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Innovative Approaches to Reducing Data Traffic in IoT Networks Using Deep Learning and Compressive Sensing

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Abstract

The exponential growth of internet of things (IoT) devices has posed unprecedented challenges in managing the massive data generated by real-time monitoring, automation, and analytics. Existing network infrastructures lack scalability, bandwidth, and suffer from latency problems, further making data transmission less efficient. This study surveys innovative approaches using deep learning and compressive sensing to reduce IoT data traffic. Deep learning is able to upgrade data processing by means of very effective pattern extraction and predictive modeling, while compressive sensing reduces redundancy using sparsity in data. The number of IoT devices has been growing quickly, and data generated by these devices ranges from analytics to real-time monitoring and automation. Given that the world is largely dependent on the Internet, thanks to developments like 5G and fiber optics, which enable users to access and create IoT. Data generation has skyrocketed, and solutions are very inexpensive. Despite the fact that this expansion offers numerous benefits, it severely strains network infrastructures that were not built to handle the large volume of data traffic from IoT devices. All the three together are scalable, energy-efficient, and latency-aware solutions for the IoT ecosystems. These techniques together are studied across applications such as smart cities, healthcare, and industrial automation, underlining their transformative potential. Difficulties like resource constraints, heterogeneity, and security risks are also presented and future research directions along with technological progress are included.

Keywords: Internet of things (IoT), data traffic reduction, deep learning, compressive sensing, smart cities, edge computing, data compression, signal reconstruction, machine learning, energy efficiency

INTRODUCTION

Internet of things (IoT) devices have been rapidly increasing, with the generation of data spanning from real-time monitoring and automation to analytics. Since the world heavily depends on the Internet, spurred by technological advancements such as 5G and fiber optics, which allow people access and make IoT solutions highly affordable, data generation has exploded [1, 2]. Although this growth has many advantages, it puts massive pressure on existing network infrastructures not designed to absorb this tremendous amount of data traffic from IoT devices. Bottlenecks arise from bandwidth limitation, network congestion, and latency degrading the performance and user experience of these systems [3]. Poor data handling exacerbates these challenges, including latency and energy consumption, especially in latency-sensitive applications such as autonomous vehicles and healthcare monitoring. Excessive energy consumption due to redundant or unoptimized data transmission results in the shortening of IoT devices' lifespan and higher operational costs.

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Scalability is another pressing concern as more devices join the network, posing barriers for widespread IoT adoption. In IoT environments, devices are heterogeneous and resource-constrained, requiring lightweight communication protocols (e.g., Zigbee, Bluetooth low-energy [BLE], long-range wide area network [LoRaWAN]), as well as efficient network management systems to function correctly [4, 5]. To that end, innovative techniques for instance deep learning and compressive sensing are being researched on. These methods optimize data management, improve energy efficiency, and enhance scalability and transform the IoT ecosystem into an even more efficient and sustainable one. The launch of IoT solutions is still plagued by security risks and unclear strategies on how to handle the same. The IoT is an evolving technology, and its benefit can only be taken advantage of with robust strategies for integrating and optimizing technologies so that secure and efficient operations of IoT applications are facilitated across all sectors [6]. Figure 1 illustrates a smart traffic management system that utilizes IoT layers, which are perception, network, and application layers, to integrate smart traffic signals, mobile users, Google Maps, and cloud-based data processing to control traffic efficiently and effectively manage congestion.

The exponential growth of the IoT has revolutionized the way devices communicate, creating a dynamic and interconnected ecosystem that generates substantial data traffic. IoT networks encompass a wide range of devices, from smart home appliances to industrial sensors, all of which continuously transmit and receive data. This constant flow of information leads to an intricate web of data traffic that requires efficient management and analysis. With billions of devices expected to be connected in the coming years, understanding and optimizing this data flow becomes crucial for ensuring network reliability and performance.

Data traffic in IoT networks presents unique challenges due to the diverse nature of the devices and the types of data being exchanged. Unlike traditional networks, where data is primarily generated by a limited number of users, IoT networks feature a vast array of devices that communicate at varying frequencies and volumes. This heterogeneity demands sophisticated algorithms for data routing and prioritization, as well as robust protocols to accommodate the latency and bandwidth constraints inherent in many IoT applications. Additionally, the reliance on cloud services for data processing introduces further complexity, as it necessitates effective strategies to minimize latency and maximize throughput.

Moreover, security considerations play a vital role in managing data traffic in IoT networks. The proliferation of connected devices increases the potential attack surface for cyber threats, making it imperative to implement robust security measures to safeguard data in transit. Encryption, authentication, and anomaly detection are essential technologies that help protect sensitive information from unauthorized access. Furthermore, as data privacy regulations become more stringent globally, IoT networks must evolving to ensure compliance while efficiently handling the substantial volume of data traffic generated by these devices.

In summary, data traffic in IoT networks is a multifaceted issue that necessitates careful consideration of technical, operational, and security aspects. As the IoT ecosystem continues to grow, advancing technologies such as edge computing, machine learning, and network slicing will play a crucial role in optimizing data flow, enhancing security, and enabling real-time analytics. Harnessing the full potential of IoT data traffic will not only improve system performance but also unlock new opportunities for innovation across various sectors, from healthcare to agriculture and smart cities.

The IoT refers to the growing network of interconnected devices that communicate and exchange data seamlessly. From smart home appliances and wearable health monitors to industrial machinery and connected vehicles, IoT technologies are revolutionizing how we interact with the physical world. With the exponential growth in the number of IoT devices, understanding the characteristics of data traffic within these networks has become paramount. IoT-based architecture of smart traffic management system for metropolitan cities is shown in Figure 1.

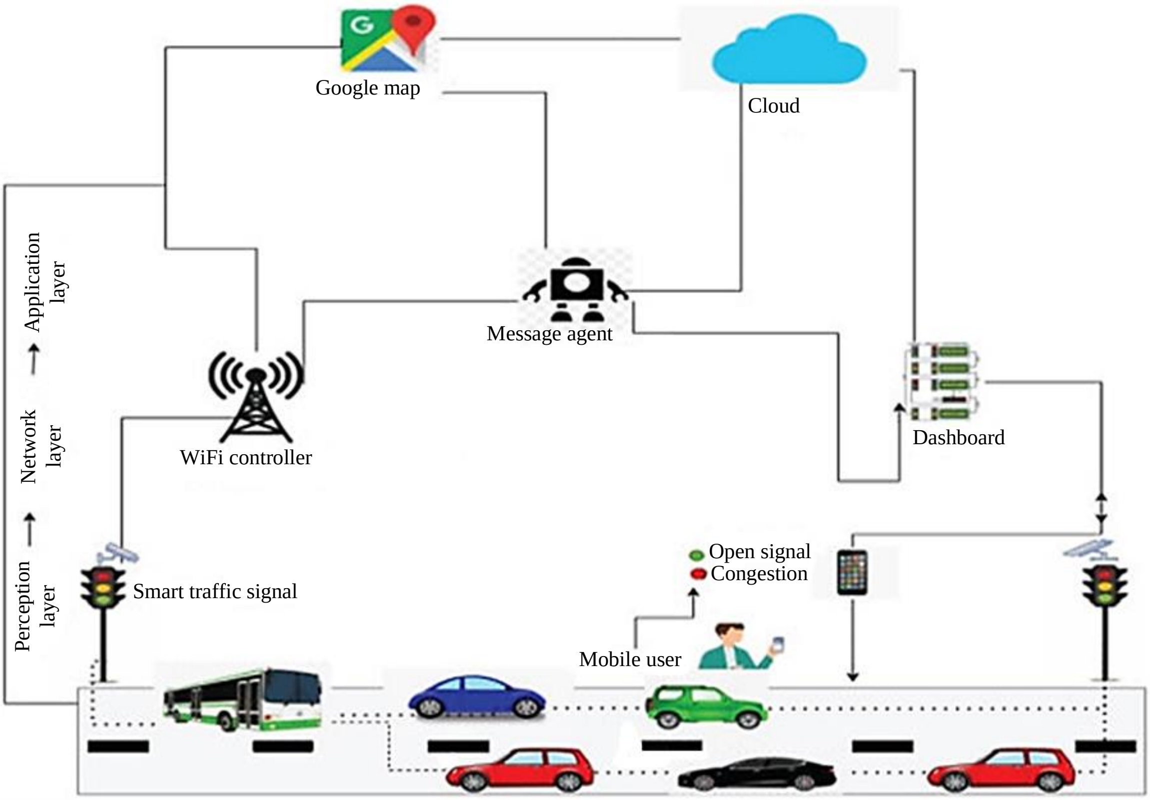

Figure 1. Internet of Things (IoT)-based architecture of smart traffic management system for metropolitan cities.

The Nature of Internet of Things Data Traffic

At its core, IoT data traffic encompasses the transmission of data between devices and the cloud, as well as between devices themselves. This traffic can be categorized into several types:

1. *Real-Time Data:* Many IoT applications, such as smart health monitoring systems or autonomous vehicles, require real-time data transmission. This involves rapid data processing and minimal latency to ensure timely actions based on the information received.
2. *Periodic Data:* Devices such as weather stations and smart meters often send data at regular intervals. This type of transmission can be more manageable but must still account for potential congestion within the network.
3. *Event-Driven Data:* Certain IoT applications operate based on specific triggers, such as security cameras sending alerts upon detecting motion. This sporadic yet crucial traffic must be handled efficiently to avoid bottlenecks and ensure reliability.
4. *Aggregate Data:* With numerous devices generating continuous streams of information, aggregating and summarizing this data before transmission can be beneficial. This approach reduces the amount of data sent over the network and lowers congestion while still providing valuable insights.

Deep learning is one of the tools used in IoT data processing, which has the capability of conducting advanced extracting patterns from complex and high-dimensional information. Such methodology also made feasible the kind of efficient data compression, anomaly detection, predictive analytics, and real-time decision-making, which is adequately suited in dynamic and diverse requirements of a large amount of data required in IoT applications. For example, the most familiar ones include autoencoders and convolutional neural networks (CNNs) are more inclined for compressing or analyzing big volumes of IoT data [7]. Conversely, compressive sensing, is one of the mathematical frameworks conceived to eliminate redundancy in the collection and conveyance of data; it functions based on the sparsity principle, allowing the recovery of high-dimensional signals from fewer measurements than are typically required. Compressive sensing is thus an optimal solution for IoT devices characterized by limited computational and communication resources as it diminishes the volume of data that must be transmitted with very minimal loss of information [8]. The synergy between deep learning and compressive sensing thus provides innovative ways to deal with some of the key challenges in IoT. Compressive sensing reduces the initial load of data by intelligently sampling and transmitting only the information considered necessary, whereas deep learning helps enhance signal reconstruction and optimizes further data processing. This blend enables scalable, energy-efficient, and latency-aware IoT ecosystems that accommodate the increasingly high demands in modern applications, including smart cities, health care, and industrial automation [9, 10].

CHALLENGES IN REDUCING DATA TRAFFIC IN INTERNET OF THINGS NETWORKS

Scalability and Device Heterogeneity

IoT networks are made up of an enormous number of devices, ranging from basic sensors measuring temperature or humidity to sophisticated industrial machinery performing complex operations. This diversity creates great difficulties in creating standardized protocols for communication and data handling. Each device could have its own varied hardware specifications, communication standards, and data formats, thus causing problems with interoperability within the network. Thus, the inability to have a uniform architecture seriously creates seamless integration of these heterogeneous devices into a comprehensive IoT system that hinders the efficiency of data collection and processing mechanisms [11]. The scalability of IoT networks increases with the exponential growth in the number of connected devices; increased density of devices increasingly puts immense strain on bandwidth and network infrastructure, thereby causing bottlenecks that hinder the performance of systems. With this burgeoning data traffic, routing and management systems become hard to cope with, eventually resulting in slow responses, reduced reliability, and thereby decreased user satisfaction. Without proper solutions for dealing with the issues related to scalability and heterogeneity, large-scale IoT ecosystems, like smart cities or industrial IoT setups, are hard to deploy [12].

Resource Constraints on Internet of Things Devices and Networks

Then, as a fundamental characteristic, IoT devices are usually characterized by small, low-cost, and energy-efficient designs, which inherently limit their ability in terms of computational power, memory, and storage capacity. This limitation becomes a significant challenge in processing and storing large volumes of data generated by such devices. Further, many IoT systems still rely on central servers or cloud platforms for complex data analytics, which introduces latency and increases dependency on network connectivity [13]. This reliance can be particularly problematic in remote or bandwidth-limited environments, where access to cloud resources may not be readily available. Another pressing issue is the trade-off between energy efficiency and performance. IoT devices often run on limited battery power, making energy consumption a critical factor. Frequent data transmission and processing consume significant energy, shortening device lifespans and escalating operational costs. The need to balance energy consumption with performance demands the development of lightweight and energy-efficient algorithms for data compression and traffic reduction. These techniques must optimize data handling without overburdening the limited computational and storage capacities of IoT devices, ensuring their long-term viability in resource-constrained environments [14, 15]. Challenges in reducing data traffic in IoT networks are shown in Figure 2.

Security, Privacy, and Real-Time Data Processing Issues

Techniques like data compression, despite its efficiency in reducing data redundancy, inherently introduce new security risks. Compressed streams are subject to easier compromise from interception if uncompressed data is accessed, as redundancy-less data does not correct errors as easily. In healthcare and financial systems and any other such critical application that deals with privacy-sensitive information, it becomes quite essential to ensure proper encryptions and privacy-preserving mechanisms [16, 17]. Without these safeguards, the risk of data breaches or leaks can damage user trust and lead to non-compliance with the law, affecting the mass adoption of IoT solutions.

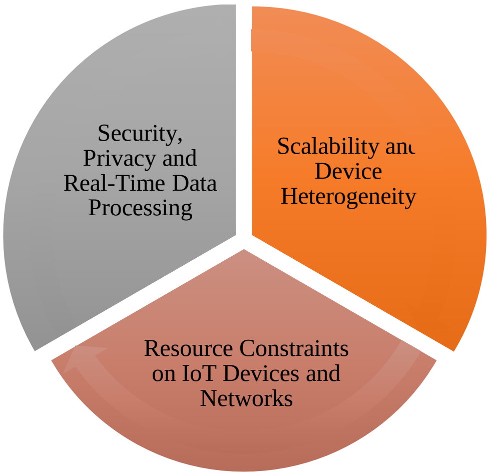

Figure 2. Challenges in reducing data traffic in internet of things (IoT) networks.

Low-latency high-speed applications in IoT, such as autonomous vehicles, industrial automation, and emergency response, pose additional challenges. It is much more complex to ensure that low-latency data processing applications have sufficient guarantees on data security and efficiency simultaneously. Any delay due to encryption/compression protocols can compromise system performance and, in critical scenarios, endanger lives. Developing solutions that can process data in real time with privacy and security is important in reducing data traffic effectively and making IoT systems operate reliably in dynamic environments [18].

Thus, addressing these challenges requires an integrated approach that harmonizes scalable network management, lightweight algorithms for data reduction, and robust security measures that take into consideration the constraints of IoT ecosystems.

THE ROLE OF DATA TRAFFIC IN INTERNET OF THINGS NETWORKS FOR APPLICATIONS IN WEATHER AND ENVIRONMENTAL MONITORING

IoT networks consist of interconnected devices that collect, transmit, and analyze data. These devices can range from simple sensors that measure temperature and humidity to more complex systems that monitor air quality, soil moisture, and water levels. The key to these networks is the ability to transmit vast amounts of data in real-time, ensuring timely decision-making and response to environmental conditions.

At the core of IoT networks is the data traffic generated by various sensor nodes. This data traffic represents the flow of information, which is essential for effective monitoring and analysis. The type and volume of data generated can depend on several factors, including the number of sensors deployed, the frequency of data collection, and the bandwidth of the network.

Real-Time Monitoring

One of the primary benefits of leveraging IoT networks for weather and environmental monitoring is the capacity for real-time data collection and analysis. Continuous data flow allows researchers and authorities to track weather patterns, air quality, and other environmental parameters as they unfold. For instance, real-time monitoring of air pollution levels can help identify pollution sources and facilitate timely interventions to protect public health.

Data Aggregation and Analysis

IoT networks enable the aggregation of data from remote and diverse locations, providing a comprehensive picture of weather and environmental conditions. This accumulated data can be analyzed to identify trends, predict weather events, and assess environmental impacts over time. For example, data collected from multiple sensors can be processed using machine learning algorithms to enhance forecasting accuracy, leading to more reliable weather predictions.

Enhancing Accuracy and Decision-Making

The data collected from IoT sensors contributes to more informed decision-making. By utilizing large datasets, policymakers and environmental scientists can develop models that predict future environmental conditions and weather patterns. This capability is critical for disaster preparedness and management, such as predicting floods, hurricanes, or drought conditions.

Smart Agriculture

The integration of IoT networks in agriculture has enabled smart farming practices. Farmers can access real-time weather updates, soil moisture levels, and crop health data, optimizing their irrigation and fertilization routines. This smart application not only increases yield but also contributes to sustainable practices by minimizing water and chemical usage.

Climate Change Monitoring

IoT networks play a crucial role in monitoring climate change. Sensors measuring temperature, precipitation, and atmospheric conditions provide valuable data for studying climate trends over time. This data aids researchers in understanding the effects of climate change on ecosystems and biodiversity, facilitating informed conservation efforts.

Despite the immense potential of IoT networks for weather and environmental monitoring, there are challenges associated with data traffic:

1. *Data Overload:* The sheer volume of data generated can lead to overcrowded networks, posing challenges in data management and transmission. Efficient data handling techniques, such as edge computing, are necessary to mitigate this issue.
2. *Security Concerns:* The transmission of sensitive ecological data is susceptible to cyber threats. Robust security measures must be in place to protect data integrity and privacy.
3. *Standardization:* The lack of universal data standards poses challenges for interoperability. Developing common protocols can enhance data sharing and collaboration among institutions and countries.

Data traffic in IoT networks plays an essential role in advancing weather and environmental monitoring capabilities. As technology continues to evolve, the potential for improved data collection, analysis, and reporting will only grow. By harnessing the power of real-time data, stakeholders can make informed decisions that enhance climate resilience, promote sustainable practices, and ultimately protect our planet. The future of environmental monitoring lies in embracing IoT technology and the vast data it generates, paving the way for a more efficient and adaptive approach to understanding and responding to our changing environment.

DATA TRAFFIC REDUCTION METHODS IN INTERNET OF THINGS NETWORKS APPLICABLE FOR WEATHER AND ENVIRONMENTAL MONITORING

The IoT has transformed the landscape of connectivity, enabling smart devices to communicate and share data across various applications. However, the rapid proliferation of IoT devices has led to an exponential increase in data traffic. This surge poses significant challenges to network efficiency, bandwidth consumption, and data storage. As organizations embrace IoT technology, it becomes crucial to implement effective data traffic reduction methods to optimize performance and minimize resource usage. This article explores several strategies to mitigate data traffic in IoT networks [19–35].

Data Aggregation

One of the most effective ways to reduce data traffic in IoT networks is through data aggregation. Instead of sending individual data points from each device to the cloud or central server, data from multiple devices can be collected and combined locally before transmission. This method decreases the frequency and size of data packets being sent over the network [36–46].

Techniques for Data Aggregation

- *Local Processing:* Perform initial processing on-device to filter out redundant data before transmitting it.
- *Event-Based Aggregation:* Send data only when specific events occur, rather than continuously transmitting data points at regular intervals.

Data Compression

Data compression techniques can substantially reduce the amount of transmitted data by encoding information more efficiently. This approach ensures that the relevant data can be sent with lower bandwidth requirements without losing essential information [47–63].

Common Compression Techniques:

- *Lossless Compression:* Algorithms such as Gzip or LZ77 can compress data without losing any information, making them suitable for critical applications where data integrity is paramount.
- *Lossy Compression:* Techniques such as JPEG or MP3 can be used for non-critical data where some loss of information is acceptable for the sake of reduced data sizes, such as in video or audio transmission.

Edge Computing

Edge computing pushes data processing closer to the source of data generation, thereby reducing the need to send large amounts of data to centralized servers. By processing data locally on edge devices, unnecessary data transfers can be minimized, leading to lower latency and reduced bandwidth usage.

Benefits of Edge Computing:

- *Real-Time Processing:* Critical applications needing immediate responses can be processed without relying on distant cloud services.
- *Reduced Latency:* Local processing decreases the time data takes to travel across networks, which is vital for applications like autonomous vehicles or real-time monitoring.

Protocol Optimization

IoT networks often utilize various communication protocols, each with inherent efficiencies and inefficiencies. Optimizing these protocols can significantly reduce data traffic and improve overall network performance.

Recommended Protocols:

- *MQTT (Message Queuing Telemetry Transport):* This lightweight protocol is designed for low-bandwidth, high-latency networks. It uses a publish-subscribe model that minimizes the need for constant connections.
- *CoAP (Constrained Application Protocol):* Developed specifically for constrained devices, CoAP reduces overhead significantly, making it ideal for IoT applications.

Intelligent Data Filtering

Implementing intelligent data filtering mechanisms can help prevent unnecessary data from being transmitted in the first place. By utilizing techniques such as machine learning or rule-based filters, IoT devices can evaluate and selectively transmit data that is most relevant for analysis.

Approaches to Filtering

- *Threshold-Based Filtering:* Data is sent only if it exceeds a predefined limit, reducing traffic from event noise.

- *Anomaly Detection:* Non-normative data can trigger alerts while ignoring routine streams, ensuring that only significant deviations require attention.

Scheduled Data Transmission

In many IoT applications, real-time data transmission is not critical. Scheduling data transmission can greatly alleviate network congestion by allowing devices to transmit data during non-peak hours or at predefined intervals.

Advantages of Scheduled Transmission

- *Bandwidth Optimization:* By transmitting at off-peak hours, overall network utilization can be significantly improved.
- *Energy Conservation:* Scheduled transmissions can allow devices to enter low-power modes, conserving battery life.

The continuous growth of IoT devices poses significant challenges in data traffic management. Employing strategies such as data aggregation, compression, edge computing, protocol optimization, intelligent filtering, and scheduled transmission can effectively reduce data traffic and enhance overall network efficiency. As organizations increasingly rely on IoT technology, implementing these methods will be essential for maintaining robust, scalable, and cost-effective IoT architectures, ultimately driving innovation across industries while minimizing resource consumption.

DEEP LEARNING-BASED TECHNIQUES FOR INTERNET OF THINGS TRAFFIC REDUCTION

Data Compression Using Neural Networks

Autoencoders are special neural networks tailored for unsupervised learning with a significant application in compressing the IoT data while retaining all significant features of it. Autoencoders decrease the dimensionality of data to only transfer necessary information, thereby reducing the traffic within resource-scant IoT networks. Autoencoders balance compression with fidelity of reconstruction at the receiver's end. Generative adversarial networks (GANs) take this ability one step further by compressing inputs into realistic data. GANs are combinations of a generator and a discriminator network operating in tandem to produce approximations of high-quality data. Such applications make GANs useful in scenarios where missing or incomplete IoT data needs to be reconstructed or augmented, with the process ensuring data consistency while keeping transmission volumes low [64]. Hybrid techniques tend to blend compression techniques with predictive modeling in order to optimize IoT data traffic. Hybrid models do deep learning for the ability to predict future trends of data. This helps reduce redundant transfers by only updating in cases of significant deviations. For example, hybrid frameworks can integrate autoencoders with recurrent neural networks (RNNs) in order to compress historical data while making predictions about future values. Results on various case studies have established that these approaches outperform the traditional compression algorithms and support more efficient and scalable IoT networks [65].

Optimized Data Transmission Using Reinforcement Learning

Reinforcement learning (RL) brings about a new paradigm in IoT data transmission with adaptive strategies to optimize devices' transmission policies. It allows the IoT devices to learn by trying and decide dynamically based on real-time parameters, for example, network congestion, device states, and application demands regarding transmission of frequency, size, and priority of the data. Among the many RL techniques, Q-learning and deep Q-networks (DQNs) stand out because of their capacity to learn the complex state-action maps. For example, DQNs can analyze and learn from network traffic patterns so that resources can be intelligently allocated for efficient communication in heterogeneous and dynamic IoT environments [66, 67]. Adaptability is indeed crucial for managing the diverse traffic loads caused by applications at one end (such as wearable health monitors) and industrial automation systems at the other end. RL can be applied to IoT data traffic management, showing potential utility in smart traffic routing; it optimizes the usage of roads by real-time redirection of vehicles and energy-efficient communication through optimal reduction of transmissions to be made on the devices for conserved power. Applications of congestion control in IoT networks take advantage of RL-based approaches that suppress delays and packet loss in times of heavy flows [68]. These implementations also result in enhanced efficiency in the network while ensuring increased reductions in operational costs through optimal resource utilization. The integration of RL into IoT systems can facilitate more efficient and scalable data transmission, robust service delivery with quality, and the ability to adapt to ever-changing network conditions. This adaptation to changing network conditions makes RL an important tool for future applications in IoT [69, 70].

COMPRESSIVE SENSING METHODS FOR INTERNET OF THINGS OPTIMIZATION

Sparse Signal Representation in Internet of Things Data

The core idea behind compressive sensing (CS) is the representation of data as a sparse signal where only a few elements contain significant information. In IoT, data streams are generally sparse in their native domain or can be made sparse by transforming them (e.g., by wavelets or Fourier transforms). By exploiting this sparsity, compressive sensing enables efficient sampling and transmission by IoT devices without gathering every data point, significantly reducing the amount of data traffic [71]. Sparse representation techniques are especially useful in resource-scarce contexts like low-power IoT devices. They guarantee that data acquisition and processing remain lightweight, a characteristic that is essential for deployment, especially in applications such as wireless sensor networks and battery-operated devices [72, 73].

Signal Recovery and Reconstruction Algorithms

Compressive sensing relies on advanced algorithms to reconstruct the original signal from sparse measurements, ensuring efficient data recovery. Among the most popular reconstruction methods are basis pursuit (BP) and matching pursuit (MP). BP uses optimization techniques to identify the sparsest signal that aligns with the measured data, offering high precision but demanding significant computational resources [74]. On the other hand, MP employs an iterative approach, incrementally reconstructing the signal by matching it to a dictionary of potential components. While MP is faster and computationally lighter, it can sometimes sacrifice accuracy compared to BP. Given the diverse requirements of IoT applications, selecting the appropriate reconstruction algorithm involves balancing accuracy, computational efficiency, and resource utilization [75]. For real-time IoT scenarios with limited processing capabilities, such as edge devices or low-power sensors, this trade-off becomes particularly critical. Achieving the right balance ensures that IoT systems maintain reliable performance without overburdening their constrained resources, enabling the effective deployment of compressive sensing in practical, dynamic environments [76].

Real-Time Applications of Compressive Sensing in Internet of Things

Based on how critical rapid data processing is for real-time IoT applications, compressive sensing has high potential in edge computing environments. Reducing the amount of data transmitted to the centralized server is one-way CS minimizes latency and conserves bandwidth, making it suited for real-time monitoring systems-such as smart cities, healthcare, and industrial automation [77]. Integrating compressive sensing with IoT protocols and architectures, for instance, lightweight communication frameworks (e.g., MQTT, CoAP) further adds to its utility. Such integrations enable efficient end-to-end data handling at the device level to reconstruction at the edge or cloud. More and more CS techniques are being deployed together with machine learning models to enhance the efficiency and accuracy of IoT data processing, ensuring real-time response with reduced consumption of resources.

These methods make compressive sensing a more scalable and energy-efficient solution for optimizing IoT networks facing problems such as high data traffic and limited resources in real-time operational demands [78].

INTEGRATING DEEP LEARNING AND COMPRESSIVE SENSING

Deep learning integrated with compressive sensing provides a robust framework for the optimization of IoT data management using sparse measurements that capture the essence of the data, thereby enabling efficient reconstruction with neural networks. Since it reduces data transmission costs, improves computational speed, and delivers high accuracy at low latency, collaborative models are especially suited to resource-constrained IoT environments. For example, CNNs and autoencoders have proven to exhibit superior real-time signal reconstruction performance comparing with traditional methods [79]. When the complexity of IoT systems increases, the balance between compression efficiency and reconstruction quality becomes indispensable, with regard to evaluation metrics of compression ratio (CR), reconstruction accuracy in terms of mean square error (MSE) or signal-to-noise ratio (SNR), as well as latency. These integrated approaches always outperform their traditional counterparts, thus justifying the interest in bandwidth- and energy-limited settings [80]. The importance of model compression goes beyond IoT to wider machine learning applications. Compression techniques have become an essential tool to deploy artificial intelligence (AI) systems in environments with limited computational resources, such as mobile devices and edge computing. By researching lightweight design architectures systematically, it becomes clear that the relationship between model performance and computational burden must be optimized so as to not compromise sustainability. Hybrid approaches that use more than one compression promise improved efficiency, and intelligent frameworks that can select the best strategy for a given application hold large promise for advancing AI technology. Such methods increase sustainability while preserving high performance in constrained resource settings, thus ushering in responsible AI innovation [81, 82].

In the realm of image CS, the adaptive technique-based deep learning models have drastically transformed the performance scenario. Adaptive sensing allows the sampling matrix to be dynamic, whereas adaptive feature learning employs the associations within image data to enhance representation. Third, scalable model adaptation schemes have brought out scalability features across all sampling modes. Some of these innovations, which have struck out the major drawbacks of inflexibility and weak generalization, open up the doors for practical applications in multimedia and real-time image reconstruction. Further developments must achieve their broadest impact by refining these techniques to develop adaptive frameworks by overcoming the remaining challenges [83]. The rapid progress of next generation wireless communications has accelerated machine learning adoption in cognitive radio networks (CRNs), especially in spectrum sensing and dynamic spectrum sharing. The different types of machine learning algorithms applied here are supervised and unsupervised learning and reinforcement learning, which help optimize cooperative spectrum sensing and the dynamic distribution of spectrum resources in dynamic spectrum sharing (DSS). Efficient use of spectrum can be established in the CRNs addressing the continually increasing demand for wireless communications. The integration of machine learning algorithms into CRNs presents intelligent, scalable solutions that can optimize network efficiency and overcome the scarcity of spectrum [84].

Deep learning combined with federated learning (FL) and blockchain technology provides innovative solutions for specific challenges, such as detecting deepfakes. This approach will address data heterogeneity by integrating both SegCaps and CNNs for image feature extraction and CNs for enhanced generalization, ensuring secure global model training. Extensive experiments demonstrate that such methods can outperform existing detection systems in order to show significant improvements in both accuracy and AUC metrics. This approach not only counters the proliferation of deepfake content but also emphasizes media authenticity and security, thus making the relevance of such a technique well-spread across journalism, entertainment, and digital security [85]. Recent advancements in compressive sensing have also escalated innovation in reconstruction networks. Deep unfolding networks (DUNs), which rely on optimization principles, face certain limitations in feature characterization based on single-channel input-output structures. Addressing these limitations, MMU-Net introduces multi-channel, multi-scale architectures incorporating attention mechanisms and multi-scale blocks to enhance feature extraction. On benchmark datasets, MMU-Net shows superior reconstruction performance for all the images, both natural and remote sensing, bearing testimony to the applicability of this model in the image recovery task [86]. Video SCI has also made effective use of memory-efficient models like multi-group reversible 3D convolutional neural networks. These models use much fewer memory resources without reducing state-of-the-art results in large-scale video SCI applications, for example, high-speed reconstruction, color video reconstruction, and bridging the practical implementation challenges in video compression.

As a whole, integrating deep learning with compressive sensing offers a profoundly transformative approach to data management in the IoT and advanced applications domains, while optimizing efficiency and ensuring scalability. These developments, along with improvements in spectrum sensing, image CS, and video SCI, indicate the potential of hybrid models for revolutionizing AI and IoT ecosystems that are adaptable, efficient, and sustainable for diverse domains. Comparative analysis of research contributions in machine learning and compressive sensing applications is shown in Table 1.

Table 1. Comparative analysis of research contributions in machine learning and compressive sensing applications.

Ref. No.	Key Findings	Model Used	Limitations	Applications
[82]	Emphasizes the role of model compression techniques in enhancing AI model efficiency for resource-constrained environments and sustainability.	Hybrid model compression methods combining multiple techniques.	Lack of intelligent frameworks for automatic selection of compression techniques for specific applications.	Mobile devices, edge computing, IoT systems, sustainable AI development.
[83]	Reviews adaptive learning for image compressed sensing (CS), focusing on adaptive sensing, feature learning, and model adaptation to improve flexibility and generalization.	Adaptive sensing and deep learning-based CS frameworks.	Limited scalability and weak generalization across different sampling modes.	Image compression, multimedia applications, real-time image reconstruction.
[84]	Surveys ML-based algorithms for cooperative spectrum sensing (CSS) and dynamic spectrum sharing (DSS) in cognitive radio networks (CRNs).	Supervised, unsupervised, and reinforcement ML algorithms.	Challenges in applying ML to diverse CRN scenarios and addressing performance trade-offs.	Spectrum sensing and sharing in next-generation wireless communication systems.
[85]	Proposes a blockchain-based federated learning (FL) framework to counter deepfake threats while preserving data source anonymity.	Federated learning combined with SegCaps and CNN models.	High computational requirements for blockchain integration and potential data heterogeneity issues.	Deepfake detection, media authenticity, journalism, and digital security.
[86]	Introduces MMU-Net, a multi-channel and multi-scale CS reconstruction network that enhances feature characterization and performance.	Multi-channel and multi-scale unfolding network (MMU-Net) with Adap-SKConv attention mechanism.	Limited to specific benchmark datasets and may require adaptation for other data types or domains.	Image reconstruction for natural and remote sensing datasets.
[87]	Develops a memory-efficient network for large-scale video snapshot compressive imaging (SCI) using multi-group reversible 3D convolutional neural networks.	Multi-group reversible 3D convolutional neural networks with Bayer measurement reconstruction.	High computational cost of deep networks and memory occupation, limiting their practicality in broader applications.	High-speed video compression, color video recovery, large-scale SCI applications.

Deep learning and compressive sensing together have all sorts of applications across IoT domains:

- *Smart Cities:* With lower data volume, real-time analytics would help infrastructures like traffic monitoring and energy management. In fact, compressive sensing reduces the amount of data transmitted through sensors whereas deep learning models examine patterns for congestion management and efficient power distribution.
- *Healthcare:* Such amalgamation in healthcare applications, like wearable devices and remote patient monitoring, compress and analyze high-speed streams of continuous health data so that accurate diagnostics could be done without overloading network and computation resources.
- *Industrial IoT (IIoT):* Predictive maintenance of processes across industries generates very high frequency data. In their integrated models, real-time anomalous or maintenance signals can be identified without overloading the network.

CONCLUSION

The convergence of deep learning with compressive sensing, which seems to be one of the game-changing approaches at addressing data traffic problems on an IoT network, takes advantage of methods that diminish redundancy in data, enhancing reconstruction efficiency to optimize this resource-constrained environment for IoT, contributing to scalability and improved operational performance. Real-time analytics and energy-efficient systems are demonstrations of smart cities, healthcare, and industrial automation. Despite such transformative abilities, heterogeneity, resource constraints, and data security issues have remained to date significant unmet challenges for further considerations. Hybrid models and adaptive frameworks combining both techniques will be essential when IoT networks are developed on scales to come nearer to sustainable and efficient IoT ecosystems. Future work is to improve interoperability, defend against security breaches, and exploit emerging technologies for developing a strong, scale-out, and secure IoT infrastructure.

REFERENCES

1. Ouallane AA, Bahnasse A, Bakali A, Talea M. Overview of road traffic management solutions based on IoT and AI. Procedia Computer Sci. 2022; 198: 518–523. doi: 10.1016/j.procs.2021.12.279.
2. Al Neyadi E, Al Shehhi S, Al Shehhi A, Al Hashimi N, Mohammad Q, Alrabaee S. Discovering public Wi-Fi vulnerabilities using Raspberry Pi and Kali Linux. In: 2020 12th Annual Undergraduate Research Conference on Applied Computing (URC), Dubai, UAE, April 15–16, 2020. pp. 1–4.
3. Kuzovkova TA, Salutina TY, Sharavova OI. Integral assessment of the state and development potential of info-communication infrastructure for ensuring sustainable digital development. In: CEUR Workshop Proceedings. AISI 2021 – Proceedings of the International Workshop on Advances in Information Systems, Mathematical Modeling, and IT Applications in Industry, Barnaul, Russia, October 21, 2021. pp. 76–85.
4. Azab A, Khasawneh M, Alrabaee S, Choo KKR, Sarsour M. Network traffic classification: techniques, datasets, and challenges. Digital Commun Netw. 2024; 10 (3): 676–692. doi: 10.1016/j.dcan.2022.09.009.
5. Aboubakar M, Kellil M, Roux P. A review of IoT network management: current status and perspectives. J King Saud Univ – Computer Inform Sci. 2022; 34 (7): 4163–4176. doi: 10.1016/j.jksuci.2021.03.006.
6. Shafiq M, Gu Z, Cheikhrouhou O, Alhakami W, Hamam H. The rise of "internet of things": review and open research issues related to detection and prevention of IoT-based security attacks. Wireless Commun Mobile Comput. 2022; 1: 8669348. doi: 10.1155/2022/8669348.
7. Machidon AL, Pejović V. Deep learning for compressive sensing: a ubiquitous systems perspective. Artif Intell Rev. 2023; 56 (4): 3619–3658. doi: 10.1007/s10462-022-10259-5.
8. Noura HN, Azar J, Salman O, Couturier R, Mazouzi K. A deep learning scheme for efficient multimedia IoT data compression. Ad Hoc Netw. 2023; 138: 102998.
9. Machidon AL, Pejovic V. Deep learning techniques for compressive sensing-based reconstruction and inference – a ubiquitous systems perspective. arXiv preprint arXiv:2105.13191.

10. Zhang M, Zhang H, Fang Y, Yuan D. Learning-based data transmissions for future 6G enabled industrial IoT: a data compression perspective. IEEE Netw. 2022; 36 (5): 180–187. doi: 10.1109/MNET.109.2100384.
11. Nasif A, Othman ZA, Sani NS. The deep learning solutions on lossless compression methods for alleviating data load on IoT nodes in smart cities. Sensors. 2021; 21: 4223. doi: 10.3390/s21124223.
12. Kumar SS, Ramachandran P. Review on compressive sensing algorithms for ECG signal for IoT based deep learning framework. Appl Sci. 2022; 12: 8368. doi: 10.3390/app12168368.
13. Sadeeq MM, Abdulkareem NM, Zeebaree SR, Ahmed DM, Sami AS, Zebari RR. IoT and cloud computing issues, challenges and opportunities: a review. Qubahan Acad J. 2021; 1 (2): 1–7. doi: 10.48161/qaj.v1n2a36.
14. Zikria YB, Ali R, Afzal MK, Kim SW. Next-generation internet of things (IoT): opportunities, challenges, and solutions. Sensors. 2021; 21: 1174. doi: 10.3390/s21041174.
15. Krishna RR, Priyadarshini A, Jha AV, Appasani B, Srinivasulu A, Bizon N. State-of-the-art review on IoT threats and attacks: taxonomy, challenges and solutions. Sustainability. 2021; 13: 9463. doi: 10.3390/su13169463.
16. Zafar A, Samad F, Syed HJ, Ibrahim AO, Alohaly M, Elsadig M. An advanced strategy for addressing heterogeneity in SDN-IoT networks for ensuring QoS. Appl Sci. 2023; 13 (13): 7856. doi: 10.3390/app13137856.
17. Shah Z, Levula A, Khurshid K, Ahmed J, Ullah I, Singh S. Routing protocols for mobile internet of things (IoT): a survey on challenges and solutions. Electronics. 2021; 10 (19): 2320. doi: 10.3390/electronics10192320.
18. Rao PM, Deebak BD. Security and privacy issues in smart cities/industries: technologies, applications, and challenges. J Ambient Intell Humanized Comput. 2023; 14 (8): 10517–10553. doi: 10.1007/s12652-022-03707-1.
19. Liyakat KKS. Machine learning approach using artificial neural networks to detect malicious nodes in IoT networks. In: Udgata SK, Sethi S, Gao XZ, editors. Intelligent Systems. ICMIB 2023. Lecture Notes in Networks and Systems, vol 728. Singapore: Springer; 2024. pp. 123–134. doi: 10.1007/978-981-99-3932-9_12.
20. Nasif A, Othman ZA, Sani NS. The deep learning solutions on lossless compression methods for alleviating data load on IoT nodes in smart cities. Sensors. 2021; 21 (12): 4223.
21. Liyakat KKS. Detecting malicious nodes in IoT Networks using machine learning and artificial neural networks. In: 2023 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, March 1–3, 2023. pp. 1–5. doi: 10.1109/ESCI56872.2023.10099544.
22. Kasat K, Shaikh N, Rayabharapu VK, Nayak M. Implementation and recognition of waste management system with mobility solution in smart cities using internet of things. In: 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, August 23–25, 2023. pp. 1661–1665. doi: 10.1109/ICAISS58487.2023.10250690.
23. Moon A, Kim J, Zhang J, Son SW. Evaluating fidelity of lossy compression on spatiotemporal data from an IoT enabled smart farm. Computers Electron Agric. 2018; 154: 304–313.
24. Al-Qurabat AK, Mohammed ZA, Hussein ZJ. Data traffic management based on compression and MDL techniques for smart agriculture in IoT. Wireless Pers Commun. 2021; 120 (3): 2227–2258.
25. Kazi K. Modelling and simulation of electric vehicle for performance analysis: BEV and HEV electrical vehicle implementation using Simulink for e-mobility ecosystems. In: Nagpal N, Kassarwani N, Varthanan G, Siano P, editors. E-Mobility in Electrical Energy Systems for Sustainability. Hershey, PA, USA: IGI Global; 2024. pp. 295–320. doi: 10.4018/979-8-3693-2611-4.ch014.
26. Kazi KS. Computer-aided diagnosis in ophthalmology: a technical review of deep learning applications. In: Garcia M, de Almeida R, editorials. Transformative Approaches to Patient Literacy and Healthcare Innovation. Hershey, PA, USA: IGI Global. (pp. 112–135. doi: 10.4018/979-8-3693-3661-8.ch006.
27. Liyakat KKS, Magadum PK, Machine learning for predicting wind turbine output power in wind energy conversion systems. 15th International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2024, 2024, 1, pp. 2074–2080.

28. Neeraja P, Kumar RG, Kumar MS, Liyakat KKS, Vani MS. DL-based somnolence detection for improved driver safety and alertness monitoring. In: 2024 IEEE International Conference on Computing, Power, and Communication Technologies, IC2PCT 2024, Greater Noida, India, February 9–10, 2024. pp. 589–594. doi: 10.1109/IC2PCT60090.2024.10486714.
29. Das L, Garg D, Srinivasan B. Neural compression: a machine learning approach to compress high frequency measurements in smart grid. Appl Energy. 2020; 257: 113966.
30. Moon A, Kim J, Zhang J, Liu H, Son SW. Understanding the impact of lossy compressions on IoT smart farm analytics. In: 2017 IEEE International Conference on Big Data (Big Data), Boston, MA, USA, December 11–14, 2017. pp. 4602–4611.
31. Veena C, Sridevi M, Liyakat KKS, Saha B, Reddy SR, Shirisha N. HEECCNB: an efficient IoT-cloud architecture for secure patient data transmission and accurate disease prediction in healthcare systems. In: 2023 Seventh International Conference on Image Information Processing (ICIIP), Solan, India, November 22–24, 2023. pp. 407–410. doi: 10.1109/ICIIP61524.2023.10537627.
32. Rajendra Prasad K, Santoshachandra Rao K. AI in public-private partnership for IT infrastructure development, J High Technol Manage Res. 2024; 35 (1): 100496. doi: 10.1016/j.hitech.2024.100496.
33. Putra KT, Chen HC, Prayitno, Ogiela MR, Chou CL, Weng CE, Shae ZY. Federated compressed learning edge computing framework with ensuring data privacy for PM2.5 prediction in smart city sensing applications. Sensors. 2021; 21 (13): 4586.
34. Kazi K. Machine learning (ML)-based Braille lippi characters and numbers detection and announcement system for blind children in learning In: Sart G, editor. Social Reflections of Human-Computer Interaction in Education, Management, and Economics, Hershey, PA, USA: IGI Global; 2024. pp. 16–39. doi: 10.4018/979-8-3693-3033-3.ch002.
35. Kazi KS. Artificial intelligence (AI)-driven IoT (AIIoT)-based agriculture automation. In: Satapathy S, Muduli K, editors. Advanced Computational Methods for Agri-Business Sustainability. Hershey, PA, USA: IGI Global; 2024. (pp. 72–94. doi: 10.4018/979-8-3693-3583-3.ch005.
36. Liyakat KKS, Konnur RG. Vehicle health monitoring system (VHMS) by employing IoT and sensors. In: 15th International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2024, 2024. pp. 5367–5374.
37. Liyakat KKS. A novel approach on ML based palmistry. In: 15th International Conference on Advances in Computing, Control, ad Telecommunication Technologies, ACT 2024, 2024. pp. 5186–5193.
38. Liyakat KKS. IoT based boiler health monitoring for sugar industries. In: 15th International Conference on Advances in Computing, Control, ad Telecommunication Technologies, ACT 2024, 2024. pp. 5178–5185.
39. Liyakat KKS. Explainable AI in healthcare. In: Explainable Artificial Intelligence in Healthcare Systems. Hauppauge, NY, USA: Nova Science; 2024. pp. 271–284.
40. Kazi KS. Machine learning-based pomegranate disease detection and treatment. In: Zia Ul Haq M, Ali I, editors. Revolutionizing Pest Management for Sustainable Agriculture. Hershey, PA, USA: IGI Global; 2024. pp. 469–498. doi: 10.4018/979-8-3693-3061-6.ch019.
41. Ananthi J, Sengottaiyan N, Anbukaruppusamy S, Upreti K, Dubey AK. Forest fire prediction using IoT and deep learning. Int J Adv Technol Eng Exploration. 2022; 9 (87): 246–256.
42. Lin C, Han G, Qi X, Du J, Xu T, Martínez-García M. Energy-optimal data collection for unmanned aerial vehicle-aided industrial wireless sensor network-based agricultural monitoring system: a clustering compressed sampling approach. IEEE Trans Indus Inform. 2020; 17 (6): 4411–4420.
43. Vedavalli P, Ch D. A deep learning based data recovery approach for missing and erroneous data of IoT nodes. Sensors. 2022; 23 (1): 170.
44. Liyakat KK. Heart health monitoring using IoT and machine learning methods. In: Shaik A, editor. AI-Powered Advances in Pharmacology. Hershey, PA, USA: IGI Global. (pp. 257–282. doi: 10.4018/979-8-3693-3212-2.ch010.

45. Kazi KS. AI-powered-IoT (AIIoT)-based decision-making system for BP patient's healthcare monitoring: KSK approach for BP patient healthcare monitoring. In: Aouadni S, Aouadni I, editors. Recent Theories and Applications for Multi-Criteria Decision-Making. Hershey, PA, USA: IGI Global; 2024. pp. 205–238). doi: 10.4018/979-8-3693-6502-1.ch008.
46. Kazi KS. AI-driven-IoT (AIIoT)-based decision making in drones for climate change: KSK approach. In: Aouadni S, Aouadni I, editors. Recent Theories and Applications for Multi-Criteria Decision-Making. Hershey, PA, USA: IGI Global; 2025. pp. 311–340. doi: 10.4018/979-8-3693-6502-1.ch011.
47. Haupt J, Bajwa WU, Rabbat M, Nowak R. Compressed sensing for networked data. IEEE Signal Process Mag. 2008; 25 (2): 92–101.
48. Kazi K. Machine learning-driven-internet of medical things (ML-IoMT) based healthcare monitoring system. Soufiene BO, Chakraborty C, editors. Responsible AI for Digital Health and Medical Analytics, Hershey, PA, USA: IGI Global; 2025.
49. Ng PC, She J, Ran R. A compressive sensing approach to detect the proximity between smartphones and BLE beacons. IEEE Internet of Things J. 2019; 6 (4): 7162–7174.
50. Sarma S. Essence: Machine Learning Approaches to Scalable and Energy Efficient Sense-making for Internet-of-Things (IoT). MSc Thesis. Irvine, CA, USA: University of California, Irvine; 2015.
51. Zheng H, Guo W, Xiong N. A kernel-based compressive sensing approach for mobile data gathering in wireless sensor network systems. IEEE Trans Syst Man Cybern Syst. 2017; 48 (12): 2315–2327.
52. Kazi K. Red Deer algorithm based polycystic ovarian syndrome by using random forest classifier. Mulani A, Cengiz K, Tripathi S, editors. AI, Machine Learning, and IoT for Communication and Medical Applications. Hershey, PA, USA: IGI Global; 2025.
53. Liyakat KKS, Malicious node detection in IoT networks using artificial neural networks. In: Singh VK, Sagar AK, Nand P, Astya R, Kaiwartya O, editors. Intelligent Networks: Techniques and Applications. Boca Raton, Fl, USA: CRC Press; 2024. pp.182–197.
54. Pandey C, Angryk RA, Aydin B. Solar flare forecasting with deep neural networks using compressed full-disk HMI magnetograms. In: 2021 IEEE International Conference on Big Data (Big Data), Orlando, FL, USA, December 15–18, 2021. pp. 1725–1730.
55. Liyakat KKS. Advancing towards sustainable energy with hydrogen solutions: adaptation and challenges. In: Özsungur F, Semsari MC, Bayraktar HK, editors. Geopolitical Landscapes of Renewable Energy and Urban Growth. Hershey, PA, USA: IGI Global; 2025.
56. Liyakat KKS. Machine learning for brand protection: a review of a proactive defense mechanism. In: Khan M, Amin Ul Haq M, editors. Avoiding Ad Fraud and Supporting Brand Safety: Programmatic Advertising Solutions. Hershey, PA, USA: IGI Global; 2025.
57. Liyakat KKS. Braille-Lippi numbers and characters detection and announcement system for blind children using KSK approach: AI-driven-decision making. In: Ponnusamy S, Antari A, Jeon G, Assaf M, Sharma B, editors. Revolutionizing Education with Remote Experimentation and Learning Analytics. Hershey, PA, USA: IGI Global; 2025.
58. Liyakat KKS. AI-Driven-IoT (AIIoT) based jawar leaf disease detection: KSK approach for jawar disease detection. In: Bhatti U, Aamir A, Gulzar Y, Bazai SU, editors. Modern Intelligent Techniques for Image Processing. Hershey, PA, USA: IGI Global; 2025.
59. Liyakat KKS. AI-powered IoT (AI IoT) for decision-making in smart agriculture: KSK approach for smart agriculture. In: Hai-Jew S, editor. Enhancing Automated Decision-Making Through AI. Hershey, PA, USA: IGI Global; 2025.
60. Razzaque MA, Dobson S. Energy-efficient sensing in wireless sensor networks using compressed sensing. Sensors. 2014; 14 (2): 2822–2859.
61. Liyakat KKS. Machine learning-powered-IoT (MLIoT) for retail apparel industry. In: Tarnanidis T, Papachristou E, Karypidis M, Manda VK, editors. Sustainable Practices in the Fashion and Retail Industry. Hershey, PA, USA: IGI Global; 2025.
62. Liyakat KKS. KK approach to increase resilience in internet of things: a T-cell security concept. In: Darwish D, Charan K, editors. Analyzing Privacy and Security Difficulties in Social Media: New Challenges and Solutions. Hershey, PA, USA: IGI Global; 2025.

63. Halli UM. Nanotechnology in IoT security. J Nanosci Nanoeng Appl. 2022; 12 (3): 11–16.
64. Wale AD, Rokade D, et al. Smart agriculture system using IoT. Int J Innov Res Technol. 2019; 5 (10): 493–497.
65. Sunil Kumar M, Ganesh D, Turukmane AV, Batta U. Deep convolution neural network based solution for detecting plant diseases. J Pharm Negative Results. 2022; 13 (Special Issue I): 464–471.
66. Alsubai S, Dutta AK, Sait ARW. Hybrid deep learning-based traffic congestion control in IoT environment using enhanced arithmetic optimization technique. Alexandria Eng J. 2024; 105: 331–340. doi: 10.1016/j.aej.2024.06.072.
67. Lydia EL, Jovith AA, Devaraj AFS, Seo C, Joshi GP. Green energy efficient routing with deep learning based anomaly detection for internet of things (IoT) communications. Mathematics. 2021; 9: 500. doi: 10.3390/math9050500.
68. Ferrag MA, Shu L, Djallel H, Choo KKR. Deep learning-based intrusion detection for distributed denial of service attack in Agriculture 4.0. Electronics. 2021; 10: 1257. doi: 10.3390/electronics 10111257.
69. Sarhan M, Layeghy S, Moustafa N, Gallagher M, Portmann M. Feature extraction for machine learning-based intrusion detection in IoT networks. Digital Commun Netw. 2024; 10 (1): 205–216. doi: 10.1016/j.dcan.2022.08.012.
70. Muthanna MSA, Muthanna A, Rafiq A, Hammoudeh M, Alkanhel R, Lynch S, Abd El-Latif AA. Deep reinforcement learning based transmission policy enforcement and multi-hop routing in QoS aware LoRa IoT networks. Computer Commun. 2022; 183: 33–50. doi: 10.1016/j.comcom.2021.11.010.
71. Damadam S, Zourbakhsh M, Javidan R, Faroughi A. An intelligent IoT based traffic light management system: deep reinforcement learning. Smart Cities 2022; 5: 1293–1311. doi: 10.3390/smartcities5040066.
72. Selva E. Digitization, Compression and Reconstruction of a Large-Scale Radio Traffic for the Internet of Things. Doctoral Dissertation. Gif-sur-Yvette, France: Centrale Supélec; 2021.
73. Kuldeep G, Zhang Q. A novel efficient secure and error-robust scheme for internet of things using compressive sensing. IEEE Access 2021; 9: 40903–40914. doi: 10.1109/ACCESS.2021.3064700.
74. Salim A, Ismail A, Osamy WM, Khedr A. Compressive sensing based secure data aggregation scheme for IoT based WSN applications. PLoS ONE. 2021; 16 (12): e0260634. doi: 10.1371/journal.pone.0260634.
75. Azar J, Tayeh GB, Makhoul A, Couturier R. Efficient lossy compression for IoT using SZ and reconstruction with 1D U-Net. Mobile Netw Appl. 2022; 27 (3): 984–996. doi: 10.1007/s11036-022-01918-6.
76. Vivekanand V. A Theoretical Framework for Sparse Recovery Algorithm Design and Evaluation in Compressed Sensing Perspective. Doctoral Dissertation. Thiruvananthapuram, India: Indian Institute of Space Science and Technology; 2023.
77. Zhou J, Yang J. Compressive sensing in image/video compression: sampling, coding, reconstruction, and codec optimization. Information. 2024; 15: 75. doi: 10.3390/info15020075.
78. de Oliveira MA, da Rocha AM, Puntel FE, Cavalheiro GGH. Time series compression for IoT: a systematic literature review. Wireless Commun Mobile Comput. 2023; 1: 5025255. doi: 10.1155/2023/5025255.
79. Kahdim AN, Manaa ME. Design an efficient internet of things data compression for healthcare applications. Bull Electric Eng Inform. 2022; 11 (3): 1678–1686. doi: 10.11591/eei.v11i3.3758.
80. Dantas PV, Sabino da Silva Jr W, Cordeiro LC, Carvalho CB. A comprehensive review of model compression techniques in machine learning. Appl Intell. 2024; 54: 11804–11844. doi: 10.1007/s10489-024-05747-w.
81. Xie Z, Liu L, Chen Z. Image compressed sensing: From deep learning to adaptive learning. Knowledge-Based Syst. 2024; 293: 111659. doi: 10.1016/j.knosys.2024.111659.
82. Janu D, Singh K, Kumar S. Machine learning for cooperative spectrum sensing and sharing: a survey. Trans Emerg Telecommun Technol. 2022; 33 (1): e4352. doi: 10.1002/ett.4352.

83. Heidari A, Navimipour NJ, Dag H, Talebi S, Unal M. A novel blockchain-based deepfake detection method using federated and deep learning models. Cogn Comput. 2024; 16: 1073–1091. doi: 10.1007/s12559-024-10255-7.
84. Zeng C, Xia S, Wang Z, Wan X. Multi-channel representation learning enhanced unfolding multi-scale compressed sensing network for high quality image reconstruction. Entropy. 2023; 25: 1579. doi: 10.3390/ e25121579.
85. Cheng Z, Chen B, Liu G, Zhang H, Lu R, Wang Z, Yuan X. Memory-efficient network for large-scale video compressive sensing. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Nashville, TN, USA: June 20–25, 2021. pp. 16246–16255.
86. Humayun M, Afsar S, Almufareh M, Jhanjhi N, AlSuwailem M. Smart traffic management system for metropolitan cities of Kingdom using cutting edge technologies. J Adv Transport. 2022; 2022: 4687319. doi: 10.1155/2022/4687319.
87. Chen Z, Li R, Li Y, Feng Y, Hou X, Qian X. Deep motion regularizer for video snapshot compressive imaging. IEEE Trans Comput Imaging. 2024; 10: 1519–1532.