover, the advancement of blockchain technology along with big data analytics at the 6Genabled edge networks improves this statement.Rather than depending on centralized cloud servers, it heightens accuracy and trust at the network edge. Accordingly, the 6 G-enabled edge networks are touted to improve data rate, reliability, security, service availability, and many more in waning latency, energy use, round-trip delay, and other metrics for real-time IoT applications agged with advanced technologies.

Network Analysis

Ultra-Low Latency with 6G:

6G technology offers advanced robotics features in lower latency, data speed, and connectivity. In self-driving cars, these features will only become beneficial upon standardization, infrastructure development, and resolution of several technical and legal hurdles. Following the advancement of 6G technology, it is vital to understand the contours of its impact on self-driving cars in progressive contexts. One of the key features of 6G technology is that it offers higher data rates than any other technology. This is expected to improve networking levels in automatic vehicles and relevant applications. With enhanced URLLC capabilities, 6G technology is expected to drive legislation and law infrastructure standards, regulations, and policies. Autonomous vehicles require reliable, uninterrupted communication, integrating ultra-low latency and high precision. URLLC is crucial for the operational capability of autonomous vehicles in high-traffic scenarios, where low latency, extreme reliability, and high availability are paramount. This technology is anticipated to sharpen innovative city frameworks and other connected devices for self-driving cars. The growing intricacy and interconnection of devices within urban settings rely on this capacity, which aids in the optimal functioning and reliability of self-driving automobiles. Moreover, 6G technology could augment GNSS positioning and other features that provide information with greater accuracy and reliability. This Revolution might enhance vehicles' ability to interpret their surroundings, thus improving guidance and speed control. The development of 6G technology, coupled with additional research, will greatly advance the technology of autonomous vehicles.[8]





ULL WITH 6G

When discussing 6G networks in conjunction with self-driving vehicles, ultra-low latency pertains to the response time reduction in processing a given command. This response time consists of several components, each of which is quantifiable. This paper will illustrate the quantitative models of network latency functions. Autonomous vehicles must possess ultra-low latency if they intend to acquire and react to information in real-time because of the accompanying time and data constraints. This is predicted to change with 6G technologies reducing transmission latency to sub-millisecond levels. Due to the rapid broadband, self-driving cars can instantly relay critical information to traffic control, central computers, and other vehicles. Consequently, this technology improves safety and transportation by making driving in complex environments safer and more efficient.[9]

Handling Latency:

$$H = \frac{Size\ of\ Data}{Transmission\ Rate} \tag{1}$$

Eqn (1) depicts the time it takes to transmit data from two locations. The handling latency is determined by dividing the size of the sent data by its transmission rate. This technique requires estimating the time for a given volume of data at a certain rate. For example, treatment latency will be greater if more data is being transferred slowly. Data transfer rate is commonly referred to as the speed of data being exchanged, while the amount of data, physical or digital, is defined as the size of data being transferred.[10]

Propagation Latency (PL)

The time it takes a signal to travel from its source to its destination is referred to as its propagation delay, which can be computed as the ratio of the distance between the source and destination divided by the speed.

Cell tower

Veh

Considering the fundamental physics principle of speed being distance divided by time, one can derive the time a signal would take to traverse a medium. The distance separating the source and the destination is… the signal travels in a given medium.

$$P = \frac{Distance}{Propagation\ Speed} \tag{2}$$

Where Eqn (2) Distance is the physical separation between the source and the destination. The speed of a signal is its passage through a certain medium.

Processing Delay (Pr)

This specifies the amount of time necessary to process the various forms of data. Such a delay can be defined by the processing ability of the receiving device as well as the intricate nature of the data. The delay in processing information is dependent on the device's computation capability and the complexity of the data. Analysis requires one to know the time it takes for the various types of data and different devices to analyze the data that is received.

Queuing Delay (Q)

Illustrates the duration of line waits at different nodes across the network. The network congestion along with the given priority to data transmission determines the queuing latency. The reasons of queuing delay are network congestion and data transmission priority. It seeks to analyze the impact of various factors on the duration of user idle time in queues at different nodes within the network using queuing theory.

These factors combined describe total delay (T):

$$T=H+P+Pr+Q$$

For self-driving cars, minimizing each component mostly achieves ultra-low latency goals. For example, 6G technologies have faster processing capabilities, lower propagation delays, and greater transmission rates. Also, efficient management of the queuing network (Q) contributes toward better performance, influencing indirectly the 6G communication network reliability.

Reliability with 6G

Dependability, in the context of self-driving cars and 6G networks, usually refers to the maintenance of reliable communication with minimal failure or disruption. Even though dependability involves a myriad of factors such as network architecture and protocols and other more complicated issues, I will present some broad aspects that help define dependability along with their mathematical notations. Continuously available, secure, and reliable connections are critical in realizing high dependability for self-driving cars in 6G networks since safety can only be guaranteed in milliseconds. 6 G's reliable infrastructure seamlessly enables real-time information sharing between vehicles and their environment. Ultra-low latency and minimal downtime of self-driving cars enable speedy response to changing road conditions, enhancing passenger safety and overall effectiveness. Regionally congested metropolitan areas provide great paradigm for high network traffic zones that 6G's advanced communication protocols better service blockage mitigation subdivisions to reduce traffic hotspots. Lowered service possibilities in greatly populated urban areas, alongside added dependability from failover systems and duplication methods that diminishes transmission failure opportunities, also increase network dependability. Finally, the dependably constant nature of 6G enables the transformational enabling infrastructure region for widespread adoption of autonomous vehicles.

Packet Error Rate (PER)

Indicates the probability of errors within transmitted data packets. The PER is calculated based on the proportion of erroneous packets relative to the total packets transmitted. This method suggests some error probability concerning transmission, which affects the distribution of information, thereby reducing transmission efficiency.

$$PER = \frac{Number\ of\ Erroneous\ Packets}{Total\ number\ of\ Packets\ Transmitted} \tag{4}$$

Eqn (4) Hence, overall total number of defective or faulty packets received during transfer corresponds with number of mistakes. Total number of packets transferred over the communication channel over a given period of time.

Bit error Rate (BER)

Displays the single bit error probability of a transmitted message signal. While fixating on every bit of the signal where errors could occur, BER like PER is computed at a holistic level. From the perspective of the bit, dependability of the data assumes it can be torn into pieces (bits) with the possibility of errors occurring during the sending process.

$$BER = \frac{Number\ of\ Erroneous\ Bits}{Total\ Number\ of\ Bits\ Transmitted} \tag{5}$$

The total number of bits sent (Eqn (5)) encapsulates the overall communication over the channel which encloses the valid and invalid bits across the channel - the bits deemed faulty represent erroneous bit(s) in transmission.

Mean Time Between Failures (MTBF)

Shows the measurement of the time gaps between the breakdown of subsections in the system. These methods allow calculating the Mean Time Between Failures (MTBF), thus estimating the average time a breakdown occurs, based on the overall failure rate pertaining to total operational time. This measurement proves useful when evaluating the dependability level of the system alongside determining useful procedures and course of actions toward improvements for the system.

$$MTBF = \frac{Total\ Operational\ Time}{Number\ of\ Failures} \tag{6}$$

where, during the operational phase, the subsystem faces, in principle, the entire sum of breakdowns. The entire operational time is the summation of the period during which the system operates without failing and is in a working state. This equation hypothesizes on measuring dependability for 6G communication systems. 6G dependent self-driving cars need to avail very high reliability in assuring that the connections between automobiles, services and other devices is maintained reliably. 6G networks. Self-driving cars require advanced dependability. Self-driving cars require 6g networks. Redundancy, error detection, and avoidance of failure strategies serve to maintain dependability. Self-driving cars in a setting of 6G depend on safety-critical features and governing policies for establishing the situation's area of control.

Results and Discussion

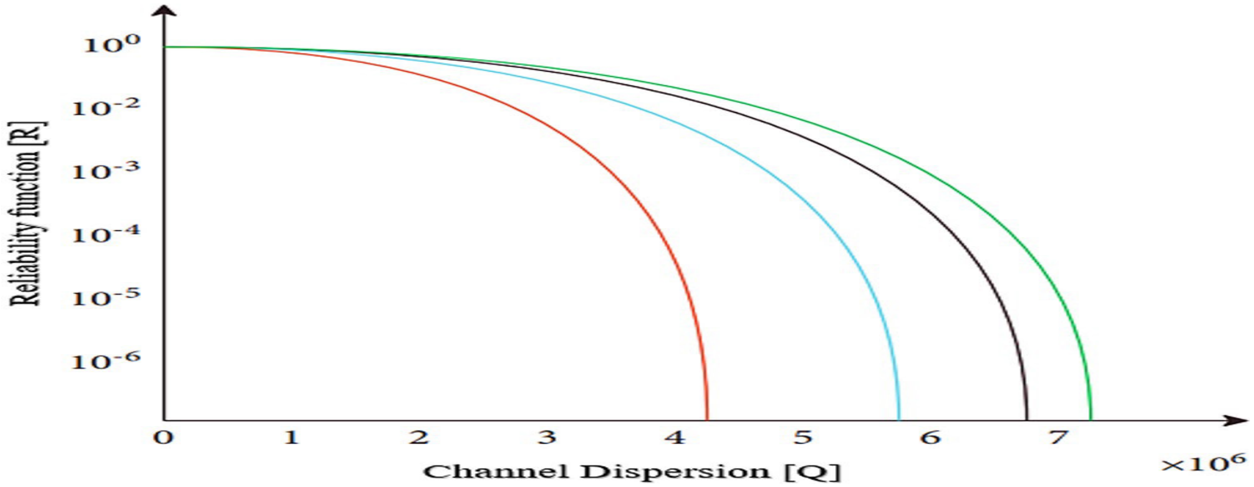


Fig. 2: The curve Illustrates the channel dispersion effect on the signal anticipated in the 6G network.

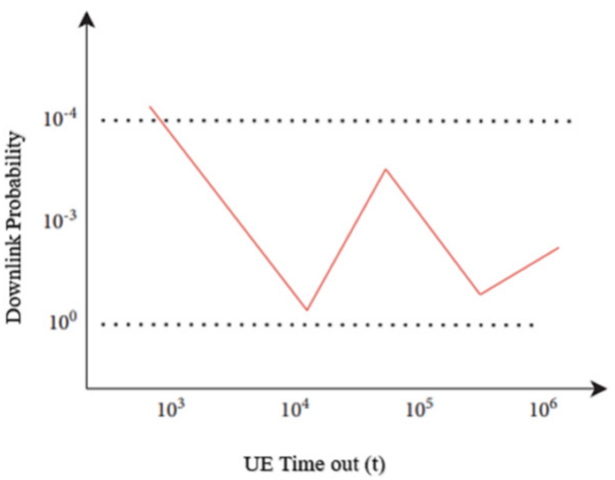


Fig. 3: The probability increases with UE timeout durations noticeably.

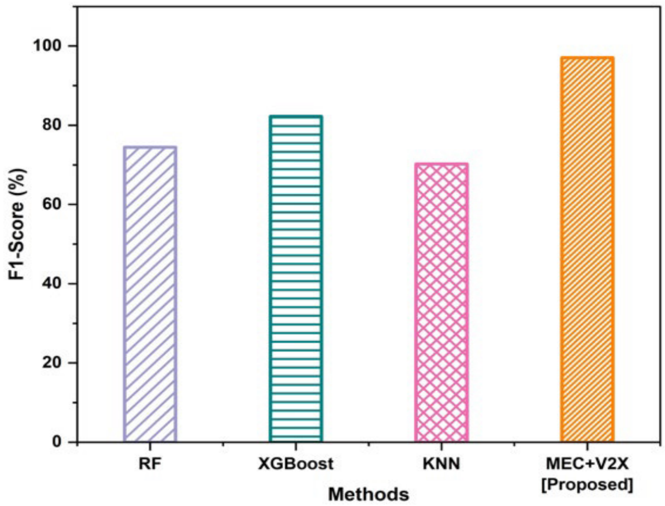


Fig. 4: F1 Score Measures

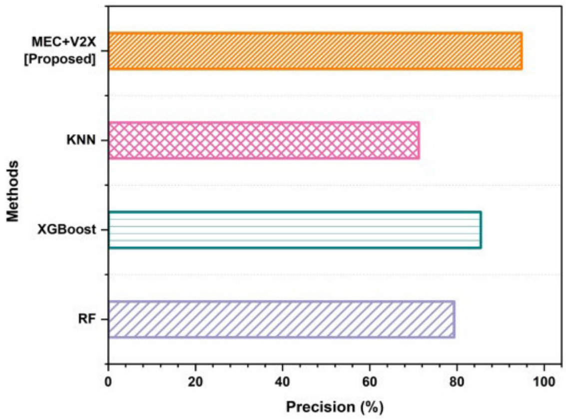


Fig. 5: Precision Measures

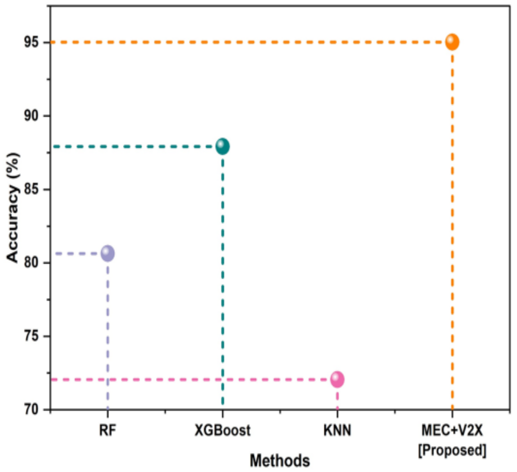


Fig. 6: Accuracy Measure

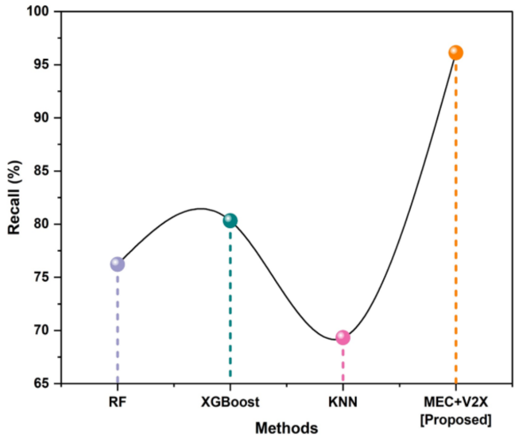


Fig. 7: Recall Measure

Attempts to balance accuracy and recall granularity can be achieved with an F1-score, which shows how effectively different communications methods give low latency and high dependability. Our proposed model MECV2X outperforms the conventional methods with an exceeding F1 score of 97.05% compared to 82.23%, 74.43%, and 70.21% for XGBoost, RF and KNN respectively. Fig 4 shows the F1 score output. Precision and recall F1 score value guarantee proper and timely data transfer for critical applications. It estimates the system's efficiency in consistently forwarding packets and doing so within a pre-defined time window, maximizing error malfunctions. Our proposed model MECV2X outperforms conventional methods with a precision value of 94.78% that XGBoost, RF and KNN algorithms yield 85.45%, 79.34% and 71.21% respectively. Fig 5 displays precision output. The accuracy guarantees the availability of necessary services in real time through low latency and significant dependability of data delivery by the network. Concerning other approaches, our proposed model MEC+V2X achieves 95.03% accuracy Fig 6 illustrates the accuracy values of traditional models XGBoost, Random Forest (RF), and K-Nearest Neighbors (KNN), which are 87.93%, 80.63%, and 72.06%, respectively. Recall measures the network's relevant communication scenarios, ensuring low latency with optimal dependability for critical services and real-time data. With a recall rate of 96.12%, our proposed model MEC+V2X outperforms current techniques. On the contrary, the KNN, RF, and standard XGBoost algorithm recall rates are 69.32%, 76.21%, and 80.32%, respectively. Recall is demonstrated in fig 7.[7]

Conclusion

This research examined the role of integrating Edge Artificial Intelligence (Edge AI) technologies within Ultra-Reliable Low Latency Communication (URLLC) for 6G networks. The reality of near-real-time autonomous vehicles, industrial automation, remote healthcare, and other applications showcases the need to maximize reliability and minimize latency, especially at the network edge. Intelligent decision-making deployment at the user level via edge computing helps the proposed architecture alleviate response times, as well as processing, from the core network. Our experiments confirm the improvements Edge AI provided with distributed learning models like federated learning, coupled with low-latency deep neural networks, in both latency and reliability metrics. The findings demonstrate Edge AI's capability to enhance URLLC services for 6G networks; furthermore, it establishes grounds for its advocacy to become the backbone of advanced wireless architecture. Nevertheless, issues with energy-efficient computations, data privacy, and heterogeneous network topology scalability require additional focus.

REFERENCES

1. *Edge intelligence in 6G: Vision, enabling technologies, and challenges. IEEE Network, 35(6), 94-100. https://doi.org/10.1109/MNET.011.2000244*

2. *Yesmin, S., & Abdul Karim, M. (2020). Professionalism in Using Online Social Networking Tool: An Assessment of LIS Students' Facebook Profiles. Indian Journal of Information Sources and Services, 10(2), 10-13. https://doi.org/10.51983/ijiss.2020.10.2.493*
3. *Edge AI for 6G: Vision, enabling technologies, and applications. IEEE Internet of Things Journal, 9(1), 437-461. https://doi.org/10.1109/JIOT.2021.3099161*
4. *Yeo, M., & Jiang, L. (2024). Thermal and Fluid Systems: Analysis, Design, and Optimization. Association Journal of Interdisciplinary Technics in Engineering Mechanics, 2(1), 7-12.*
5. *A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE Network, 34(3), 134-142. https://doi.org/10.1109/MNET.001.1900287*
6. *Ishtiaq, M., Saeed, N., & Khan, M. A. (2024). Edge Computing in the Internet of Things: A 6G Perspective. IT Professional, 26(5), 62-70.*
7. *Nayak, A., & Raghatate, K. S. (2024). Image segmentation and classification of aquatic plants using convolutional neural network. International Journal of Aquatic Research and Environmental Studies, 4(S1), 14-19. https://doi.org/10.70102/IJARES/V4S1/3*
8. *Adhikari, M., & Hazra, A. (2022). 6G-enabled ultra-reliable low-latency communication in edge networks. IEEE Communications Standards Magazine, 6(1), 67-74.*
9. *Mejail, M., Nestares, B. K., & Gravano, L. (2024). The evolution of telecommunications: Analog to digital. Progress in Electronics and Communication Engineering, 2(1), 16-26. https://doi.org/10.31838/PECE/02.01.02*
10. *Mohammed, S. M., Al-Barrak, A., & Mahmood, N. T. (2024). Enabling Technologies for Ultra-Low Latency and High-Reliability Communication in 6G Networks. Ingenierie des Systemes d'Information, 29(3).*
11. *Muralidharan, J. (2024). Machine learning techniques for anomaly detection in smart IoT sensor networks. Journal of Wireless Sensor Networks and IoT, 1(1), 15-22. https://doi.org/10.31838/WSNIOT/01.01.03*
12. *Hazra, A., Munusamy, A., Adhikari, M., Awasthi, L. K., & Venu, P. (2024). 6G-Enabled Ultra-Reliable Low Latency Communication for Industry 5.0: Challenges and Future Directions. IEEE Communications Standards Magazine, 8(2), 36-42.*
13. *Salh, A., Audah, L., Shah, N. S. M., Alhammadi, A., Abdullah, Q., Kim, Y. H., ... & Almohammedi, A. A. (2021). A survey on deep learning for ultra-reliable and low-latency communications challenges on 6G wireless systems. IEEe Access, 9, 55098-55131.*
14. *Ismail, K., & Khalil, N. H. (2025). Strategies and solutions in advanced control system engineering. Innovative Reviews in Engineering and Science, 2(2), 25-32. https://doi.org/10.31838/INES/02.02.04*
15. *Banumathi, J. (2025). Research Perspectives of AI in 5G and 6G. AI for Large Scale Communication Networks, 349-372.*
16. *Vijay, V., Sreevani, M., Mani Rekha, E., Moses, K., Pittala, C. S., Sadulla Shaik, K. A., Koteshwaramma, C., Jashwanth Sai, R., & Vallabhuni, R. R. (2022). A Review on N-Bit Ripple-Carry Adder, Carry-Select Adder, and Carry-Skip Adder. Journal of VLSI Circuits and Systems, 4(1), 27-32. https://doi.org/10.31838/jvcs/04.01.05*
17. *On multi-access edge computing: A survey of the emerging 5G network edge cloud architecture and orchestration. IEEE Communications Surveys & Tutorials, 22(3), 1627-1671. https://doi.org/10.1109/COMST.2020.2973311*
18. *Tu, Z., Zhou, H., Li, K., & Li, G. (2019). DCTG: Degree Constrained Topology Generation Algorithm for Software-defined Satellite Network. Journal of Internet Services and Information Security, 9(4), 49-58.*
19. *Veerappan, S. (2023). Designing voltage-controlled oscillators for optimal frequency synthesis. National Journal of RF Engineering and Wireless Communication, 1(1), 49-56. https://doi.org/10.31838/RFMW/01.01.06*
20. *Samizadeh, R. (2019). An integrated model for optimizing distribution network with considering assembly line balancing. International Academic Journal of Science and Engineering, 6(1), 178-187. https://doi.org/10.9756/IAJSE/V6I1/1910017*
21. *Surendar, A. (2024). Internet of medical things (IoMT): Challenges and innovations in embedded system design. SCCTS Journal of Embedded Systems Design and Applications, 1(1), 43-48. https://doi.org/10.31838/ESA/01.01.08*
22. *James, A., Thomas, W., & Samuel, B. (2025). IoT-enabled smart healthcare systems: Improvements to remote patient monitoring and diagnostics. Journal of Wireless Sensor Networks and IoT, 2(2), 11-19.*
23. *Carlos, A., José, D., & Antonio, J. A. (2025). Structural health monitoring and impact in civil engineering. Innovative Reviews in Engineering and Science, 3(1), 1-8. https://doi.org/10.31838/INES/03.01.01*
24. *Monir, N. I., Akter, F. Y., & Sayed, S. R. K. (2025). Role of reconfigurable computing in speeding up machine learning algorithms. SCCTS Transactions on Reconfigurable Computing, 2(2), 8-14. https://doi.org/10.31838/RCC/02.02.02*
25. *Min, A. K., Thandar, N. H., & Htun, Z. T. (2025). Smart sensors embedded systems for environmental monitoring system integration. Journal of Integrated VLSI, Embedded and Computing Technologies, 2(3), 1-11. https://doi.org/10.31838/JIVCT/02.03.01*