Advancements in IoT Data Transmission and Reconstruction: A Review of Compressive Sensing and Neural Network Integration

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Abstract:

The rapid proliferation of IoT devices has led to massive, heterogeneous, and high-speed data generation, thereby straining bandwidth, energy efficiency, and real-time processing. Compressive Sensing (CS) is a promising approach considered for the transmission load reduction by means of acquiring sparse signals while compressed and containing the information in them. Nevertheless, traditional CS mechanisms suffer from complex computation, becoming sensitive to noise and incapable of solving dynamic problems in IoT environments. Integration of neural networks into CS-based frameworks provides a way to circumvent these hurdles by learning highly non-linear mappings from the compressed observations to the original signals for faster and more accurate recovery. Neural network-based CS methods further benefit from the intrinsic structure of the IoT data, e.g., sparsity and low-rankness, to improve reconstruction fidelity in the face of noise, packet loss, and heterogeneous data. This review further synthesizes the literature on CS-neural network approaches for IoT data transmission and reconstruction, discussing relevant architectures, optimization methods, and application areas. It brings out research challenges in latency, reliability, energy efficiency, and adaptability. These would usher in future directions for the development of intelligent IoT systems that can work efficiently in situations demanding real-time speed and resources.

Keywords: *Compressive Sensing, Neural Networks, IoT Data Transmission, Signal Reconstruction, Data Sparsity, Low-Rank Modeling*

I. INTRODUCTION

The Internet of Things (IoT) is defined as an ecosystem containing myriad interconnected devices, sensors, and systems that generate and exchange data continuously. Such networks lend themselves to the monitoring and decision-making in real-time within healthcare, industrial automation, smart grid, or environmental surveillance domains [1]. A considerable growth in the number of IoT deployments brought a host of unprecedented challenges that include the efficiency of data transmission methods, network channel utilization, energy consumption, and the reconstruction of signals in a timely manner. Traditional methods of transmission often cannot keep pace with the volume and heterogeneity of data present in IoT. Measurements are burdened with high dimensionality, redundancy, and noise and weigh down the communication channels, bringing about congestion, latency, and high power consumption. Therefore, the need for transmission-efficient methods arose to reduce the communication overhead while maintaining the essential fidelity of signals [2].

Compressive Sensing (CS), being a technology that leverages the inherent sparsity of numerous real-world signals, observes signals in a compressed form with negligible information loss. As fewer measurements are transmitted, CS effectively reduces bandwidth pressure and energy demands [3]. Nonetheless, in IoT applications, its efficacy is limited due to computational complexity, noise sensitivity, and scalability constraints faced by traditional reconstruction algorithms.

Recently, machine learning, particularly neural network approaches, has received attention in tackling these reconstruction problems. Neural networks do well at modeling complex and non-linear relationships between compressed measurements and their original forms, thus affording much faster and more accurate recovery [4]. They can model random behavior or noise, use structural priors such as sparsity and low-rankness, and perform recovery almost in milliseconds-a useful feature for latency-aware IoT applications. Wherein the literature is growing into the integration of CS and neural networks for IoT data processing, it investigates end-to-end architecture jointly optimizing compression and reconstruction; domain-specific adaptations for applications such as remote health monitoring; and lightweight models deployable on the edge side. While most of these works report on reconstruction speed and accuracy improvement, there are significant gaps yet to be covered. Common limitations of are: dependence on large annotated datasets; robustness issues under highly dynamic network conditions; and problems of computational efficiency in model design for low-power IoT nodes [5].

The goal of the review is to provide a systematic treatment on existing research on the integration of CS and neural networks for IoT data transmission and reconstruction. The discussion revolves around algorithmic frameworks, architectural peculiarities, metrics, and case studies of applications. It then brings out the lagging issues of model generalizability, interpretability, and energy efficiency, while looking forward to some emerging ones like federated learning, adaptive sampling, and hybrid optimization [6]. The review synthesizes state-of-the-art techniques and how open research problems shape modern IoT frameworks that are efficient in communication and stronger in data recovery. The ultimate aim is to achieve scalable, energy-aware, and intelligent IoT platforms that can fulfill the requirements of increasingly complex and data-intensive environment. Fig. 1 shows principles of compressive sensing. [7]

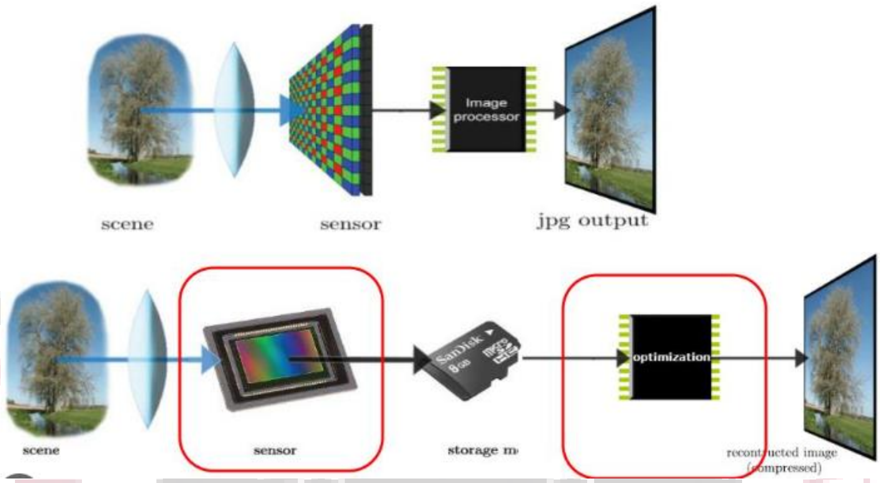

Fig. 1: Principles of Compressive Sensing [7]

II. LITERATURE REVIEW

Nimisha Ghosh et al. [1] (2023) provided knowledge of Compressive Sensing (CS) for conservation of energy in disconnected IoT environments where only compressed data is transmitted by mobile collectors. While this approach suffers reduction in transmission volume and latency, NP-hard joint tree construction and recovery complexity, and loss of accuracy at high noise/loss rates become significant impediments. Some heuristic approaches may hold promise, but their use in large-scale real-time environments has yet to be undertaken.

Ahmed Mohammed Hussein et al. [2] (2023) Propose Distributed Prediction-Compression-Based Mechanism (DiPCoM) in order to allow ARIMA predictions and multiple compression methods to avoid unnecessary transmissions in IoT networking. It showed energy efficiency compared to previous approaches but would suffer from errors in prediction in dynamic environments, computationally expensive compression, and lower reconstruction accuracy in the mixture of streams.

Deepa Devasenapathy et al. [3] (2023) presented enhanced grid-based synchronized routing with Bayesian CS for correlated sensor data aggregation, resulting in an accuracy improvement of up to 16.93% and a lifetime enhancement of about 22.9%. The limitations include sensitivity to grid-size errors, computational overhead of the Bayesian computations, and poor performance with irregular sensing patterns.

B. Lal, et al. [4] (2023) propose a Light-weight CS based ECG monitoring had been developed for energy efficiency and security without actually burdening the sensor node with computational complexity. The system offers high compression and low energy usage at the edge; however, reconstruction suffers from degradation, particularly under high noise and synchronization overhead, with ambiguity in cross-device generalization performance.

Gen-Sen Dong et al. [5] (2023) Used DCGAN together with 1D symmetric U-Net for vibration data reconstruction from an accuracy and speed point of view that proved to be better than the rival approaches. Challenges include the requirement of a very large dataset, GAN instability, poor robustness under low sampling rates, and limited generalization to unseen patterns.

Y. Zhang et al. [6] (2023) propose a method based on DCT-based lossy compression and CKKS homomorphic encryption, a secure and communication-efficient FL system was introduced. High accuracy was maintained at extreme compression, but encryption cost a lot computability-wise, in theory secured.

X. Tang et al., [7] 2023 applied CS on thermal and acoustic images to reduce CNN training time and to raise diagnostic accuracies to 99.39%. Potential weaknesses include a drop of performance with noisy and low-quality data, disputed CS sampling rates, and higher complexity introduced by a dual-sensor setup.

C. Sureshkumar et al. [8] (2023) proposed Adaptive Adjacent-based Compressive Sensing (AACS) using sparse matrices and fuzzy logic for energy-efficient WSN data reconstruction, thus yielding massive improvements in throughput and error. Limitations include the need for accurate location-AACS computation with degraded performance under high mobility and fuzzy logic computational cost.

Xiaoling Huang et al. [9] (2023) designed an image encryption scheme based on CS and IWT with chaotic-RSA integration. The drawbacks are heavy computational load of RSA, accuracy-sensitive generation of chaotic parameters, and limited scalability to large and real-time IoT images.

Alina L. Machidon et al. [10] (2023) review of CS–DL integration for sampling rate reduction, adaptive sensing, and robust reconstruction in heterogeneous devices. Identified gaps in standard benchmarks, hardware adaptation, and resistance to distribution shifts under latency/energy constraints.

N. Iqbal et al. [11] (2023) design an energy and traffic reduction-bandwidth lightweight CS algorithm for seismic data through sensing compressed and reconstructing via DCNN without having any prior assumptions. The SNR of 30 dB was obtained with a compression gain of 16; in terms of performance, it surpassed all the existing methods. Some of the limitations include huge training data requirements, noise sensitivity, and inferencing expense in low-resource settings.

Nayak et al. [12] (2023) an adaptive fuzzy rule-based CS system based on saliency, and edge features was proposed for automatic selection of sampling rate. The method yielded very good performance in terms of PSNR and SSIM redounded to the Standard, CCTV, Kodak and Set5 dataset, outperforming all competing state-of-the-art CS methods. Computational complexity and the risk of performance drop in the case of highly textured/noisy images stand as roadblocks of this approach.

Zhang et al. [13] (2023) a new Chained Secure and Low-Energy Consumption Data Transmission (CS-LeCT) scheme was designed that has reconstruction performance much superior compared to the traditional CCS method. Both simulation experiment results and theoretical analysis proved the superior performance of CS-LeCT. Security assessments further demonstrate that CS-LeCT can stand up to several potential threats, including ciphertext-only attacks (COAs), known-plaintext attacks (KPAs), and man-in-the-middle attacks (MiTMs).

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Enas Wahab Abood et al. [14] (2023) Presented a CS-based audio compression and encryption system with Gaussian random sensing and Moore–Penrose pseudoinverse reconstruction. It reduces size by around 28%, while maintaining a high correlation and good PSNR/SSIM values. However, it suffers from concerns about computational load and scalability to real-time IoT scenarios.

Vinay Pathak et al. [15] (2023) Designed a hybrid WSN–WBAN architecture using CS for biomedical data, providing up to 88.11% compression and reducing consensus time by 24%. It further improves PRD by 34.21%, all while consuming low CPU usage. The limitations consist of noise vulnerability, dependency on network connectivity, and scalability troubles.

R. Gambheer and M. S. Bhat et al. [16] (2023) Applied CS to CCD/CMOS camera sensors for reduced measurements with high SNR on FPGA hardware for IoT imaging. CCD yields 13% power and 15% memory savings under no-light conditions at 25.76 dB PSNR. CMOS systems show worse performance in very low light, and embedding hardware complicates the system.

S. Chen et al. [17] (2023) developed a CS-privacy-preserving FL scheme with gradient perturbation that safeguards data and labels from each other while curbing communication costs. Strong privacy and competitive accuracy were delivered with low computation. Effectiveness depends on appropriate perturbation parameters.

Leming Wu et al. [18] (2023) elevated CS-based federated learning by refining the measurement matrix through genetic algorithms and through interleaving training and reconstruction, resulting in higher accuracy with large compression ratios. Some drawbacks, however, are the computational overhead of GA and the dependency on tuning of parameters.

W. Ma et al. [19] (2023) STRCS was proposed for channel reconstruction with FRI in the angular domain, where AoDs/AoAs are estimated from a finite number of channel measurements. They outperformed the existing techniques in terms of accuracy and pilot overhead. They stand to lose their viability in highly dynamic or dense multipath environments.

Z. Gao et al. [20] (2023) studied CS-based GFMA for massive access by portraying a roadmap from single-antenna to large-scale cooperative MIMO and sourced/unsourced access. They pointed out the shortcomings of present random access schemes and the major challenges that lie ahead. Complexity of implementation and standardization remain to be addressed.

Liqiang Xu et al. [21] (2024) established a method called Mob-ISTA-1DNet that combines deep learning with ISTA for adaptive CS compression/recovery of smartphone sensor data. The method performs the reconstruction of sensor measurements more accurately and faster than existing methods for various types of sensor readings. They also designed a smartphone application whose performance has been validated by one month, 30-volunteer data-set.

R. K. Kaushal et al. [22] (2024) proposed Energy-Efficient Artificial Neural Network-Based Clustering Protocol (EEANNCP), which is an ANN-based energy-efficient clustering protocol for WSNs by selecting only one cluster head per cluster. The simulation results confirm that this approach proves to conserve more energy than other approaches and consequently increases the lifetime of the network. However, its scalability with the increasing size of the network and adaptability to dynamic topologies are yet to be tested.

Wang et al. [23] (2024) The OS algorithm combines graph CS and RBM and considers KL divergence as the distortion metric to optimize node deployment in task-oriented WSNs, enhancing both reconstruction accuracy and network performance with respect to baseline. It can only provide optimization gains if the network conditions are stable.

Luyang Liu et al. [24] (2024) processed experiments with realistic datasets from actual sensors, showing superior performance over state-of-the-art CS sampling on STL10, Intel, Imagenette (classification) and KITTI (object detection). Achieved classification accuracy improvements of 26.23%, 11.69%, and 18.25% at certain sampling rates compared to uniform sampling. Maintained robustness even at very low sampling rates, ensuring essential CV task information retention.

Xin Zhu et al. [25] (2024) presented the DCST-based multilayer autoencoder with trainable thresholding, thus reducing parameters at the same time improving reconstruction quality. At the very least, the method delivers a 32.35 percent gain in quality score on the gearbox datasets. This approach may require fine-tuning when used in other domain applications with different data characteristics.

Di Xiao et al. [26] (2024) discuss a Meta-learning-based Compressed Sensing Reconstruction in the Cloud (MetaCSRC), which is a restorative end-to-end imaging paradigm addressing such constraints For better security for measurement transmission, local differential privacy noise is added to the measurements prior to uploading to the cloud server. Experimental results prove that MetaCSRC is superior when it comes to reconstruction speed and accuracy, while also providing privacy protection.

Shuai Bian et al. [27] (2024) Proposed NL-CS-Net, unrolling non-local sparse-regularized optimization into a two-stage learnable network. Hence, it gave the state-of-the-art reconstruction in MRI and natural-image reconstruction. The benefits are chiefly due to high-quality training and appropriate non-local priors.

Bo Liu et al. [28] (2024) Enhanced CNN architecture in IoT domain for art data analysis by usage of deeper layers, batch normalization, and dropout. Multimodal sensor/image data integration to provide accurate feedback for art design education. For other domains, it needs transformations.

Darmawan Utomo et al. [29] (2024) Utilized ConvLSTM to reconstruct missing geospatial and environmental data based on temporal-spatial relationships. Outperformed its LSTM variant in RMSE under multiple missing data scenarios. Accuracy is heavily dependent on input data completeness and quality.

Jingyi Hu et al. [30] proposed ADMM-1DNet, which maps the steps of ADMM into a deep network to reconstruct vibration signals under heavy ambient noise. It makes the accumulated noise very hard to suppress and hence yields better accuracy and feature preservation than all the competing methods and systems. The flexibility allows for diverse applications in monitoring.

Table 1: Compressive Sensing Techniques for Efficient IoT Data Transmission

Reference & Year	Proposed Method/Model	Key Features	Results	Advantages	Limitations/Challenges
Nimisha Ghosh et al. (2023) [1]	Compressive sensing with mobile collectors in disconnected WSN networks	Transmits compressed data from sensor subsets; mobile data gathering	Heuristic solutions show promising simulation results	Reduces transmission volume & latency	NP-hard tree construction/link scheduling, complex recovery, accuracy drops with noise/loss, scalability issues
Ahmed Mohammed Hussein et al. (2023) [2]	Distributed Prediction–Compression-Based Mechanism (DiPCoM) for IoT power saving	Uses ARIMA for prediction; adaptive compression techniques (APCA, differential encoding, SAX, LZW)	Simulations on real data show better energy efficiency than existing approaches	Improved energy efficiency in IoT networks	Prediction errors in dynamic environments, high compression overhead, less accuracy for heterogeneous streams
Deepa Devasenapathy et al. (2023) [3]	Grid-Based Synchronized Routing with Bayesian Compressive Sensing (GSR-BCS)	Exploits parameter correlations; optimizes grid size for data aggregation	16.93% improvement in data accuracy; 22.9% extension in network lifetime	16.93% better data accuracy; 22.9% longer network lifetime	Sensitive to grid size; computational overhead; less effective in dynamic/irregular environments
B. Lal, M. H. Conde et al. (2023) [4]	CS-based ECG monitoring with intrinsic encryption	Lightweight CS reduces sampling and encrypts measurements simultaneously	Strong compression and security; power consumption cut at edge	Energy efficient; strong compression and security	Reconstruction degradation under noise/arrhythmia; key management overhead; latency on low-power MCUs
Guan-Sen Dong et al. (2023) [5]	Deep Convolutional GAN (DCGAN) for vibration data reconstruction	Modified 1D symmetric U-Net generator; 1D classifier discriminator	Superior accuracy and speed vs. existing methods	High accuracy & speed; outperforms existing methods	Requires large paired datasets; GAN training instability; less robust under low data/high noise; generalization issues
Xiaoli Tang et al. (2023) [7]	CS-based Dual-Channel CNN for gearbox fault diagnosis	Combines thermal and acoustic MSB images; exploits sparsity for faster CNN training	99.39% diagnostic accuracy; outperforms single-channel methods	99.39% diagnostic accuracy; outperforms single-channel methods	Performance drops with noisy/low-quality data; sensitive to sampling rate; complexity in dual-sensor acquisition
C. Sureshkumar et al. (2023) [8]	Adaptive Adjacent-based Compressive Sensing (AACS) for WSNs	Uses sensor coordinates for sparse matrix; fuzzy logic-based forwarder selection	54.7% higher network throughput; 76.9% lower routing overhead; 44% less relative error	54.7% higher throughput; 76.9% lower routing overhead; 44% less error	Needs accurate location info; degrades in dynamic topologies; fuzzy logic overhead on resource-limited nodes
Xiaoling Huang et al. (2023) [9]	CS with Integer Wavelet Transform (IWT) + chaotic systems + RSA for image encryption	Chaotic initial values encrypted by RSA; chaotic & Hadamard matrices for measurement;	High normalized correlation; robust against plaintext attacks	Robust against known/chosen-plaintext attacks; imperceptibility	RSA overhead; dependency on chaotic parameter accuracy; scalability issues for large/real-time images

		info entropy-based initialization			
Alina L. Machidon et al. (2023) [10]	Survey on CS and deep learning integration	Explores design patterns for CS-DL pipelines; addresses heterogeneous devices	Provides guidance; identifies gaps for practical deployment	Practical deployment guidance; highlights research trends	Lack of benchmarks; hardware heterogeneity; robustness under distribution shifts; latency/energy tradeoffs on edge
N. Iqbal et al. (2023) [11]	Standalone lightweight CS for seismic data with DCNN reconstruction	Exploits sparsity for compressed sensing; DCNN for reconstruction without prior data stats	~30 dB SNR; compression gain of 16 on real-field data; outperforms existing techniques	Energy efficient; adaptable to diverse datasets	Requires sufficient DCNN training data; degradation under extreme noise; deep learning inference burden in field
Vinay Pathak et al. (2023) [15]	Hybrid WSN based on WBAN for biomedical data with CS	Achieves higher compression ratio and PRD; reduces consensus time and CPU usage	88.11% higher compression; 34.21% better PRD; 24% reduced consensus time; low CPU usage	Cost-effective; efficient data transmission	Degraded in high noise; needs stable connectivity; scalability issues
R. Gambheer and M. S. Bhat et al. (2023) [16]	CS for CCD and CMOS sensors with FPGA hardware implementation	New sampling scheme and sparsity-inducing transform; evaluated under various lighting	13% power saving; 15% memory saving; 25.76 dB PSNR for CCD in no-light; CMOS fails in no-light	Low-power embedded IoT imaging	CMOS sensor limitations; scalability & real-time issues not detailed
Z. Gao et al. (2023) [20]	Survey on CS-based grant-free massive access (GFMA) in communications	Reviews evolution of massive access paradigms; highlights challenges and future research	Identifies roadmap and gaps for GFMA	Comprehensive survey of massive access with CS	Hardware and algorithmic challenges; open research issues
R. K. Kaushal et al. (2024) [22]	EEANNCP: Energy-Efficient ANN-Based Clustering Protocol for WSN	ANN-based cluster head selection; energy-efficient clustering	Substantial energy conservation; extended network lifespan	Energy efficient; prolongs network lifetime	High computational cost
W. Wang et al. (2024) [23]	OS algorithm for node deployment in task-oriented WSNs using graph CS and RBM	Network partition into subnetworks; graph CS; Restricted Boltzmann Machines; brainstorm optimization	Reduced reconstruction errors; enhanced network performance	Efficient sensor selection and fusion	High computational cost
Xin Zhu et al. (2024) [25]	DCST layer replacing linear layers in multi-layer autoencoder	Trainable DCST filter; hard-thresholding sparsification;	Quality score improvements 2.00%–32.35% on gearbox datasets	Reduced parameters; improved reconstruction accuracy	Limited dataset training

		fewer parameters			
Di Xiao et al. (2024) [26]	MetaCSRC: meta-learning CS reconstruction in cloud	Adaptive sampling network on client; deep meta-learning convolutional network on cloud; local differential privacy	Excellent reconstruction speed and accuracy; enhanced privacy protection	Offloads computation to cloud; privacy-aware	Cloud dependence

III. NEURAL NETWORK APPROACHES FOR CS RECONSTRUCTION

Neural network approaches for Compressive Sensing (CS) reconstruction have evolved from conventional architectures to advanced deep learning-based solutions, offering significant improvements in speed, accuracy, and adaptability. Conventional CS reconstruction methods, such as Basis Pursuit, Orthogonal Matching Pursuit, and iterative shrinkage-thresholding algorithms (ISTA) [20], rely on optimization techniques grounded in mathematical sparsity priors. While effective in many scenarios, these methods are computationally intensive, sensitive to noise, and less adaptable to complex or heterogeneous IoT data. Deep learning-based reconstruction overcomes these constraints by learning non-linear mappings between compressed measurements and original signals directly from data, removing the need for hand-crafted priors. Convolutional Neural Networks (CNNs) have been widely adopted for CS due to their ability to capture local spatial features efficiently, making them particularly effective in image and sensor data reconstruction. Recurrent Neural Networks (RNNs), including LSTM and GRU variants [21], extend this capability to sequential or time-series data, enabling accurate recovery of IoT signals such as environmental, vibration, or biomedical readings [22]. More recently, Transformer-based models have emerged, leveraging self-attention mechanisms to capture long-range dependencies and contextual relationships within the compressed measurements, thus improving reconstruction quality in highly complex or structured datasets. Hybrid optimization strategies, such as deep unfolding, combine the interpretability of classical iterative solvers with the learning power of neural networks, mapping each iteration step into a trainable network layer for faster convergence and higher accuracy [23]. Additionally, learned sampling techniques integrate trainable measurement matrices into end-to-end architectures, optimizing both the compression and reconstruction processes simultaneously. This joint optimization ensures that the sampling strategy is tailored to the data distribution, maximizing reconstruction fidelity while minimizing the number of measurements. Together, these neural network-based approaches mark a paradigm shift in CS reconstruction, enabling real-time, energy-efficient, and highly accurate recovery for IoT applications across diverse sensing environments [24].

IV. INTEGRATION OF CS AND NEURAL NETWORKS IN IOT SYSTEMS

When Compressive Sensing (CS) meets Neural Networks (NNs) in IoT, it provides data transmission and reconstruction pipelines that address bandwidth constraints and also lack of computational capacity. Central to this integration are end-to-end architectures that jointly optimize sensing (compression) and reconstruction processes into a single framework. Such architectures eschew fixed measurement matrices and separate recovery algorithms in favor of trainable sensing layers working in tandem with deep reconstruction networks, thereby allowing the system to optimize sampling methods tailored to a data distribution or application [25]. This synergy tremendously reduces the maximum number of measurements required while maintaining or improving reconstruction accuracy. The corresponding adaptive and application-based framework further fine-tunes the CS–NN models based on domain requirements, that is, environmental monitoring, biomedical diagnostics, structural health, or industrial process control. Domain priors, sensor characteristics, or some specific noise profiles usually figure into application-aware frameworks, thus ensuring robustness under varying operating conditions. However, the deployment environment itself counts a lot [26]. The choice of implementing on the Edge, Fog, or Cloud introduces a set of trade-offs with respect to latency, energy consumption, and available processing power. Edge computing shall run lightweight CS–NN models in IoT nodes or at gateways minimizing transmissions and enabling almost real-time analytics. Fog computing pushes processing one layer further into the network to provide a balance between computational load on the devices and centralized servers, thus reducing latency involved. Perhaps cloud implementations can assume complex computational tasks involved in reconstruction, enabling more advanced deep learning architectures and large-scale analytics while releasing the IoT devices from heavy computation [27]. This choice also depends on how large the data are, privacy requirements, available infrastructure, and latency constraints imposed by the application. Together, the tight integration between CS and neural networks at levels of end-to-end, adaptive, and distributed computing paradigms has the potential to revolutionize the scalability, energy efficiency, and resilience of real-world data transmission challenges for IoT systems [28].

V. APPLICATION DOMAINS

- **Remote health care monitoring:**

CS–NN systems transmit biomedical signals, e.g., ECG, EEG, and vital signs from wearable or implantable devices, with minimized bandwidth while preserving diagnostic quality. Neural networks maximize reconstruction quality, even under noisy or lossy channels. This has direct implications in telemedicine for continuous, real-time patient monitoring while requiring minute energy consumption on the device itself.

- **Smart Grids and Industrial IoT:**

In smart grids, CS reduces the amount of high-frequency sensor and meter data, while NNs reconstruct and predict system states for forecasting demand and fault detection. Industrial IoT applications gain from mitigated overhead cost of communications and accurate recovery of vibration, thermal, and process signals. This mixture brings operational expense down and downtime up [29].

- **Environmental and Structural Monitoring....**

CS enables sparse sampling for large-scale sensor networks that measure parameters such as air quality, temperature, soil moisture, or structural vibrations. NNs reconstruct missing or compressive data with precision so that executive-level decisions can be made in cases of anomalies or structural degradation on time. Thus, remote scalable monitoring in an energy-constrained environment is made feasible.

- **Intelligent Transport and Smart Cities:**

Vehicle, traffic, and infrastructure sensors produce enormous data streams that CS compresses for low-latency transmission to control centers. [30] NNs reconstruct and analyze data for congestion prediction, accident detection, and infrastructure planning. Such systems permit better mobility, safety, and sustainability within the city.

VI. CONCLUSION

Combining Compressive Sensing with neural networks depicts a cutting-edge avenue in IoT data transmission and reconstruction, thereby strategically addressing bandwidth and energy consumption issues along with latency constraints and still guaranteeing a high reconstruction accuracy. In CS, the transmission is reduced by exploiting the sparsity of signals, while neural networks recover effectively, adaptively, and quickly in the presence of noise and data loss. State-of-the-art research spells considerable gains in efficiency and scalability, especially when domain-specific priors such as sparsity or low rank are embedded in learning architectures. Nevertheless, many issues remain of concern, such as large annotated datasets, heavy computation, and model interpretability for safety-critical IoT applications. In addition, most of these solutions are not compatible with dynamically changing network conditions, heterogeneous data types, and extreme resource constraints at the edge. Future research should investigate lightweight and adaptive neural architectures, transfer learning for limited data settings, and hybrid optimization strategies balancing performance with computational cost. Standardized benchmarks and operating studies will serve as a bridge to close the gap between theoretical potential and real-world application. Filling these gaps will propel CS–neural network frameworks as one of the fundamental enabling technologies for next-generation realization of IoT-based networks toward the realization of reliable, secured, and intelligent data-driven decision making in various application domains.

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