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Review Article

A Comprehensive Review of Deep Compressive Sensing for Efficient IoT Data Management

Hemant Rajoriya*

Assistant professor, Department of Electronics & Communication Engineering, Ram Krishna Dharmarth Foundation University, Bhopal, Madhya Pradesh, India.

Dr. Balajee Sharma

Assistant professor, Department of Electronics & Communication Engineering, Ram Krishna Dharmarth Foundation University, Bhopal, Madhya Pradesh, India

Corresponding Author Email id. - hemantrajoriya25@gmail.com

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Abstract: The Internet of Things has revolutionized data-driven ecosystems and offers advanced services, such as live monitoring and automation in various domains: smart cities, healthcare, and industrial automation. However, with the exponential growth of IoT devices, comes a large amount of data generation, which poses considerable problems like network congestion, latency, and energy inefficiency. Compressive sensing (CS), one of the newest signal processing methodologies, has emerged as an enabler to meet these challenges as it reduces the requirement of data acquisition and transmission without moving away from its signal fidelity. Moreover, integration of CS with deep learning enhances the utility as it enables efficient reconstruction and adaptive processing within the IoT network. This review analyzes the basics of CS, particularly its applicability to IoT context regarding optimizing data management and overcoming limitations of resources. Real-time applications such as traffic monitoring through smart cities and biometric signal transmission in healthcare discuss how robust the framework can be for a CS-based approach. Moreover, the study delves into the idea about deep learning and reconstruction accuracy and scalability - which is still unbound to create an even more intelligent system for IoT applications. CS and deep learning form an essential convergence in managing data overhead, optimizing energy and bandwidth usage, and paving the way for sustainable IoT ecosystems.

Keywords: Internet of Things (IoT), Compressive Sensing (CS), Deep Learning, Data Traffic Optimization, Energy Efficiency, Signal Reconstruction

I. INTRODUCTION

The Internet of Things (IoT) can be de need as a platform where virtual and physical objects are interconnected and communicate with each other [1]. IoT systems consist of different technologies such as wireless sensor networks, cloud computing and embedded intelligence. IoT systems capture environmental data by using RFID (Radio Frequency Identifier), cameras, sensors and so on. Some of the examples of sensors include free detectors, accelerometers, air quality monitors, cameras, barometers and thermometers in monitoring the environment as well as tracking objects and other unlimited applications. They can perform numerous activities that may include collection, processing, and transmission of environmental data like temperature and solar radiation and relative humidity. Because of these operations, information will be transferred to other Things through the Internet [2]. These systems o er advanced services such as real-time remote monitoring, online analytics and remote management. IoT is applied in many remote monitoring applications in vast domains from healthcare to smart factories, and including smart homes, smart cities, smart agriculture, improving productivity and reducing costs [3]. Centralized as well as globally distributed, Cloud computing has gone to be an integral part of processing IoT data. Yet, high energy consumption, bandwidth constraint, and delays in transmission are some of the challenges that cloud assisted Internet of Things faces. The massive energy taken to transmit an individual bit over a cellular network for instance reduces IoT system lifespan significantly [4].

It is a revolutionary technology and performs intelligent sensing and actuation for numerous objects by exchanging information with a core network. IoT Ecosystem Hierarchy shown in Figure 1. People can remotely manage or monitor the behavior of devices from systems hundreds of kilometers away with the help of various types of IoT technology. In academics and industry [5], IoT-based systems have proliferated in the last few years, providing multiple new applications such as smart homes, intelligent transportation, smart hospitals, and smart cities [6], [7], [8]. Based on these emerging applications, the number of IoT devices is expected to grow from 7 billion in 2018 to 22 billion in 2025 [9]. Massive IoT is thus a new paradigm in the field of IoT networks; as opposed to communication speed, the networks are driven by scale. The number of devices connected in massive IoT can vary from hundreds to billions. The main aim of massive IoT is to transmit a small amount of sensing data through a large number of devices efficiently. Thus, the process of designing intelligent, efficient, adaptive, and cost-effective IoT systems within the context of a massive IoT paradigm has been complicated through the ever-increasing number of IoT connectivity demands and varying application requirements [10].

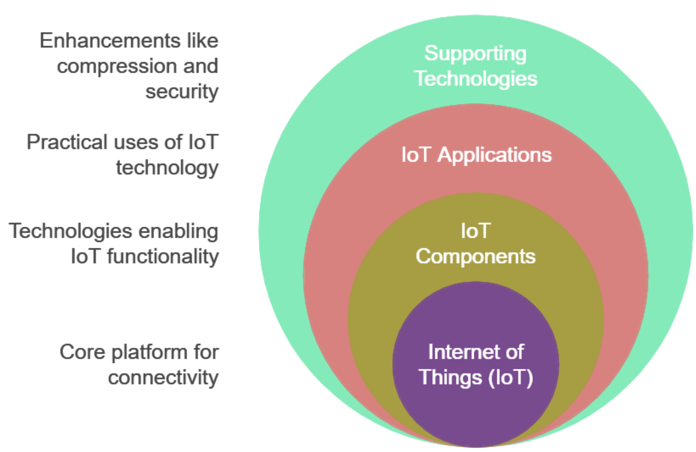

Figure 1: IoT Ecosystem Hierarchy

Different algorithms can be applied to achieve the compression ratio; some maintain the original information, described as lossless, and some are lossy, and often lose unique information upon compression. Every compression method is made for a specific type of image and cannot work well with unintended images. Most algorithms allow you to set variables and adjust the compression to obtain a more aesthetic image. Authenticity will be ensured by using the cryptography method prior to message concealment. There are numerous known algorithms available for cryptography. They include Advanced Encryption Standard (AES), Blowfish, Data Encryption Standard (DES), RC4 Rivest-Shamir Adleman (RSA) [11]. Optimizing the bandwidth by effective data compression and transmission will help reduce costs and enable faster error-free data transfer. Compression improves the efficiency of storage by reducing data size, enables the support of real-time applications, and makes information accessible even in low-infrastructure areas. This is quite important for emerging technologies such as IoT and edge computing because of resource constraints that push for more streamlined data handling. It also helps in environmental sustainability through energy consumption and carbon footprint reductions of data centers. With exponential growth in data volumes, efficient compression ensures scalability, thereby making digital systems more accessible, secure, and sustainable while supporting technological advancements [12].

II. IMPORTANCE OF DATA TRAFFIC REDUCTION IN IOT

A. Importance of Data Traffic Reduction in IoT

Intensive proliferation of the IoT system has resulted in unprecedented data generation through interconnected devices, sensors, and machines. The endless data inflow challenges the IoT ecosystem with respect to performance and scale. First, a large volume of data often causes latency and bottlenecks in data transmission, where the networks get overwhelmed by handling simultaneous streams of data from various devices at the same time. This is critically important for any real-time applications such as health monitoring, self-driving cars, and industrial automation since delays in data delivery may deteriorate system reliability, safety, and efficiency. Furthermore, the constant growth of data traffic is causing a huge burden on network infrastructure through overlaying routers, gateways, and cloud servers. In addition to this, it results in poor service quality and thus increases the cost of operations since there is frequent need to upgrade the infrastructure as per demand. For instance, bandwidth capacity expansion, data storage facility improvement, and processing power improvement all call for huge investments that may not always be feasible for organizations with fewer workforce members or large-scale deployments at distant locations [13, 14].

Excessive data transmission disrupts the responsiveness of IoT systems, with potential service interruptions or inability to meet fundamental performance benchmarks. In mission-critical cases, such as remote patient monitoring within the scope of healthcare and industrial IoT predictive maintenance, processing data may be either delayed or incomplete, including failure of equipment or compromised patient health. Reducing data traffic is also closely linked to energy efficiency and sustainability. Being the case, there will be a marginal energy reserve in IoT devices-particularly those that are battery powered and distant. Continued high-volume data transmission depletes these quickly shortening their lifespan as well as augmenting maintenance. The reduction of unnecessary data transmissions can significantly cut down power, leading to increased device operation time and minimizing breakdowns [15].

Furthermore, data traffic reduction supports the scalability of IoT networks. This is because the number of interconnected devices grows exponentially. Thus, there will be an effective way to manage data without reducing its quality. Data aggregation, compression, and prioritization of important data are also key techniques that only allow essential information to filter through the networks, thus eliminating congestion and improving performance in total. The challenges of too much data traffic become evident in real-world applications. Many sensors are used in smart cities to monitor the flow of traffic, air quality, and utilization of energy. If the data is not efficiently managed, it can make the networks of sensors congested, causing delays or gaps in necessary information. Similarly, in health care, wearable devices produce vast streams of biometric data that must be processed and streamed to the cloud quickly enough to not overwhelm cloud systems. Industrial IoT faces similar challenges: high-rate data gathered from machines in factories must be sent close to real time for predictive maintenance, risking downtime or failure if networks cannot keep up [16, 17].

B. Energy Efficiency and Bandwidth Optimization

Reducing data traffic is essential to improve energy efficiency in IoT networks, especially for devices that are supplied by resource-limited energy sources such as batteries. Wireless communication is one of the dominant features of IoT devices, being significantly energy-consumptive and accounting for a major share of power consumption. High data transmission drains batteries rapidly; thus, devices have a relatively short lifespan, and replacing them incurs higher maintenance costs, especially in remote or inaccessible locations. Devices can save energy, prolong their lifetimes, and guarantee the long-term reliability of IoT deployments by employing data reduction techniques including data aggregation, compression, and edge computing [18].

Optimization of bandwidth is also equally important since it is an IoT network shared across many devices and it is a finite resource. Inefficient bandwidth utilization creates congestion, slows the data rate, and increases latency, thereby affecting the performance of applications such as healthcare monitoring or industrial automation that depend on timely data delivery. Reduction of data traffic helps in decongesting bandwidth by transmitting only the information that is necessary, thus making IoT networks scalable and denser without degrading performance. Being energy-efficient and optimizing bandwidth at the same time, IoT eco-systems remain sustainable, cost effective, as well as capable of supporting the burgeoning demands of connected devices and applications [19, 20].

C. Real-World Examples of Data Overhead in IoT

Considering the sheer number of deployed sensors and devices in smart city environments, data overhead is expected to be one of the critical challenges. Every second, such sensors tracking traffic flow, air quality, weather conditions, energy usage, and public safety generate immense volumes of data. For instance, a traffic monitoring system may rely on real-time data from cameras and sensors monitoring the movement of vehicles; if these data are transmitted in their raw form, they might overwhelm municipal networks. In a smart city, even energy grids rely on IoT sensors to monitor electricity consumption, distribution efficiency, or faults. Without efficient data reduction techniques, such streams may cause network congestion and delay data processing processes, in addition to increasing the operational cost of communication networks, thus hindering the ability to respond promptly to critical events like power outages or traffic jams [21]. The health care sector also has significant data overhead challenges with the emergence of wearable devices and remote patient monitoring systems. Examples of such devices include smartwatches, glucose monitors, and heart rate trackers that continuously transmit biometric data to cloud servers for analysis. This could cause floods of data that gradually fill and overwhelm storage and processing systems, especially during peaks in usage or when large populations are monitored simultaneously. The amount of data can send delays to critical insights or even make real-time monitoring infeasible. In industrial IoT, predictive maintenance systems collect high-frequency data from machinery sensors to detect the possibilities of failure or optimization of performance. High-volume datasets need to be transmitted and processed efficiently to avoid delays in the identification of faults that can result in costly downtime or even safety hazards. These examples in the real world reflect the need to adopt data reduction techniques such as edge computing, data compression, and selective sampling to effectively manage IoT data with the service quality and system reliability at the end [22].

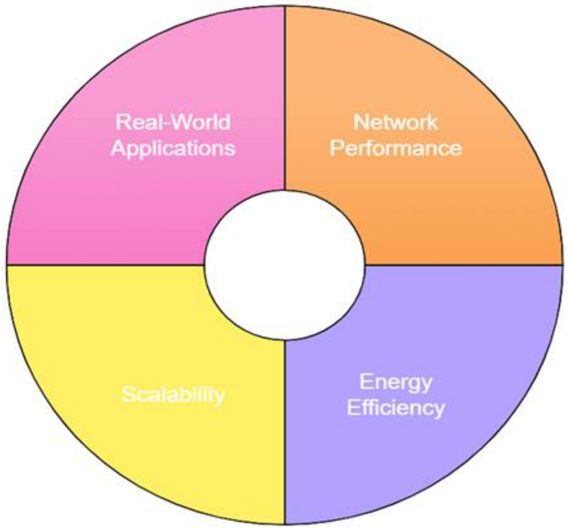

Figure:2 Navigating Iot Data Challenges

III. COMPRESSIVE SENSING

CS is a revolutionary signal processing technique that enables efficient acquisition and reconstruction of signals based on sparsity and incoherence principles. In contrast to traditional approaches to signal acquisition, CS captures data representations with fewer measurements. It reduces large computational and storage needs without losing the ability to recover the original signal. Navigating Iot Data Challenges shown in Figure 2. Compressive sensing theory fundamentally depends on two principles: sparsity and incoherence. It means that many natural signals have on a suitable basis (for example, Fourier or wavelet), only a few nonzero significant coefficients while the rest are nearly zero. Incoherence ensures that the sampling domain and the representation domain are sufficiently unrelated, allowing the captured measurements to contain adequate information about the sparse representation of the signal [23, 24].

In the context of the IoT, compressive sensing plays a pivotal role in achieving efficient acquisition and transmission of data. The devices themselves are subject to severe conditions such as limitations on power, bandwidth, and computation resources. Most IoT signals are naturally sparse by nature, like environmental sensor data, video streams, health monitoring signals, etc. With these properties, it is further enhanced for CS-based acquisition and recovery. This decreases the volume of transmitted data while keeping signal integrity [25]. For example, environmental monitoring sensors may send compressed measurements, which are later reconstructed using CS techniques at central or edge computing nodes. This corresponds to reducing communication overhead while also prolonging the battery life of IoT devices. In addition, through the integration with machine learning models, it can improve signal recovery accuracy and robustness to advance its utility in fields of IoT, such as smart cities, industrial automation, and real-time health monitoring. While compressive sensing is fundamentally different from the way any current conventional data compression technique, like JPEG or MP3, works by first gathering the whole signal and then applying lossy or even lossless compression algorithms. CS integrates acquisition and compression into one step by capturing directly only the most critical parts of the signal [26]. Table 1 gives the comparative analysis of Compressive Sensing (CS) and Conventional Data Compression Techniques under various aspects of data acquisition, resource efficiency, robustness to noise, adaptability, and application suitability. It points out the benefits of compressive sensing - especially in resource-constrained environments and real-time acquisition - over the traditional approach based on full-resolution data capture and subsequent compression [27,28].

Table 1: Comparison of Compressive Sensing and Conventional Data Compression Techniques

Aspect	Conventional Data Compression	Compressive Sensing (CS)

Acquisition Methodology	Full-resolution data is acquired first, then compressed (e.g., JPEG, MP3).	Combines acquisition and compression into a single step.
Data Capture	Requires a complete signal for subsequent compression.	Captures only reduced-resolution measurements directly.
Resource Efficiency	High memory and computational resources required during acquisition.	Lightweight acquisition, suitable for resource-limited devices.
Noise Robustness	Less effective at handling noisy data.	Inherently resilient to noise due to sparsity principles.
Adaptability to Signals	Rely on predefined compression schemes, specific to signal types (e.g., Huffman coding).	Universally adaptable to various signal types and domains leveraging sparsity.
Use in Resource-Limited Environments	Less suited for constrained devices due to computational and storage demands.	Ideal for IoT, edge devices, and real-time applications with limited resources.
Compression Timing	Compression occurs post-acquisition.	Compression occurs during data acquisition.
Application Domains	Widely used for media storage and transmission (e.g., images, audio).	Effective for sensing, IoT, medical imaging, and scientific data acquisition.

IV. RELEVANCE OF COMPRESSIVE SENSING TO IOT AND THE ROLE OF DEEP LEARNING

Compressive Sensing (CS) is beginning to change the way signals are acquired and processed. It has the potency and the capabilities to emerge as a viable alternative at that territory, especially in the context of IoT. Indeed, the IoT ecosystem consists of essentially interconnected sensors or devices generating massive amounts of data in real-time. Such systems intrinsically face limitations due to scarce energy sources, inferior computation and capacities, limited storage space, and bandwidth. Traditionally, signals in data acquisition must be sampled at very high frequencies according to the Nyquist-Shannon theorem and this creates resource exhaustion in IoT applications. However, with CS, it merges the data acquisition process with compression into one step; hence, it is particularly relevant for the resource-constrained devices of IoT. Signal acquisition and reconstruction are similarly important processes in IoT which ensure that data transmitted and processed will be reliable. CS takes advantage of the sparsity of natural signals, meaning that the information of the signal is heavily concentrated in just a few important components, while the others are quite negligible. For IoT sensors, which often measure predictable or slowly changing phenomena, e.g., temperature, pressure, or ECG signals, sparsity in the frequency domain or in the wavelet domain is typically present. Instead of collecting and storing full-resolution data, CS captures only a reduced set of linear measurements that contain the most critical information. This approach minimizes power consumption and storage requirements. On the receiver side, reconstruction algorithms such as Basis Pursuit or advanced iterative methods reconstruct the original signal by solving an underdetermined system using sparsity priors. This is particularly beneficial for IoT networks where data is processed centrally, therefore allowing lightweight sensors to offload computational burdens [29-31].

The appropriateness of CS for IoT devices can be attributed to the optimization of data acquisition and resource usage reduction. IoT devices are often situated in surroundings with no or limited access to power infrastructure, for instance, remote monitoring stations, wearable health devices, or industrial IoT nodes. Significant energy constraints are realized by such devices because powering high-resolution sensors and transmission of large amounts of datasets consuming considerable battery power. By reducing the amount of data acquired and transmitted, CS directly addresses this challenge, extending the operational lifespan of battery-powered devices. CS robustness to noise and signal degradation also ensures that IoT devices operating in harsh or noisy environments, such as industrial plants or urban centers, can still provide reliable data. Its ability to allow lossy communication channels makes it highly useful for remote sensing applications where stable connections are not guaranteed. CS offers a variety of advantages in resource-constrained environments [32]. It captures sparse measurements that reduce the cost of transmitting data substantially, which is critical in IoT networks as bandwidth is often limited or perhaps shared among many devices.

CS also reduces the memory footprint on the IoT sensors to enable them to function, hence cost-effective and less complex designs. These are the principles of CS, making it very scalable and allowing dense IoT networks without a heavy infrastructure burden. For instance, in smart agriculture, hundreds of sensors can measure many different parameters, say soil moist or air quality, without having any heavy data, therefore not getting too bulky data at the central processing unit. Similarly, in health service, wearable devices which contain CS algorithms can be used to transmit biometric data such as blood pressure and ECG with compressed format in real-time [33].

Its integration with deep learning has added further amplification to its potential, especially in the critical stage of signal reconstruction, though classical CS reconstruction techniques, like Basis Pursuit or Orthogonal Matching Pursuit, are effective but computationally demanding and require iterative processing, which is not suitable for real-time applications. Deep learning, with the possibility of modeling complex, nonlinear functions, has modified CS by providing fast and accurate reconstruction methods in a scalable manner. Neural networks in the form of convolutional neural networks, autoencoders, and recurrent neural networks have shown remarkable performance in reconstructing signals from highly under sampled measurements. The type of information thus learned from vast data sets by those models has helped them understand the inherent structure and patterns of sparse signals much better, yielding better reconstruction accuracy compared to traditional methods. Recent advances in deep compressive sensing models have introduced novel architectures combining strengths both of CS and neural networks. For instance, convolutional autoencoders have been widely adopted for their capability to compress and reconstruct simultaneously [34]. These are models, during training, learn the optimal feature representations so that even very compressed measurements can be reconstructed accurately. Some other breakthroughs are generative adversarial networks, which have now been applied to perceptual quality improvements in reconstructed signals, especially for image and video applications. Hybrid models that relieve both classical CS techniques and recovery using neural networks have been recently proposed. For example, combining sparsity-based optimization with deep learning enhances both computational efficiency and reconstruction fidelity [35].

The role of deep learning in CS, especially in IoT systems, extends beyond mere reconstruction toward adaptive intelligent data processing. Real-time applications of high-resolution data have to be reconstructed immediately from compressed streams through deep models of CS. For example, through surveillance cameras equipped with CS, smart cities can capture compressed video, using deep learning for the subsequent reconstruction for traffic monitoring or security analysis. Similarly, in healthcare, compressed physiological signals, such as heart rate or respiratory patterns, can be transmitted through wearable devices and reconstructed in real-time for monitoring critical conditions. Such applications demonstrate how CS and deep learning together are spearheading IoT innovation in the face of resource constraints, data deluges, and real-time processing needs. CS merged with deep learning contributes to optimizing efficiency, scalability, and intelligence for IoT systems. Such a combination does not only reduce resource consumption and operational costs but will open up entirely new possibilities for adaptive sensing, real-time decision making, and large-scale deployments. The increased pace of development of deep learning models will make synergy between CS and IoT crucially important in shaping the future of connected systems [36, 37].

V. CONCLUSION

The rapid growth of IoT has created unprecedented data management challenges and calls for innovative ways to optimize system performance and scalability. Therefore, compressive sensing has demonstrated a revolutionary perspective in the acquisition, processing, and communication of data in resource-constrained IoT networks. CS demarcates itself from other methods by compressing data at the acquisition stage, thus reducing bandwidth and energy consumption while preserving signal integrity. This makes it particularly relevant for applications in areas such as smart cities, healthcare, and industrial automation, where efficient data handling is critical. Introducing deep learning further enhances the potential of CS frameworks. Deep learning models, including CNN's and Autoencoders, perform well in reconstruction of signals from sparse measurements with superior accuracy and real-time processing capabilities. These advances not only reduce the computation burden on IoT devices but also help to create intelligent, adaptive systems that can process high-dimensional data. Applications such as smart traffic monitoring and wearables for health illustrate the revolutionary depth in compressive sensing. Despite all these benefits, CS encounters some challenges with its implementation- high computational complexity and challenges adapting dynamically with ever-changing IoT environments. Future research should concentrate on perfecting CS algorithms, improving hardware compatibility, and exploring hybrid models that combine traditional optimization with neural networks. Overcoming these hurdles will help CS systems gain broader adoption and unlock new possibilities for innovation in IoT technologies. Conclusively, the convergence between compressive sensing and deep learning has paved the way for a new wave of efficient yet sustainable IoT systems. As a result, these technologies will increasingly become pivotal in how IoT continues to evolve, in intelligent, scalable, and resource-efficient networks to suit the demands of a world that is hyper-connected-precision and resilience.

REFERENCES

[1] Al-Qurabat, A. K. M., & Kadhum Idrees, A. (2020). Data gathering and aggregation with selective transmission techniques to optimize the lifetime of Internet of Things networks. International Journal of Communication Systems, 33(11), e4408.

[2] Abdulzahra, S. A., Al-Qurabat, A. K. M., & Idrees, A. K. (2021). Compression-based data reduction techniques for IoT sensor networks. Baghdad Science Journal, 18(1), 0184-0184.

[3] Al-Qurabat, A. K. M., & Idrees, A. K. (2019). Two level data aggregation protocol for prolonging lifetime of periodic sensor networks. Wireless Networks, 25(6), 3623-3641.

[4] Al-Qurabat, A. K. M., Mohammed, Z. A., & Hussein, Z. J. (2021). Data traffic management is based on compression and MDL techniques for smart agriculture in IoT. Wireless Personal Communications, 120(3), 2227-2258.

[5] Benaddi, H., Ibrahimi, K., Benslimane, A., Jouhari, M., & Qadir, J. (2022). Robust enhancement of intrusion detection systems using deep reinforcement learning and stochastic games. IEEE Transactions on Vehicular Technology, 71(10), 11089-11102.

[6] Centelles, R. P., Meseguer, R., Freitag, F., Navarro, L., Ochoa, S. F., & Santos, R. M. (2021). LoRaMoto: A communication system to provide safety awareness among civilians after an earthquake. Future Generation Computer Systems, 115, 150-170.

[7] Simo, A., Dzitac, S., Dzitac, I., Frigura-Iliasa, M., & Frigura-Iliasa, F. M. (2021). Air quality assessment system based on self-driven drone and LoRaWAN network. Computer Communications, 175, 13-24.

[8] Hoang, Q. L., Jung, W. S., Yoon, T., Yoo, D., & Oh, H. (2020). A real-time LoRa protocol for industrial monitoring and control systems. IEEE Access, 8, 44727-44738.

[9] Zhang, F., Chang, Z., Niu, K., Xiong, J., Jin, B., Lv, Q., & Zhang, D. (2020). Exploring lora for long-range through-wall sensing. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 4(2), 1-27.

[10] Alshaikhli, M., Elfouly, T., Elharrouss, O., Mohamed, A., & Ottakath, N. (2021). Evolution of Internet Things from blockchain to IOTA: A survey. IEEE Access, 10, 844-866.

[11] Jeromel, A., & Žalik, B. (2020). An efficient lossy cartoon image compression method. Multimedia Tools and Applications, 79(1), 433-451.

[12] Wahab, O. F. A., Khalaf, A. A., Hussein, A. I., & Hamed, H. F. (2021). Hiding data using efficient combination of RSA cryptography, and compression steganography techniques. IEEE access, 9, 31805-31815.

[13] Neelakandan, S. B. M. A. T. S. D. V. B. B. I., Berlin, M. A., Tripathi, S., Devi, V. B., Bhardwaj, I., & Arulkumar, N. (2021). IoT-based traffic prediction and traffic signal control system for smart city. Soft Computing, 25(18), 12241-12248.

[14] Kumar, P., Gupta, G. P., & Tripathi, R. (2021). Toward design of an intelligent cyber-attack detection system using hybrid feature reduced approach for iot networks. Arabian Journal for Science and Engineering, 46(4), 3749-3778.

[15] Ahmed, A., Abdullah, S., Bukhsh, M., Ahmad, I., & Mushtaq, Z. (2022). An energy-efficient data aggregation mechanism for IoT secured by blockchain. IEEE Access, 10, 11404-11419.

[16] Awaisi, K. S., Hussain, S., Ahmed, M., Khan, A. A., & Ahmed, G. (2020). Leveraging IoT and fog computing in healthcare systems. IEEE Internet of Things Magazine, 3(2), 52-56.

[17] Ghosh, A. M., & Grolinger, K. (2020). Edge-cloud computing for Internet of Things data analytics: Embedding intelligence in the edge with deep learning. IEEE Transactions on Industrial Informatics, 17(3), 2191-2200.

[18] Hisaharo, S., Nishimura, Y., & Takahashi, A. (2024). Optimizing llm inference clusters for enhanced performance and energy efficiency. Authorea Preprints.

[19] Ahmed, S., Chowdhury, M. Z., & Jang, Y. M. (2020). Energy-efficient UAV-to-user scheduling to maximize throughput in wireless networks. IEEE Access, 8, 21215-21225.

[20] Abedin, S. F., Munir, M. S., Tran, N. H., Han, Z., & Hong, C. S. (2020). Data freshness and energy-efficient UAV navigation optimization: A deep reinforcement learning approach. IEEE Transactions on Intelligent Transportation Systems, 22(9), 5994-6006.

[21] Dayalan, U. K., Fezeu, R. A., Salo, T. J., & Zhang, Z. L. (2022, August). Kaala: scalable, end-to-end, IoT system simulator. In Proceedings of the ACM SIGCOMM Workshop on Networked Sensing Systems for a Sustainable Society (pp. 33-38).

[22] Lukic, M., Sobot, S., Mezei, I., Vukobratovic, D., & Danilovic, D. (2020, August). In-depth real-world evaluation of nb-iot module energy consumption. In 2020 IEEE International Conference on Smart Internet of Things (SmartIoT) (pp. 261-265). IEEE.

[23] Wang, H. (2023). Compressed sensing: Theory and applications. In Journal of Physics: Conference Series (Vol. 2419, No. 1, p. 012042). IOP Publishing.

[24] Khosravy, M., Nitta, N., Nakamura, K., & Babaguchi, N. (2020). Compressive sensing theoretical foundations in a nutshell. In Compressive sensing in healthcare (pp. 1-24). Academic Press.

[25] Gambheer, R., & Bhat, M. S. (2024). Optimized Compressed Sensing for IoT: Advanced Algorithms for Efficient Sparse Signal Reconstruction in Edge Devices. IEEE Access.

[26] Ahmed, I., Khalil, A., Ahmed, I., & Frnda, J. (2022). Sparse signal representation, sampling, and recovery in compressive sensing frameworks. IEEE Access, 10, 85002-85018.

[27] Rajula, H. S. R., Verlato, G., Manchia, M., Antonucci, N., & Fanos, V. (2020). Comparison of conventional statistical methods with machine learning in medicine: diagnosis, drug development, and treatment. Medicina, 56(9), 455.

[28] Bégaint, J., Racapé, F., Feltman, S., & Pushparaja, A. (2020). Compressai: a pytorch library and evaluation platform for end-to-end compression research. arXiv preprint arXiv:2011.03029.

[29] Nasif, A., Othman, Z. A., & Sani, N. S. (2021). Deep learning solutions on lossless compression methods for alleviating data load on IoT nodes in smart cities. Sensors, 21(12), 4223.

[30] Azar, J., Makhoul, A., Couturier, R., & Demerjian, J. (2020). Robust IoT time series classification with data compression and deep learning. Neurocomputing, 398, 222-234.

[31] Vanjari, H. B., & Kolte, M. T. (2022). Machine learning improvements to compressive sensing for speech enhancement in hearing aid applications. World Journal of Engineering, 19(2), 216-223.

[32] Wang, Y., Yang, J., Liu, M., & Gui, G. (2020). LightAMC: Lightweight automatic modulation classification via deep learning and compressive sensing. IEEE Transactions on Vehicular Technology, 69(3), 3491-3495.

[33] Zhang, M., Zhang, H., Zhang, C., & Yuan, D. (2022). Communication-efficient quantized deep compressed sensing for edge-cloud collaborative industrial IoT networks. IEEE Transactions on Industrial Informatics, 19(5), 6613-6623.

[34] Taha, A., Alrabeiah, M., & Alkhateeb, A. (2021). Enabling large intelligent surfaces with compressive sensing and deep learning. IEEE access, 9, 44304-44321.

[35] Qiao, M., Meng, Z., Ma, J., & Yuan, X. (2020). Deep learning for video compressive sensing. Apl Photonics, 5(3).

[36] Liang, P., Fan, J., Shen, W., Qin, Z., & Li, G. Y. (2020). Deep learning and compressive sensing-based CSI feedback in FDD massive MIMO systems. IEEE Transactions on Vehicular Technology, 69(8), 9217-9222.

[37] Bao, Y., Tang, Z., & Li, H. (2020). Compressive-sensing data reconstruction for structural health monitoring: a machine-learning approach. Structural Health Monitoring, 19(1), 293-304.