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Review article

Data compression techniques in IoT-enabled wireless body sensor networks: A systematic literature review and research trends for QoS improvement

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A B S T R A C T

The rapid proliferation of Wireless Sensor Networks (WSN) and other linked devices has given rise to several notions that blend the virtual and real worlds. A vision in which billions of intelligent objects are joined together to provide connectivity for anything, not just everyone. The data quantities gathered and transferred will expand significantly as the number of participants in the future Internet of things grows, rendering the traditional data gathering and processing methods impaired. As a result, the volume of data should be decreased so that decision-makers can mine and evaluate such massive amounts of data.

In the Internet of things (IoT), dedicated to healthcare, various data may be collected from diverse body sensors, ambient sensors, and other data sources such as cameras, voice recorders, and so on. The processing, synchronization, aggregation, and compression of these heterogeneous data are crucial tasks for providing accurate real-time healthcare services. Energy efficiency imposes a strict limitation on wearable WSNs since wireless transmission consumes a large amount of power. Several compression approaches have been presented in the literature to tackle the issue of energy consumption. These approaches can be divided into three categories: communication compression, sampling compression, and data compression. Data compression mechanisms should lessen the data length and compress data using fewer resources. The peculiarities of the data should be addressed during the compression process. Irrelevant data might be eliminated depending on the user's capacity to use or comprehend such data. Data compression techniques are extensions of compression algorithms and data aggregation methods. Data compression algorithms play a substantial role in WBSNs as the sensors in WBSNs have restricted memory and low battery power. Furthermore, data should be transmitted quickly and lossless to provide real-time services. Despite the availability of many review papers on data compression techniques in wireless sensor networks, there is a lack of surveys that identify gaps in existing data compression techniques, highlight areas for future research, and provide a comprehensive analysis of the current trends and practices in the IoT-enabled WBSN, primarily the healthcare domain. This paper will fill the gap, provide a clear analysis, and review data compression mechanisms in IoT-enabled WBSN. We outline the main requirements for IoT-enabled WBSN, existing methods, and state-of-the-art solutions. Furthermore, we evaluated the performance of the current techniques in the literature based on several criteria such as compression ratio, complexity, energy saved, minimized transmission, energy consumption, Net energy saved, energy efficiency, reliability, and scalability. More importantly, we discussed how data compression

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methods could be a crucial enabler in solving many IoT problems. The paper also identifies open research problems and challenges for IoT-enabled WBSN.

Introduction

With the emergence of mHealth and eHealth, the role of technology in healthcare has grown significantly. Many sensors are fitted to patients to constantly track their health using a variety of behavioral, physiological, and environmental parameters. One of the pivotal inventions that benefit contemporary healthcare applications is smart and wearable devices. Such wearables can collect data on an unprecedented scale due to refinements in the Internet of Things (IoT).

A Wireless Sensor Network (WSN) is a distributed network, including autonomous and scattered sensor nods. Every sensor node makes up of a power source (usually a battery), a transceiver (communication component), a microcomputer (computing component), and several sensor(s) depending upon the area of application [17,63,108]. Technology for wireless sensor networks (WSNs) is essential to the widespread and effective implementation of the Internet of Things (IoT) [40]. WSNs can be employed for diverse applications such as national surveillance and defense, natural disaster relief, environmental monitoring and seismic sensing, biomedical health monitoring, industrial monitoring, agriculture monitoring, animal monitoring, and military target tracking [17,71]. WSN is an illustration of communication between people and machines [110]. WSNs are usually deployed on a short or extensive range (based on the applications and requirements) to gather the necessary data from sensors. In healthcare and biomedical applications, sensor nodes are placed within, near, or on the human body to provide uninterrupted and continuous monitoring of vital human signs, such as blood oxygen, temperature, blood pressure, blood sugar level, electroencephalogram (EEG), electrocardiogram (ECG), and heartbeat. Generally, this sort of WSN is referred to as Wireless Body Sensor Network (WBSN). The conventional wired connections in monitoring healthcare applications could be problematic and awkward for the patient wearing it because it hinders the mobility of a patient. Hence, in a healthcare requirement where a person should be monitored continuously and concerned with mobility, WBSN can be an effective solution.

Wireless Body Sensor Networks (WBSNs) facilitate the ability of enormous wellness and healthcare applications from ongoing vital signs and biochemical parameters monitoring of patients. Indeed, WBSNs are evolving as one of the most significant contributors to big data in this era. Such networks enclose many sensors deployed in human body to transmit periodic data, about the body's vital signs, to a sink node. This technology enables a variety of novel and intriguing applications in the healthcare and medical fields, including distant patient monitoring, examining hospital and elderly patients, and monitoring patients with chronic diseases, in which the vital signs of patients are constantly monitored to oversee their healthiness condition and deliver therapy in the event of an emergency [109].

One of the critical challenges in WBSNs is energy efficiency, as wireless transmission consumes a large amount of energy [63]. WBSNs nodes, in particular, should be small to maximize wearability and decrease invasiveness, and they should have a long battery life to allow for extensive data collecting. Such criteria are critical because the capacity and the size of the battery is the primary factor in establishing the dimensions of a WBSN node [59]. One of the most straightforward methodologies to minimize energy is to limit the number of bits that need to be transmitted [76]. WBSN applications gather a tremendous amount of data daily; most of such data is useless and redundant. As a result, minimizing the amount of redundant data reduces network power consumption while delivering cleansed data to data scientists [53]. Indeed, the power consumption in a network is associated with the quantity of data transmitted [96].

Data compression could be considered a method to decrease energy consumption. Some data reduction mechanisms, such as sampling, adaptive, aggregation, communication compression, and data compression, seek to lower the transmitted data quantity [35]. Communication compression aims to reduce the number of packet receptions and transmissions [76]. Data compression transforms a data stream into another one that can be represented using fewer bits [53]. Data compression methods can be deployed on sensor nodes or intermediate nodes (cluster heads) to compress the gathered vital signs before transmission to extend the lifetime of a WBSN [55]. As a result, lowering transceiver unit power consumption is believed to be an efficient way of reducing the WBSN node's energy consumption. Compression is typically more beneficial if it is applied at cluster heads. Cluster heads gather data across time; consequently, the temporal and spatial correlation can be employed in compression. Decompression should be conducted at the base station (or sink) to restore the original data. Data collection at the sink node may be delayed due to compression techniques. A delay occurs because the cluster head should retain the data before the aggregation and compression process. If a lossy compression method is applied, the compression-based approach may impact the accuracy of the gathered data. Unfortunately, traditional compression algorithms have considerable complexity. Thus, they are designed specifically for PCs and servers to get adequate storage.

Many papers have reviewed data compression mechanisms in WSNs and IoT [17,49,51,76,77,86,92,101,108]. However, there is a lack of dedicated studies that review the data compression mechanisms in IoT-enabled WBSNs, especially in the domain of healthcare.

This paper presents a comprehensive literature review of data compression techniques of IoT-enabled WBSN systems, along with a critical analysis of each mechanism. This study shows an in-depth comparison of the methodologies, a systematic assessment of the selected articles, and recommendations for further research. This review aims to highlight the motivations, obstacles, and recommendations regarding the data compression mechanisms in IoT-enabled WBSN and determine the gaps in this research direction, representing a new research direction in this area.

The rest of this paper is structured as follows. Section 2 describes the related work. Section 3 describes the methods. A Background and basic concepts are presented in section 4. Section 5 explains data compression in IoT-enabled WBSNs. Section 6 represents the reviewed data compression techniques in IoT-enabled WBSN. Section 7 involves an in-depth comparison and performance analysis. Section 8 presents a discussion and analysis. Open research issues and future directions are presented in section 9. Finally, Section 10 summarizes the conclusion.

Related works

Several studies reviewed the data compression techniques in WBSN. In a survey conducted by Raju et al. [75], several lossless data compression mechanisms (like Huffman, Lempel Zev Welch (LZW), and Run Length Encoding (RLE)) were evaluated on data from wearable devices and compared in terms of savings percentage, compression time, compression ratio, and compression factor. They also assessed a data deduplication method used for Low Bandwidth File Systems (LBFS), named the "Two Thresholds Two Divisors (TTTD)" algorithm, to decide if it could be applied to WBSN data. However, their study focused on lossless data compression techniques and ignored reviewing lossy data compression mechanisms.

Azar et al. [12] analyzed the performance of three resource-aware data compression schemes presented in recent studies: Discrete Wavelet Transform lifting, Differential Pulse Code Modulation, and Lightweight Temporal Compression scheme. Their findings revealed that the Lightweight Temporal Compression lossy approach achieved a better compression ratio on smooth data with negligible data loss. Nonetheless, the data reconstruction error was raised when the data got noisy, resulting in the loss of several critical features. On the other hand, the lossless discrete Wavelet Transform is lifting, and differential Pulse Code Modulation algorithms produced consistent performance. They reduced data by 35% to 50%, with a slight preference for the differential Pulse Code Modulation over the discrete Wavelet Transform lifting scheme. However, their study reviewed only three losses and lossy data compression techniques and ignored other data compression techniques.

Methods

This paper presents a clear overview with a systematic literature review of data compression techniques of IoT-enabled WBSN systems, along with a critical analysis of each mechanism. A systematic review is a direct approach to evaluating the scope of coverage of a literature body on a given subject, clearly indicating how many articles and books are available and summarizing the synopsis of its emphasis [62]. Language, document type, and publication year were among the criteria the authors initially chose as restrictions and recommendations in the search process for article journals in databases. The search strategy by the authors utilizing a database is better organized and applied as a suitable basis for their investigation. According to Xiao & Watson [104], there is no comprehensive and flawless electronic database, and a combination of at least two databases would be sufficient for the study. Accordingly, this study used two academic databases, Web of Science (WOS) and Scopus. This study aims to gather as many relevant details as practical from each part of the literature, including analyses, variables, and methodologies.

Systematic review process

We use the systematic literature review process based on the PRISMA method to provide a comprehensive and exhaustive synthesis of the research topic. The primary purpose of this systematic review is to justify the relevance of the following research questions:

(a) What are the research challenges in applying data compression techniques with WBSN?
(b) What are the indicators frequently used to assess the effectiveness of data compression in delivering a real-time pervasive healthcare system?
(c) What are the state-of-the-art data compression mechanisms implemented in IoT-enabled WBSNs?
(d) What are the research directions for QoS enhancement?

The following keywords were used: Data compression, Internet of Things, Wireless Body Sensor Network, and Healthcare System. Following several adjustments, the following search phrases were created: (combination of data compression and Wireless Body Sensor Networks), (IoT-enabled Wireless Body Sensor Networks), (IoT-enabled Wireless Body Area Network), and (Data compression IoT-enabled Wireless Body Sensor Networks).

This study used the IEEE, Sensors, Springer, and Science Direct (Elsevier) databases. We have applied the same search terms across all four search indexers, employing their advanced search methods. Only the articles from journals and conferences have been explored. The selected articles must have been published between 2004 and 2022. The article must contain the terms "Data compression" and "WBSN." The unselected and selected papers were also cross-checked to ensure that no article had been unintentionally excluded or included.

The search strategy was applied to the sources. Initially, the titles and abstracts of all recovered publications were reviewed and examined to the end. Depending on the research questions, the material is collected from the most recent batch of publications. Eventually, a form is created with the following details: the paper's title, authors, publisher, keywords, mechanisms, year of publication, and any upcoming works.

Review management and articles classification

Between 2004 and 2022, we found 22, 11, 7, 4, and 16 studies in IEEE, Science Direct (Elsevier), Sensors, Springer, and other journals, respectively, resulting in a total of 60 papers. After the initial screening, 31 papers were excluded as they were focused on delay, routing, telemonitoring, and aggregation of data in WBSN, which does not directly represent the data compression in the IoT-based WBSN approaches. The classification of the selected papers by different publishers is shown in Fig. 1. The distribution of the obtained papers in each publisher, depending on the publication year, is shown in Fig. 2. It shows the related selected articles from 2004 to 2022 distributed as follows, 16, 2, 2, 1, and 8 in IEEE, Science Direct (Elsevier), Sensors, Springer, and others, respectively, resulting in a total of 29 articles.

Background and basic concepts

Internet of Things (IoT)

IoT refers to an intelligent universe of entities capable of interacting with each other, where each entity is connected to the Internet [2]. In 1999 Kevin Ashton coined the term IoT for the first time in supply chain management [57].

The concept of the IoT promotes the prospect of data exchange, integration, communication, and aggregation between the objects in our environment [1]. To facilitate the communication and management among these objects, the essential IoT technologies, including devices, storage systems, RFIDs, sensors, and wireless communication, are updating and advancing daily. In this regard, the progress of the utility of wireless sensor networks in IoT as processing (global sensor network), sensors (wireless sensors), wireless operators, communications (wireless networks), and locating (wireless sensors with locating capability) has been taken place to present and receive a remarkable service automatically [111].

Wireless body sensor networks

A wireless body sensor network (WBSN) is a popular technology for patient tracking in IoT-enabled healthcare technologies, such as eHealth and mHealth. In 1996, Zimmerman proposed the idea of a body sensor network, later defined by IEEE 802.15.6. [21].

WBSN is a sort of WSN comprising physiological parameter sensors set on the body surface, in the human body, or around the body. Such sensors are commonly wearables or occasionally implanted into the patient's skin, and they can intercommunicate with the network [57]. WBSN in the domain of medicine is not just a new kind of disease monitoring, prevention solution, and healthcare services but even a significant element of the so-called IoT. The primary purpose of e-health WBSN in IoT is to deliver incorporated ubiquitous computing software, hardware, and technology platform for wireless communication. E-health WBSN is an essential requirement for the forthcoming evolution of ubiquitous healthcare monitoring applications.

Data compression in IoT-enabled WBSNs

Overview

Recent studies have presented many compression approaches to address the power consumption issue in WBSNs. These approaches can be categorized into three classes: communication compression, data compression, and sampling compression [98]. Communication compression aims to reduce the number of packet transfers and receptions [98]. Sampling compression seeks to reduce the number of sensing operations while maintaining an acceptable level of data loss [33]. Data compression converts one data stream into another one that may be represented with fewer bits [97]. This paper will focus on reviewing data compression mechanisms in IoT WBSNs.

Data compression is a valuable technique for reducing the quantity of data required to be conveyed before transmission. The underlying concept behind data compression is to eliminate irrelevant and redundant data. It compactly conveys the data without

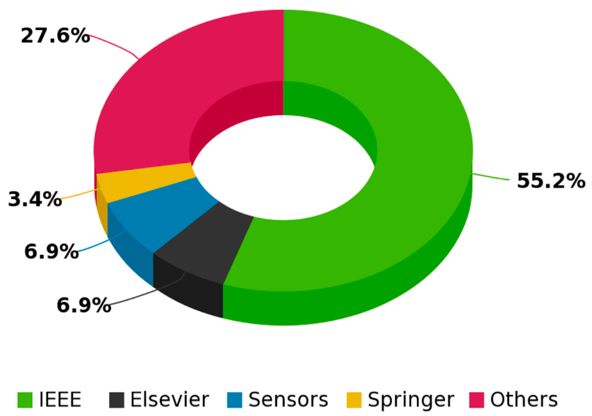

Fig. 1. Classification of the selected papers by different publishers

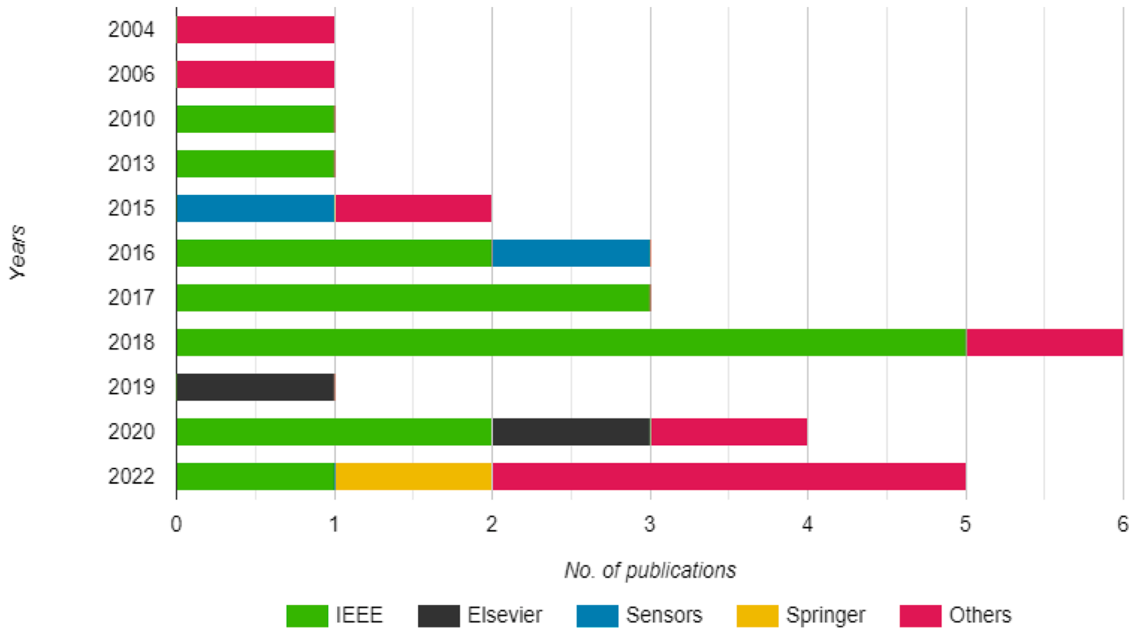

Fig. 2. Distribution of the selected papers over time in the selected publishers

sacrificing data quality to some extent. Data compression technologies are classified into two categories: lossless compression and lossy compression. The primary distinction between the two compression mechanisms is that lossless compression recovers and rebuilds the data in its original form after decompression. Whilst lossy compression does not restore data to its original shape after decompression. In the latter approach, some data features may be lost during data compression. Lossy compression reduces the quantity of information in the data, whereas lossless compression increases the density of information in its representation.

Applications of data compression in IoT-enabled WBSNs

IoT can be viewed as a convenient platform for a wide range of applications, including industrial and medical applications. IoT may be seen as a viable platform in the context of Industry 4.0, allowing the creation of big industrial systems that connect many intelligent sensors and subsequent data collecting for analytic applications. [25]. The large volume of data generated by IoT devices entails significant storage and transmission costs. Communication systems are critical infrastructure for IoT objects, and even with the advent of low-power networks [72], these systems are responsible for a large portion of device energy consumption. This consumption becomes a problem due to the power constraints of various IoT systems [17,39]. A huge dataset used by industrial systems necessitates additional processing resources and execution time. To make matters worse, the vast amount of sensed data that should be stored in the cloud and fog comes at a considerable monetary cost, as these systems often charge proportionate amounts for the stored data [40]. Data compression technologies are a suitable way to handle these challenges specially in the industry domain.

IoT has a plethora of applications in healthcare, such as intelligent beds to detect the occupancy, track patients and equipment inside the healthcare organization [58]. IoT-enabled WBSNs have emerged increasingly in recent decades, enabling pervasive healthcare by performing continuous human wellness monitoring and diagnosis using several wearable sensors. [44,9]. The bio signals obtained by these wearable sensors, such as photoplethysmography (PPG), respiratory or heart rates (RESP), and electrocardiogram (ECG) [41,58], can be used for well-being management, disease diagnosis, and elderly care [6]. As a result, reduced power consumption becomes a significant problem in continuous data collection with limited battery life. Most of the energy consumed by sensor nodes is consumed by wireless data transmission [46]. Data compression has long been investigated historically, and it is now gaining more attraction as a low-power data transmission method in wearable devices.

In this context, data compression methods are crucial in meeting scalable storage requirements, energy reduction, and communication infrastructure, becoming substantial approaches to managing a massive amount of generated sensed data by IoT-enabled WBSN systems.

Security and privacy challenges of data compression in IoT-enabled WBSNs

IoT in healthcare delivers personalized services, i.e., customized and fast access to healthcare systems, which was previously unthinkable. Both healthcare and technology equipment collaborate in these applications to offer a broad range of services. Such advancements in this arena are revolutionary, but they must be cautiously adopted due to the challenges posed by health-related data security, privacy, and sensitivity [7]. Upstream transmission of compromised data devastates the underlying data compression techniques and degrades their performance [83]. Furthermore, transmitting compromised compressed data exposes the underlying networks to various security threats, including sinkhole, Sybil, DoS, eavesdropping, denial of service (DoS), and sleep deprivation attacks [56,68]. These threats remain challenges because of the field's rapid development and the rising quantity and complexity of potential hardware and software vulnerabilities. Moreover, confidential and sensitive healthcare data, such as genetic data, electronic medical records, family history, and personal information, should be kept confidential. 72% of malicious traffic was projected to target healthcare data [48]. As a result, it is critical to secure such data from attackers by implementing security and privacy policies, both virtually and physically [56,91].

Security issues, such as access control, verification, authorization, privacy, data storage, system configuration, and management, are also considered as prime security challenges in an IoT-enabled WBSN [38,102]. For example, wearable sensors and smartphones contribute to a worldwide connection digital environment that facilitates life by being flexible, sensitive, and responsive to human requirements. Unfortunately, security and privacy cannot be assured. Users' privacy may be compromised, and the user's data may be leaked if the user signal is interrupted by an attacker. This issue should be addressed to ensure user confidence in terms of privacy and control over personal information. Moreover, an attacker can exploit shared memory technologies to gain access to unauthorized content, such as sensitive data and encryption keys [91]. Personal data contains sensitive information, as health record data can be lost or can be leaked. If login credentials are lost or leaked can lead to attackers gaining access to vital areas of services and could potentially compromise confidentiality, integrity and availability [38,84].

Encryption is required in scenarios involving highly sensitive information transit. In some cases, it may be highly advantageous to compress the data securely for the previously mentioned benefits. Because compression and encryption simultaneously can compromise data confidentiality, it is becoming more common for systems to compress parts that do not contain sensitive information [85]. Nevertheless, even if a specific technology, such as Nginx, provides the option to compress only a portion of the data being trafficked [93], this capability cannot be used by many IoT applications because user information is used on practically every page. Thus, the common factor is applying encryption after compression. According to this principle and considering the possibility of an attacker injecting malicious code even before compression and encryption processes, exploiting Side-Channel compression attacks becomes feasible. Therefore, even considering the increasing presence of data compression in IoT applications, its use with encryption is not the best choice. Developing energy-efficient and lightweight data compression techniques that maintain robust data privacy, confidentiality, and security is an intriguing subject for further investigation.

Impact of data compression on data analytics and machine learning algorithms in IoT-enabled WBSNs

Data compression can significantly impact data analytics and machine learning algorithms in IoT-enabled WBSNs. WBSN sensors produce enormous volumes of data that monitor human physiological signals. Compression techniques can minimize the quantity of data that has to be transferred, processed, and stored, allowing quicker and more efficient data processing.

Several studies had found that the classification accuracy and the performance of the machine learning algorithms did not degrade when they trained using the features extracted from compressed data. For example, Azar [11] indicates that by lowering the quantity of the data and the number of extracted features from the compressed data, machine learning algorithms can process the data more quickly and with fewer computational resources. Thus, the overall performance of the algorithms can be improved, resulting in better outcomes, faster data processing, and more effective decision-making [17]. This is especially valuable for applications like remote monitoring, anomaly detection, and predictive maintenance, where timely and accurate analysis is critical. In another study conducted by Barman et al., [18] the impact of compression on the performance of machine learning algorithms and data analytics in IoT-enabled WBSNs was evaluated. They found that the lossless compression methods can improve the accuracy of data analytics and lead to more accurate predictions. [18]. According to their study, this is due to the ability of compressed data to minimize noise and other artefacts caused during data transmission and storage. The authors in [29] believe that, with appropriate choice, data compression can dramatically decrease the quantity of transferred data with limited impact on machine learning methods. Moreover, a trade-off between compression ratio, error bound, and prediction accuracy should be considered.

However, some studies [65,36] indicated that compression may negatively impact the performance of machine learning algorithms and data analytics. For instance, compression can introduce distortions or noise in the data, which may reduce the accuracy of the machine learning models [65]. Another negative impact of compression is that it increases the complexity of data analysis. Due to the lower quality of the data, machine learning methods may struggle to discover patterns and make predictions while analyzing compressed data. This can result in longer processing times, increased complexity of data analysis, increased transmitted data points, and loss of data fidelity, leading to reduced system efficacy and accuracy [36].

One of the prime challenges of implementing data compression in WBSNs is to strike a balance between data quality, compression rate, and desired algorithm performance and accuracy level. Excessive compression rates may lead to a loss of information, resulting in erroneous data analysis and prediction [106]. On the other hand, meagre compression rates can result in reduced network throughput and increased power consumption.

Impact of network topology and routing protocols on the performance of compression techniques in IoT-enabled WBSNs

The performance of compression techniques in WBSNs is influenced by various factors, including network topology and routing protocols. Network topology refers to the way in which the sensors are interconnected to form a network, while routing protocols govern the way in which data is transmitted between sensors.

The network topology determines the structure of the WBSN and the communication paths between the sensor nodes and the sink node [17]. Designing an appropriate topology for WBSNs is critical for network reliability and energy efficiency [1]. Different topologies, such as mesh, star, and hybrid topologies can significantly affect the performance of compression techniques. According to the study in [88], a star topology, where all nodes communicate directly with the sink node, can lead to increased energy consumption due to long-range transmissions. Their results show that the relation between the compression rate of the algorithm and nodes consumption energy is not linear. For compression rates around 85%, the network lifetime is tripled. Since the damping is minimized proportional to the distance between the transmitter and the receiver, power consumption can be minimized by designing a topology with a large number of short-range hops instead of a smaller number of long-range hops [1]. As a result, the choice of network topology can have a significant impact on the performance of compression techniques in wireless sensor networks (WSNs). A well-designed network topology can lead to better compression ratios, lower energy consumption, and improved data quality.

Routing protocols are responsible for determining the optimal path for data transmission from the source node to the sink node. Different routing protocols, such as Ad-hoc On-demand Distance Vector (AODV), Destination-Sequenced Distance Vector (DSDV), and Dynamic Source Routing (DSR) [44,45], have different routing metrics that can impact the performance of compression techniques [45]. The goal of routing is to ensure that data is transmitted efficiently and reliably, with minimal delay and energy consumption [73]. Depending on the routing protocol used, different data compression techniques may be more or less effective. For example, some routing protocols, such as data-centric routing, may require transmitting all data to a central node [66], while others may allow data to be transmitted directly between nodes. In the former case, data compression techniques such as lossless compression may be more effective, since they do not introduce any errors into the data. In the latter case, lossy compression techniques may be more appropriate, since they can reduce the amount of data transmitted while still maintaining acceptable levels of accuracy. Furthermore, the choice of a routing protocol can also affect the overall efficiency of the WBSN. For example, some routing protocols such as LTR [15], LTRT [94], and ETPA [67] may be designed to minimize the number of hops required to transmit data between nodes, while others [105,61,30,5] may prioritize energy efficiency. Depending on the goals of the WBSN, different routing protocols may be more appropriate.

Review of data compression mechanisms in IoT-enabled WBSNs

This section describes the main state-of-the-art data compression techniques, their advantages, differences, and shortcomings in IoT-enabled WBSN.

Lossless data compression techniques in IoT-enabled WBSNs

Several lossless compression mechanisms have been used in IoT-enabled WBSN, like Transform-based Compression, Huffman Encoding, Dictionary-based Compression, Data Chunking and TTTD, and Run Length Encoding. The aforementioned lossless compression mechanisms are comprehensively described and reviewed below.

Transform-based compression techniques

Transform-based compression techniques such as Discrete wavelet transform (DWT) and Wavelet Transform decompose a given signal into several sets, each of which is a time series of coefficients that describe the signal's temporal evolution in the associated frequency band [52]. DWT is a mathematical transformation, which splits the signal into fine-scale data, referred to as detail coefficients, and rough-scale data, referred to as approximate coefficients [89]. The primary benefits of DWT are the time-frequency localization and multi-resolution representation feature for signals. The original time-series sketch can generally be reconstructed using the low-pass cut-off decomposition coefficients; the details are modelled by applying the middle-level decomposition coefficients; the remainder is usually treated as irregularities or noise [86]. With its hierarchical coefficients, DWT can encode the higher resolution of the original time sequence. Moreover, DWT may be computed in linear time, which is useful when working with massive datasets. However, standard techniques such as DWT do not work well when data are not correlated.

Because an image is a two-dimensional signal, the two-dimensional counterpart of DWT is used. This involves low and high filters to the sample lines, row by row, and then transferring the result to the columns using the same filters. As a result, the image is split into non-overlapping multi-resolution sub-bands like LL, LH, HL, and HH. On the first level, an image is divided into four sub-bands, and these four sub-bands are then separated into two classes of DWT coefficients. The coarse-scale DWT coefficients are represented by LL, whereas the fine-scale DWT coefficients are represented by HL, LH, and HH. The LL contains low-pass data, whereas the other sub-bands include high-pass data (diagonal, vertical, horizontal, and orientation). The quantization is performed next to lower the number of bits necessary to display an image. Following that, entropy encoding is carried out [26,69]. Encoding in DWT is carried out using an arithmetic encoder. Unlike other coder schemes, this one entirely encodes the original message and accepts it as a single integer [86].

Several studies applied DWT in their compression schemes. For instance, Azar et al. [13] proposed a lossless compression mechanism based on the DWT expanded with polynomial interpolation. The proposed mechanism aims to decrease the size of the gathered data to be transmitted. The proposed method is a lossless transform method that does not need complicated mathematical computations and additional memory space. The DWT was applied to transform the duplicative samples in the spatial domain to de-correlated coefficients in the time-frequency domain, where the initial samples are represented and compressed with fewer coefficients.

A mechanism referred to as Lifting Wise has been presented by Aboelela [4]. The LiftingWise technique is a modified version of the original DWT Lifting Scheme (LS) algorithm that can be used for any dataset regardless of its size. In contrast, the original LS is used for a signal of length 2n. Their approach processes data from objects deployed in a monitoring environment using Haar wavelets. The findings demonstrated that their approach reduced the number of bits in gathered data while considering the restricted resources of sensors.

Hussein et al. [44] proposed an adaptive compression algorithm based on compressive sensing (CS) and DWT techniques to compress EEG signals. The proposed approach uses the receiver feedback signals to swap among the two techniques (CS and DWT) depending on the hardware specifications and the application demands to build an energy-efficient and low-complexity system. The suggested approach reconfigures the compression ratio of the used compression paradigm at run-time based on the channel condition, reducing overall distortion.

Huffman encoding algorithm

Huffman encoding is a bit-encoding method that assigns smaller bit strings to more frequently occurring symbols [75]. Huffman may need a lookup table or an array of frequencies per character in the dataset as input. A test dataset can be used to compute the frequency. Huffman codes are the codes created by this method. ASCII codes store characters in files, each character taking up precisely one byte. This code has a defined length. The Huffman algorithm allocates codes to characters based on the number of repentances in the file, giving the shortest code to the most frequently used characters [39].

Huffman algorithm has been applied in a study by Khani and Shirmohammadi [50]. Their study proposed a compression method named "Ultra Energy Efficient Lossless Compression (UEELC)". UEELC applied several phases to convert each string to a small code. Every input string is transformed to its ASCII counterpart in the first step, and the yielded ASCII code is restored to its binary code. After that, the number of ones and zeros in the generated binary code is calculated to pick an ideal traversal. In the last phase, the binary code is traversed optimally, resulting in the compression method's output. Their findings showed an improvement in energy consumption by 2.7% compared with other state-of-the-art techniques.

Chen [24] proposed a design of a lossless EEG compression circuit to improve the effectiveness of EEG signal transmission via WBAN. Their design was built based on a tri-stage entropy encoder, a voting-based scheme, and an adaptive fuzzy predictor. The tri-stage entropy encoder comprises "two-stage Golomb-Rice" encoders and Huffman with a static coding table with multiplexer components and a simple comparator [24]

Run length encoding algorithm

Run-length encoding (RLE) is a relatively naive data compression method where data sequences (referred to as a run, a repeating string of characters) are saved in two elements: the count and a single data value instead of the original run [39]. In other words, RLE is a method that codes symbols/characters replicated in a sequence only once. For example, the input of "WWWWWWBBBWWWB" generates an outcome as "6W3B3W1B" when passed via the RLE algorithm. RLE works well if an input has many repeated characters, like a line graph image where the color of pixels in the background is the same [75].

In WBSNs, RLE can be employed to improve the bit-compressing rate of biomedical signals. Such an approach got some echo in the literature as the study conducted by Sarma and Biswas [80]. Their study presents a lossless compression scheme deepening on Golomb Rice and RLE encoding to improve the bit compressing rate. The proposed scheme was tested on the MIT-BIH arrhythmia database, attaining a compression ratio of 2.91. The compression method starts by calculating the first derivative from ECG signals. From the calculated first derivative samples, an 8-packet size is chosen. The packet size is calculated by determining and computing the mean value of several ECG parts, such as the high-amplitude QRS zone. The mean of the chosen sample size may contain fast fluctuations in amplitude induced by noise. To further minimize the amplitude, a division process is conducted by picking the appropriate divisor. The proper divisor is chosen by subtracting the mean of every packet from the first derivative. Their findings achieved a 6% reduction of the transmission power compared with uncompressed ECG for a 1-minute transmission period.

Dictionary-based compression techniques

Many lossless compression techniques have been proposed for text data. One prominent example is the Lempel-Ziv Welch (LZW) algorithm, which generates a dictionary dynamically for encoding new strings depending on formerly disclosed strings [101]. The LZW algorithm was proposed in 1984 by Terry Welch. LZW was enhanced ground on the L78 and LZ77 compression algorithms [47]. Without prior likelihood data, the encoder creates an adaptive dictionary representing varying-length strings. The same dictionary is dynamically constructed in the encoder by the decoder based on the incoming code. Some characters/symbols frequently appear together in text data. These characters can be memorized by the encoder and represented in a single code. According to Badshah et al. [14], LZW converts a sequence of characters from a lookup table to a code. The lookup table comprises 0-255 codes that are first employed to represent single bytes, and when LZW scans the data, it adds more codes and symbol sequences.

The LZW technique is computationally simple and has no transmission overhead. Because both the transmitter and the receiver contain duplicate initial entries in the dictionary, and all new entries can be derived from the input data stream and the existing dictionary entries, the receiver may create on the fly the whole dictionary while receiving the compressed data [19]. Based on the above observation, the work conducted by Sadler and Martonosi [79] creates an S-LZW algorithm for data compression in WBSNs. S-LZW points out that the decoder should receive all prior items in the block to decode a dictionary item in the LZW algorithm. Nevertheless, S-LZW recommends breaking the data stream into tiny, independent blocks because packet loss is prevalent in WBSNs. As a result, if a packet is missed due to interference or collision, S-LZW may ensure that this packet only impacts the packets following it in its block. Their study outcomes suggest adopting a dictionary with a length of 512 entries to fit the short memory of sensor nodes. Moreover, they also recommend compressing the sensor data into blocks of 528 bytes to earn a better performance.

Data chunking and TTTD algorithm

Data Chunking is mainly employed in data deduplication systems to minimize storage costs by deduping data in files. The algorithm divides data into smaller pieces known as 'chunks' during data chunking. After that, the chunks are fingerprinted and utilized to detect other duplicates. The most common way of data chunking, known as "Fixed size chunking", is to divide the input into equal, fixed-size chunks. Nevertheless, data chunking has several significant drawbacks, such as the "Boundary Shift problem" and considerable variation in chunk size [75].

Hybrid lossless data compression techniques

Combining multiple lossless methods carried much attention in scientific research to enhance the performance and the compression ratio. Raju et al. [75] pointed out that combining multiple losses algorithms (TTTD with Huffman) leads to a substantial reduction in transmitted sensor data and a significant saving on transmission power. Their study proved that implementing Huffman and TTTD in succession enhances the compression factor significantly against both Huffman and TTTD. Two WBSN datasets were used for performance evaluation. Their proposed approach outperformed all individual methods but with a slight boost in compression time.

Harb et al. [37] proposed a data compression mechanism by utilizing the temporal correlation in the gathered data. The proposed technique is designed depending on the "simple and computationally efficient 1-D DWT" through the "lifting scheme" and the "Differential Pulse Code Modulation (DPCM)".

Ghosh et al. [31] proposed a real-time encoding system that implements wavelet coefficient approximation and iterative thresholding for sparse encoding of bio-signals (ECG signals) to decrease the WBSN's bandwidth and energy usage. They employed the Wavelet Transform Based Iterative Thresholding (WTIT) method to extract the high-frequency components of the ECG signal. The WTIT assigned a lower approximation for higher-level coefficients and a high estimated value for lower-level coefficients. The process is repeated until it achieves greater sparsity in the ECG signal while preserving the higher frequency components. After that, the Huffman algorithm was applied to encode sparse WTIT coefficient matrices in terms of non-zero values before transmission. In the end, the receiver applies inverse wavelet modification and Huffman decoding on the received signal for time domain representation. [31]

Mohammadi et al. [64] proposed a hybrid scheme combining two lossless compression techniques, Lempel-Ziv-Welch (LZW) and Huffman encoding. They applied a binary information arrangement between LZW and Huffman algorithm such that integrating binary information achieves an information mapping fully for each piece of information. [64]

Other lossless data compression techniques

A data compression technique for WBSN was proposed by Wu et al. [103]. The proposed mechanism was developed by considering the opportunity of overhearing transmissions between the sensor nodes connected to the patient body. The authors also noted that the compression could be facilitated by spatial correlations and strong temporal between accelerometer readings collected during the body's movement. According to this mechanism, every sensory node samples its data overhears neighboring node transmissions, compresses the data, and transmits it. The spatial and temporal correlations are modeled through linear regression and differential coding. An offline method was presented to learn those correlations and adjust model parameters.

Elsayed et al. [28] investigated the use of the Walsh transform in conjunction with "moving average filtering (MAF)" for data compression in WBSNs. They applied the Walsh transform to analyze patients' actual electroencephalogram (EEG) data. Their proposed scheme passes the EEG signal to a parameter optimization block that determines the compression parameters like suitable compression ratio and filter length, depending on the chosen application. Walsh transform was used to compress the EEG data, whereas the MAF was applied to smooth the data and improve its performance. After that, the EEG data is quantized and sent via a wireless channel to the destination. It assesses the channel quality and feeds it back to the sender to adjust its compression ratio. Their results show that employing MAF with Walsh transform improves compression ratio up to 30% higher than DWT. In a similar study, Al-Nassrawy et al. [8] proposed a lossless fractals compression scheme to reduce the transmitted EEG data from the gateway cloud. The proposed method enhances data communication in WBSNs by lowering data traffic across the network.

In another study, Şişman et al. [90] proposed a data compression technique for electrocardiogram (ECG) signal. Their proposed method transmits the successive samples as one octet, whereas the exceeding portion of the data is transmitted with unique codes as two octets when the data doesn't suit into 8 bits. Because the suggested method comprises elementary arithmetic operations, it can be used in even the most basic microcontrollers.

According to Breiholz et al. [23], integrating an accelerator into a transmitter interface decreases the system power and lower user overhead. To tackle this issue, the authors proposed a low-complexity compression algorithm for ECG data compression. The algorithm is implemented on a health monitoring system as a hardware accelerator. The transmitter cycle is lowered by 3.7x, and the total system power is reduced by 2.9x, increasing the sensor node's lifespan.

Arulprakash et al. [9] proposed Self-Executing-Dynamic Cross-Propagation Clustering (SE-DCPC) method to reduce node energy usage by putting nodes into the accessible state when not in use and reawakening them when necessary. According to their method, the clusters are constructed of nodes with higher energies that send packets more sophisticatedly than nodes with lower energies. Root nodes are nodes with plenty of power. The root node transmits a data packet to demonstrate that the destination has arrived through the root node. A node that requires traditional energy to carry the packets from the cache forwarding node and broadcasts an active packet has hit its initial high threshold energy level. This guarantees that the recently found root node is likewise aware of the leaf node's root.

Mohamed et al. [63] presented a data compression method to eliminate data redundancy and reduce energy consumption. To accomplish this objective, their proposed method makes use of temporal and spatial correlations. Various mathematical equations such as Cross-Correlation, Average, Median, Min, Max, Count, and Sum are used. Additionally, a cross-correlation function based on three multivariate physiological signals was employed. The control node combines the extracted characteristics sent to it into a single unit named during the assembly stage. The features are then XORed after being regrouped using a sum transaction modulo. The results of this process are forwarded to the base station.

Lossy data compression techniques in IoT-enabled WBSNs

Lossy compression is a type of compression where some data are lost from the original message sequence [86]. Lossy compression techniques are usually used to compress audio, video, and images [52]. Accordingly, the compressed sequence cannot regenerate the original sequences. The output quality isn't necessarily lower just because some data is lost. For instance, random noise usually has extremely high data content, yet we would normally be content to ignore it if it is present in a sound file or an image. Additionally, certain losses in sound or images may be so subtle that a spectator would never notice them (e.g. the loss of too high frequencies). Consequently, lossy compression methods on photos may frequently achieve a more excellent compression ratio by a factor of two than lossless techniques with an imperceptible loss in quality [56]. Nevertheless, it's crucial to ensure that quality declines in a way that the viewer will find the least offensive when it does start to become noticeable (e.g., losing random pixels is presumably more undesirable than losing some color data).

To compress microclimate data, Schoellhammer et al. [81] proposed a straightforward lossy temporal compression technique known as "Lightweight Temporal Compression (LTC)". The authors demonstrated that the LTC performs similarly to wavelet compression and LZW, consumes minimal CPU and needs very little storage. It is appropriate for low-power devices. In a similar study, Azar et al. [11] used a rapid error-constrained lossy compression on aggregated data before transmission. They use a short error-bounded lossy compressor on the acquired data before transmission, considered the largest energy user in an IoT device. In a subsequent step, they reconstruct the transmitted data on an edge node and process it with supervised deep-learning techniques.

Yu et al. [109] proposed an accelerometer lossy data compression for WBSN to monitor and assess the stroke patients' upper "limb motor" status. The presented data compression aims to lower the quantity of data during transmission and sampling. Their findings indicated that raw accelerometer signals might be reduced and replicated adequately for automated categorization using the sink node.

Natarajan and Vyas [70] investigated the feasibility of compressing continued bio-signals in a WBSN. A "binary permuted block diagonal matrix encoder" was applied in compressing photoplethysmogram and electrocardiogram data. The sink node automatically sets compression settings to respond to the detected signals' sparsity levels and dispatches the parameters to the sensor node.

In another study, a new technique for the compression of electrocardiogram data was proposed by Huang et al. [41]. the proposed method was designed depending on feature dictionary construction and empirical mode decomposition. The proposed mechanism was designed to compress the data transferred from a wearable node. Their results have shown that the proposed compression method can attain a high compression ratio by employing self-similarities and inheriting properties of the observed signals.

Data compression based on machine learning in IoT-enabled WBSNs

Machine learning methods are increasingly being adopted throughout a vast amount of our computing infrastructure, ranging from IoT and mobile devices to data centers. As a result, there is an increasing demand for efficient and fast machine-learning mechanisms.

Recent enhancements in statistical machine learning have enabled compression algorithms to be learned end-to-end from data utilizing sophisticated generative models like generative adversarial networks, probabilistic diffusion models, variational autoencoders, and normalizing flows [107]. Data compression seeks to minimize the number of bits required to represent valuable information. To achieve this goal, neural networks and machine learning techniques can be applied for data compression, known as neural or learned compression [87,107]. Learning-based data compression can ease the optimization and development of data compression techniques in a data-driven manner. This is especially beneficial for novel or domain-specific data types, such as scientific data or VR/AR content when designing native codecs would otherwise be prohibitively expensive. Indeed, learned compression is used for emergent data forms such as implicit 3D surfaces [95], point clouds [42,74], and neural radiance fields [22]. The combination of machine learning with Lossless compression seeks to represent data with as few bits as feasible so that it can be perfectly reconstructed. The basic idea is to create a probabilistic model of the data and then feed its probabilities into an entropy coding method, which turns data into compact bit-strings [107]. Current research in neural or learned compression is heavily inspired by the advent of deep generative models, such as generative adversarial networks (GANs) [34], VAEs [78], normalizing flows[54], and autoregressive models[100].

Compression and machine learning are inextricably linked. For optimum data compression, a system that anticipates the posterior probability of a sequence based on its complete history is employed (via applying arithmetic coding on the output distribution) [20]. This comparability has been applied to justify employing data compression as a "universal intelligence". For instance, Azar proposed an error-bound lossy compression strategy for IoT-Edge applications in healthcare based on deep machine learning [10]. Their technique combines the SZ with the discrete wavelet transform lifting method, which can manage multivariate and univariate time series. They apply deep learning approaches for data compression at the edge level to eliminate damaged zones and time series filtering [10].

In another study, Vadori [99] Proposed a lossy compression technique for wearable devices. Their proposed method uses a dictionary-based methodology in which the dictionary is adjusted and learnt at runtime to reflect the physiological signals of the individual wearing the device. This is accomplished using time-adaptive self-organizing maps, which are modern neural network models with continuous adaptability and learning capabilities. The presented mechanism employs the unsupervised learning methodology of the time-adaptive self-organizing map (TASOM) to generate a "subject-adaptive codebook" for the vector quantization of a signal. The codebook is obtained and then dynamically refined in real time without prior knowledge of the signal [99].

Hybrid data compression techniques in IoT-enabled WBSNs

Hybrid compression methods combine lossless and lossy compression techniques to achieve a high compression ratio while maintaining the quality of the reconstructed data [82]. Hybrid compression approaches can increase compression quality by applying various algorithms to different sections of a data stream [60,16]. For example, one method may perform better on text data than another that works better for image data.

Several researchers were interested in combining lossy with a lossless compression to boost compression capabilities. For instance, Giorgi [32] combined Huffman coding with LTC to compress the electrocardiography signal and lower the transmitted data in WBSNs. In their work, a zero-latency predictive filter based on differential pulse code modulation is the foundation for the lossy stage. Values that exceed a certain tolerance level are chosen for transmission to a central node. To further eliminate data redundancy, a lossless compression method based on a modified exponential Golomb code that is solely dependent on the resolution of the analogue to digital converter (ADC) is used. Their findings demonstrate that even when shallow values of the maximum tolerable error are considered, suitable results may be obtained by combining a lossy and lossless stage.

Huang et al. [43] combined lossy compression into the lossless compression framework to improve compression efficiency in WBSNs. First, the actual bearing vibration signal is divided into two parts with distinct energy characteristics using the discrete cosine transform. Depending on the data features, several specially created schemes are then used for data encoding. The original signal can be fully recovered because the compression approach doesn't lose any data.

In another study, Azar et al. [12] presented an adapt lossy "Lightweight Temporal Compression" algorithm and integrated it with the "lossless Differential Pulse Code Modulation" algorithm to acquire a high level of compression and lower the data reconstruction error rate.

Abdulzahra et al. [3] presented a hybrid compression method that operates at the IoT sensor node level. The proposed method has two compression stages: a lossy SAX quantization stage that decreases the dynamic range of sensor data readings, followed by a lossless LZW compression that compresses the lossy quantization output [3].

Performance analysis of data compression algorithms in IoT-enabled WBSNs

The compression algorithm's performance is measured by how much data is reduced. Other factors besides compression performance may determine a compression algorithm's suitability for an application. Throughput, latency, size, and power consumption are examples. Most designers seeking a hardware implementation of a compression algorithm are attempting to attain throughputs that are too high for an effective CPU implementation or trying to minimize system latency or power consumption.

Performance measures

The following metrics were used to assess the performance of the reviewed data compression mechanism:

a) *Compression Ratio*
   The compression ratio is a ratio, percentage, or fraction representing the data size difference before and after compression. The higher the compression ratio, the better the resulting data compression.
b) *Energy Saved due to Minimized Transmission*
   This criterion estimates how much each algorithm's compression ratio affects transmission reduction.
c) *Energy Consumption (during Data Compression)*
   This norm evaluates the power consumed when compressing data.
d) *Net Energy Saved*
   Net Energy Saved is the difference between the energy consumed during data compression and the energy saved due to minimized transmissions. It is a critical determinant of appropriate algorithms for various applications in WBSNs.
e) *Data Types (Single/Multiple)*
   This criterion determines whether a compression algorithm is employed for single or multiple data types for each node
f) *Energy Efficiency*
   Energy efficiency refers to the ability of the network to perform its functions while minimizing energy consumption.
g) *Reliability*
   This criterion refers to the ability of the compression algorithm to accurately compress the data while maintaining the integrity of the original data. The reliability can be evaluated by measuring the compression ratio and the distortion, and using error correction codes to improve the accuracy of the compressed data.
h) *Scalability*
   Scalability refers to the ability of the compression algorithm to handle large amounts of data generated by a growing number of sensors in the network without compromising the efficiency and accuracy of the compression process. The scalability can be measured based on several factors, such as compression ratio, compression time, communication overhead, network throughput, and resource utilization.

Table 1
A comparative analysis of Lossless data compression technique

Technique	Compression Ratio	Complexity	Energy Consumption	Energy Saved: Minimized Transmission	Net Energy Saved	Energy Efficiency	Data Type	Reliability	Scalability
Azar et al. [13]	90%	O(n log n)	Low	45%	62.38%	Moderate	Single	High	High
Aboelela [4]	NA	O(n)	NA	NA	NA	NA	Single	Moderate	Low
Hussein et al. [44]	Depend on SNR	Low cost	High	Yes	Yes	Low	Single	Moderate	Moderate
Khani and Shirmohammadi [50]	NA	Low cost	Moderate	25%	2.7%	Low	Single	Low	Low
Chen [24]	14.6%	Low cost	Moderate	NA	54.77%	Moderate	Single	Moderate	Low
Sarma and Biswas [80]	2.91	Low cost	Moderate	55.55%	6%	Low	Single	Moderate	Low
Sadler and Martonosi [79]	39.7%	Low cost	Moderate	NA	16%	Moderate	Single	Low	Moderate
Raju et al. [75]	>50%	NA	Moderate	76.47	30.51	Moderate	multiple	Moderate	Moderate
Harb et al. [37]	75% - 89%	NA	Low	NA	NA	Moderate	Single	High	Moderate
Ghosh et al. [31]	NA	O(n)	Low	NA	96%	High	Single	Moderate	Moderate
Mohammadi et al. [64]	37.85%	NA	Moderate	NA	NA	Low	Single	Moderate	Moderate
Wu et al. [103]	35%	Low cost	Moderate	NA	NA	Low	multiple	Moderate	Moderate
Elsayed et al. [28]	up to 30%	NA	Moderate	Yes	Yes	Low	Single	Moderate	Low
Al-Nassrawy et al. [8]	Depend on SNR	NA	High	Yes	Yes	Low	Single	Moderate	Moderate
Şişman et al. [90]	19.4%	Low cost	Moderate	NA	NA	Low	Single	Low	Low
Breiholz et al. [23]	24%	Low cost	Moderate	NA	NA	High	multiple	Low	Low
Arulprakash et al. [9]	NA	Low cost	Moderate	95%	37%	Moderate	Single	Moderate	Low
Mohamed et al. [63]	NA	NA	NA	NA	87.32%	High	Single	Moderate	Moderate

Performance analysis and evaluation

This section provides a detailed evaluation and performance analysis of the studied techniques and methods based on the criteria in section 7.1. A comparative analysis of the lossless and lossy data compression techniques is shown in Table 1 and Table 2, respectively. A comparative analysis of machine learning-based data compression techniques is shown in Table 3. Table 4 shows a comparative analysis of hybrid data compression techniques. Finally, a summary of the essential differences between lossless and lossy data compression techniques is shown in Table 5.

Comparative analysis of different compression algorithms in terms of their suitability for specific data types

IoT-enabled WBSNs generate a wide range of data, such as physiological data, motional data, environmental data, and multimedia data which have different characteristics and require different compression algorithms. This section presents a comparative analysis of different compression algorithms for specific types of data generated by IoT-enabled WBSNs (Table 6 summarizes the suitability of compression algorithms for specific data types):

1. **Physiological/Biomedical data**: Physiological data such as EMG (Electromyography), EEG (Electroencephalogram), and ECG signals require high accuracy [58], and lossless compression techniques such as Lempel-Ziv-Welch (LZW), Arithmetic coding, and Huffman coding are suitable for such types of data. These algorithms can compress data without losing information, which is critical in patients' diagnosis and monitoring.
2. **Motional data:** Motion data like angular velocity, velocity, acceleration, are generated by sensors as gyroscopes and accelerometers. These data are frequently noisy and include repetitive patterns. Dictionary-based compression algorithms such as LZ78 and LZ77 can efficiently compress these kinds of data by exploiting the redundancy in the signal. Furthermore, transform-based compression algorithms such as Wavelet Transform and Discrete Cosine Transform (DCT) can also be employed to compress motion data.
3. **Environmental data:** Environmental data such as air quality, humidity, and temperature data are generated by sensors that measure the environment's parameters. These data are usually correlated and have seasonal trends. Transform-based compression algorithms such as Wavelet Transform and DCT are suitable for compressing environmental data, as they can efficiently capture the seasonal trends and correlations in data.
4. **Image/Multimedia data**: Multimedia and image data captured by WBSNs are frequently enormous in size and require a significant amount of storage and high transmission bandwidth. Dictionary-based compression algorithms such as LZ78 and LZ77 can be used to compress such data types.

Analysis and discussion

Several compression methods were modified to fit the general applications of WBSNs. For instance, Azar et al. [13] and Wu et al. [103] concentrated on utilizing the advantage of spatial correlation in sensor data, but they targeted specific applications. By focusing on data-centric routing and aggregation, other researchers [9,37,81] attempted to take advantage of the Spatio-temporal correlation.

Some researchers attempted to adapt existing methods to fit sensor networks, such as Saddler and Martonosi's work [79] concentrating on LZW compression and some of its modifications intended for embedded systems. Their study demonstrates that while these techniques are appropriate for embedded systems, they are generally unsuitable for sensor systems. They investigated several compression methods, such as PPMd, bzip2, ZLib, and LZO. They concluded that such methods would not be appropriate for sensor networks since the usual RAM capacity in many sensor nodes is ten kilobytes. As a consequence, they suggested an approach based on

Table 2
A comparative analysis of **Lossy** data compression techniques

Technique	Compression Ratio	Complexity	Energy Consumption	Energy Saved: Minimized Transmission	Net Energy Saved	Energy Efficiency	Data Type	Reliability	Scalability
Schoellhammer et al. [81]	72.6 % - 91.8%, based on the nature of the dataset	O(n)	Low	NA	NA	High	Single	Moderate	High
Azar et al. [11]	1.33	NA	Low	83%	27%	Moderate	multiple	Moderate	Low
Yu et al. [109]	Depend on SNR	NA	Moderate	NA	NA	Low	Single	Low	Low
Natarajan and Vyas [70]	23%	NA	Moderate	yes	3%	Moderate	Single	Moderate	Low
Huang et al. [41]	around 25%	Low cost	Moderate	yes	NA	Moderate	Single	Low	Moderate

Table 3
A comparative analysis of **machine learning-based** data compression techniques

Technique	Compression Ratio	Complexity	Energy Consumption	Energy Saved: Minimized Transmission	Net Energy Saved	Energy Efficiency	Data Type	Reliability	Scalability
Azar [11]	based on the nature of the dataset	O(n log n)	Low	NA	NA	Moderate	multiple	Low	Moderate
Vadori [99]	up to 70%	Low cost	Moderate	NA	3.25%.	Moderate	Single	Moderate	Moderate

Table 4
A comparative analysis of **Hybrid** data compression techniques

Technique	Compression Ratio	Complexity	Energy Consumption	Energy Saved: Minimized Transmission	Net Energy Saved	Energy Efficiency	Data Types	Reliability	Scalability
Giorgi [32]	Up to 100%	NA	High	NA	NA	Low	Single	Moderate	High
Huang et al. [43]	59.01%		Low		Up to 37.75%	Moderate	Single	Moderate	High
Azar et al. [12]	91% with smooth data, 63% with less smooth data	O(n)	Moderate	NA	up to 95%	Moderate	Single	Moderate	Moderate
Abdulzahra et al. [3]	95%	NA	Low	NA	90%	High	Single	High	Low

LZW termed S-LZW.

Any compression algorithm in WBSNs should have low processing and low memory requirements while delivering real-time outputs. The compression algorithm should have an overall energy saving due to the strict resource constraints of most WBSN nodes (i.e. the extra power consumed by the processor performing the compression algorithm should not exceed the saved energy of wireless transmission). On-chip memory on WBSN nodes' embedded CPUs is often limited to a few kilobytes and runs at speeds in the tens of megahertz. These limitations may restrict the implementation capability of many compression techniques. However, off-chip access time may be relatively long, and the additional resources (in particular power and area) may not be worth it, particularly in WBSNs with limited resources. In addition, many WBSN applications have considerably different features and requirements than the majority of WSN applications, including both static factors (such as fidelity requirements and high data rates) and dynamic parameters (e.g. channel conditions and rapidly varying data characteristics).

According to the findings of the reviewed studies in this paper, lossy compression algorithms may increase compression ratios on smooth data with minimal information loss. Nevertheless, as the data get noisier, the data reconstruction error rises accordingly, and specific crucial characteristics are missing. To decrease the number of transferred bits and enhance the percentage of power savings, sensor nodes should use a compression technique with a high compression ratio. Similarly, it must have a low memory complexity/ computational time such that the energy saved by transferring the compressed data should be larger than the energy wasted by carrying out additional processing and computation.

Many recent studies on sensor data compression have concentrated on lossy compression techniques since they often produce a compression ratio (CR) of 2-15 times greater than lossless techniques, which provide a CR of 1-3 times. In most circumstances, the quality of compressed data produced by lossy compression may be suitable for clinical use. Unfortunately, most nations' medical regulatory regulations do not specifically support using lossy compression algorithms in commercial equipment [27]. This is due to whether such procedures can fully maintain all patient data of potential diagnostic value.

As a result of these concerns, considerable work has lately been devoted to lossless approaches [27], which have achieved high energy efficiency and CR. Most of the existing data compression techniques have many limitations and challenges, such as fixed low compression ratio, involving complex algorithms that result in high energy consumption at the sensor level, or having a large reconstruction error when compared to original data, or all of them.

Open research issues and future directions

The aforementioned data compression techniques and many others proposed in the literature act sufficiently on stationary univariate time sequences. However, many IoT devices currently contain more than one sensor and can gather multiple features. As a result, data compression methods that operate competently with multivariate time series are highly required. Most IoT devices today have numerous sensors and may collect various data.

Accordingly, data compression schemes should be able to handle multisensory data on a single device. In real-time applications, the algorithm's decompression time should be short. In other words, the data compression technique should adapt and act well across diverse healthcare applications and systems. The loss of data is not desirable, and the lossless compression mechanisms are preferable because textual data is highly available in the WBSN datasets.

Table 5
A summary of the essential differences between Lossless and Lossy data compression techniques

Key	Lossy compression	Lossless compression
Capacity	Has a considerable data-holding capability.	Has low data-holding capacity.
Uses	It is mainly used to compress images, video, and audio data.	It primarily compresses text data, program code files, and other crucial data.
Algorithm used	Fractal compression, Discrete Wavelet Transform, Discrete Cosine Transform, Transform coding, etc.	Run length encoding, Huffman Coding, Arithmetic encoding, Lempel-Ziv-Welch, etc.
Size	It significantly decreases the size of the data.	It decreases data size, but only slightly less than lossy compression.
Quality	Lossy compression degrades quality. This results in some data loss.	No quality deterioration happens.
Restoration	It is impossible to restore a data/file to its original state.	A data/ file can be converted to its original state.
Data Elimination	Bytes that are deemed undetectable may be eliminated.	With lossless compression, even unnoticeable bytes are preserved.

Table 6
A summary of the suitability of compression algorithms for specific data types

Data Type	Compression technique	Compression category
Physiological data	LZW, Arithmetic coding, Huffman coding	Lossless compression
Motional data	LZ77 and LZ78	Dictionary-based compression
Environmental data	Wavelet Transform and DCT	transform-based compression
Multimedia Data	LZ77 and LZ78	Dictionary-based compression

WBSNs generate data that can be highly variable over time. Compression techniques that can adapt to changes in data patterns and optimize compression performance dynamically are needed to ensure that the network can handle changing conditions and provide reliable performance. Furthermore, WBSNs generate different types of data, including text, images, and videos. Future research could focus on developing compression techniques that are optimized for specific types of data, to achieve better compression performance and minimize energy consumption.

WBSNs are often used in sensitive applications, such as healthcare, where data security and privacy are critical. Compression techniques that can protect sensitive data and ensure that it cannot be accessed by unauthorized parties are needed to ensure the privacy and security of the network.

In large-scale WBSNs, it may be necessary to distribute the compression workload across multiple nodes to reduce the communication overhead and energy consumption. Future research could explore distributed compression techniques that can be used in WBSNs to achieve better scalability and efficiency.

Hybrid compression techniques that combine multiple compression techniques to improve performance and efficiency are an area of active research. By combining techniques such as lossless and lossy compression, or predictive and dictionary-based compression, it may be possible to achieve better compression performance and energy efficiency than with individual techniques alone.

Conclusion

Wireless Body Sensor Network (WBSN) is a vital component of the Internet of Things (IoT) that aids in collecting data from the body's surface area. WBSN is a sort of wireless network where sensor nodes sense the body's vital signs and transmit the sensed data to a base station.

Data compression techniques are often employed to maintain the integrity of the observed data transmission. The primary purpose of the data compression mechanisms is to compress the data in a well-organized and cost-effective manner, lower traffic load, reduce power consumption, minimize delay, increase network lifetime, etc. Given that the wireless transmission of the obtained data consumes most of the overall energy consumption in WBSN systems, data compression approaches are deemed an efficient method to improve the power efficiency of WBSNs.

This paper presents a comprehensive literature review of data compression techniques of IoT-enabled WBSN systems, along with a critical analysis of each mechanism. This study shows an in-depth comparison of the methodologies, a systematic assessment of the selected articles, and recommendations for further research.

Overall, the choice of data compression technique depends on the specific requirements of the WBSN application. For example, in applications where energy consumption is a critical concern, lossless compression may be preferred because it requires less computational overhead than lossy compression techniques. Conversely, in applications where storage capacity is a concern, lossy compression may be preferred because it can achieve higher compression ratios than lossless compression.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

References

[1] S. Abbasian Dehkordi, K. Farajzadeh, J. Rezazadeh, R. Farahbakhsh, K Sandrasegaran, M. Abbasian Dehkordi, A survey on data aggregation techniques in IoT sensor networks, Wireless Netw. 26 (2) (2020) 1243–1263.
[2] S. Abdollahzadeh, N.J. Navimipour, Deployment strategies in the wireless sensor network: a comprehensive review, Comput. Commun. 91 (2016) 1–16.
[3] S.A. Abdulzahra, A.K.M. Al-Qurabat, A.K. Idrees, Data reduction based on compression technique for big data in IoT, in: 2020 international conference on emerging smart computing and informatics (ESCI), IEEE, 2020, pp. 103–108.
[4] E. Aboelela, Liftingwise: a lifting-based efficient data processing technique in wireless sensor networks, Sensors 14 (8) (2014) 14567–14585.
[5] O. Abouelkhair, A. Elsaadny, Multipath adaptive periodic threshold-sensitive energy efficient protocol for wireless sensor networks, in: 2014 Sixth International Conference on Computational Intelligence, Communication Systems and Networks, IEEE, 2014, pp. 33–37.
[6] B. Almadani, M. Bin-Yahya, E.M. Shakshuki, E-AMBULANCE: real-time integration platform for heterogeneous medical telemetry system, Procedia Comput. Sci. 63 (2015) 400–407.

[7] N. Almolhis, A.M. Alashjaee, S. Duraibi, F. Alqahtani, A.N. Moussa, The security issues in IoT-cloud: a review. 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), IEEE, 2020, pp. 191–196.

[8] K.K. Al-Nassrawy, A.K. Idrees, D. Al-Shammary, A novel lossless EEG compression model using fractal combined with fixed-length encoding technique. AI and IoT for Sustainable Development in Emerging Countries, Springer, Cham, 2022, pp. 439–454.

[9] A. Arulprakash, K.M. Baalamurugan, R.K. Dhanaraj, K. Sampath Kumar, P. Gupta, S. Rehman, Aggregation technique using dynamic cross-propagation clustering algorithm in wireless body sensor networks, Wireless Commun. Mob. Comput. (2022) 2022.

[10] J. Azar, 2020. Data compression and deep learning for IoT healthcare applications based on physiological signals (Doctoral dissertation, Bourgogne Franche-Comté).

[11] J. Azar, R. Darazi, C. Habib, A. Makhoul, J. Demerjian, Using dwt lifting scheme for lossless data compression in wireless body sensor networks, 2018, in: 14th International wireless communications & mobile computing conference (IWCMC), IEEE, 2018, pp. 1465–1470.

[12] J. Azar, A. Makhoul, M. Barhamgi, R. Couturier, An energy-efficient IoT data compression approach for edge machine learning, Fut. Gen. Comput. Syst. 96 (2019) 168–175.

[13] J. Azar, A. Makhoul, R. Darazi, J. Demerjian, R. Couturier, On the performance of resource-aware compression techniques for vital signs data in wireless body sensor networks, in: 2018 IEEE Middle East and North Africa Communications Conference (MENACOMM), IEEE, 2018, pp. 1–6.

[14] G. Badshah, S.C. Liew, J.M. Zain, M. Ali, Watermark compression in medical image watermarking using Lempel-Ziv-Welch (LZW) lossless compression technique, J. Digit. Imaging 29 (2) (2016) 216–225.

[15] A. Bag, M.A. Bassiouni, Energy efficient thermal aware routing algorithms for embedded biomedical sensor networks, in: 2006 IEEE International Conference on Mobile Ad Hoc and Sensor Systems, IEEE, 2006, pp. 604–609.

[16] T. Banerjee, J. Choi, J. Lee, Q. Gong, J. Chen, S. Klasky, A. Rangarajan, S. Ranka, arXiv preprint, 2022.

[17] J.I. Bangash, A.H. Abdullah, M.H. Anisi, A.W. Khan, A survey of routing protocols in wireless body sensor networks, Sensors 14 (1) (2014) 1322–1357.

[18] R. Barman, S. Badade, S. Deshpande, S. Agarwal, N. Kulkarni, Lossless data compression method using deep learning, in: Machine Intelligence and Smart Systems: Proceedings of MISS 2021, Springer, Singapore, 2022, pp. 145–151. Nature Singapore.

[19] L. Barua, P.K. Dhar, L. Alam, I. Echizen, Bangla text compression based on a modified Lempel-Ziv-Welch algorithm, in: 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE), IEEE, 2017, pp. 855–859.

[20] I. Ben-Gal, On the use of data compression measures to analyze robust designs, IEEE Trans. Reliab. 54 (3) (2005) 381–388.

[21] T. Bhardwaj, C. Reyes, H. Upadhyay, S.C. Sharma, L. Lagos, Cloudlet-enabled wireless body area networks (WBANs): A systematic review, architecture, and research directions for QoS improvement, Int. J. Syst. Assur. Eng. Manag. (2021) 1–25.

[22] T. Bird, J. Ballé, S. Singh, P.A. Chou, 3d scene compression through entropy penalized neural representation functions, in: 2021 Picture Coding Symposium (PCS), IEEE, 2021, pp. 1–5.

[23] J. Breiholz, F. Yahya, C.J. Lukas, X. Chen, K. Leach, D. Wentzloff, B.H. Calhoun, A 4.4 nW lossless sensor data compression accelerator for 2.9 x system power reduction in wireless body sensors, in: 2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS), IEEE, 2017, pp. 1041–1044.

[24] C.A. Chen, C. Wu, P.A.R. Abu, S.L. Chen, VLSI implementation of an efficient lossless EEG compression design for wireless body area network, Appl. Sci. 8 (9) (2018) 1474.

[25] J.D.A. Correa, A.S.R. Pinto, C. Montez, Lossy data compression for IoT sensors: a review, Internet Things 19 (2022), 100516.

[26] M. Dawood, L. Ahila, S. Sadasivam, G. Athisha, Image compression in wireless sensor networks-a survey, Int. J. Appl. Inf. Syst. 1 (9) (2012) 11–15.

[27] C.J. Deepu, C.H. Heng, Y. Lian, A hybrid data compression scheme for power reduction in wireless sensors for IoT, IEEE Trans. Biomed. Circuits Syst. 11 (2) (2016) 245–254.

[28] M. Elsayed, M. Mahmuddin, A. Badawy, T. Elfouly, A. Mohamed, K. Abualsaud, Walsh transforms with moving average filtering for data compression in wireless sensor networks. 2017 IEEE 13th International Colloquium on Signal Processing & its Applications (CSPA), IEEE, 2017, pp. 270–274.

[29] Z. Fu, J. Jiang, Experimental study on machine learning with approximation to data streams, in: 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS), IEEE, 2019, pp. 561–566.

[30] A. Garg, Distance adaptive threshold sensitive energy efficient sensor network (DAPTEEN) protocol in WSN, in: 2015 International Conference on Signal Processing, Computing and Control (ISPCC), IEEE, 2015, pp. 114–119.

[31] A. Ghosh, A. Raha, A. Mukherjee, Energy-efficient IoT-health monitoring system using approximate computing, Internet of Things 9 (2020), 100166.

[32] G. Giorgi, A combined approach for real-time data compression in wireless body sensor networks, IEEE Sensors J. 17 (18) (2017) 6129–6135.

[33] V.K. Goyal, A.K. Fletcher, S. Rangan, Compressive sampling and lossy compression, IEEE Signal Process. Mag. 25 (2) (2008) 48–56.

[34] J. Gui, Z. Sun, Y. Wen, D. Tao, J. Ye, A review on generative adversarial networks: algorithms, theory, and applications, IEEE Trans. Knowl. Data Eng. (2021).

[35] C. Habib, A. Makhoul, R. Darazi, C. Salim, Self-adaptive data collection and fusion for health monitoring based on body sensor networks, IEEE Trans. Ind. Inf. 12 (6) (2016) 2342–2352.

[36] T. Hafeez, G. McArdle, Using dynamic perceptually important points for data reduction in IoT, in: Proceedings of the 11th International Conference on the Internet of Things, 2021, pp. 33–39.

[37] H. Harb, A. Makhoul, C. Abou Jaoude, A real-time massive data processing technique for densely distributed sensor networks, IEEE Access 6 (2018) 56551–56561.

[38] G. Hatzivasilis, O. Soultatos, S. Ioannidis, C. Verikoukis, G. Demetriou, C. Tsatsoulis, Review of security and privacy for the Internet of Medical Things (IoMT), in: 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS), IEEE, 2019, pp. 457–464.

[39] M. Hosseini, A Survey of Data Compression Algorithms and Their Applications, Network Systems Laboratory, School of Computing Science, Simon Fraser University, BC, Canada, 2012.

[40] S. Hriez, S. Almajali, H. Elgala, M. Ayyash, H.B. Salameh, A novel trust-aware and energy-aware clustering method that uses stochastic fractal search in IoT-enabled wireless sensor networks, IEEE Syst. J. 16 (2) (2021) 2693–2704.

[41] H. Huang, S. Hu, Y. Sun, Energy-efficient ECG compression in wearable body sensor network by leveraging empirical mode decomposition, in: 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), IEEE, 2018, pp. 149–152.

[42] L. Huang, S. Wang, K. Wong, J. Liu, R. Urtasun, Octsqueeze: Octree-structured entropy model for lidar compression, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 1313–1323.

[43] Q. Huang, B. Tang, L. Deng, J. Wang, A divide-and-compress lossless compression scheme for bearing vibration signals in wireless sensor networks, Measurement 67 (2015) 51–60.

[44] R. Hussein, A. Mohamed, M. Alghoniemy, Adaptive compression and optimization for real-time energy-efficient wireless EEG monitoring systems, in: The 6th 2013 Biomedical Engineering International Conference, IEEE, 2013, pp. 1–5.

[45] A.A. Hussien, S.I. Matloob, The comparative study some of reactive and proactive routing protocols in the wireless sensor network, J. Univ. Babylon Eng. Sciences 26 (4) (2018) 195–207.

[46] S.R. Islam, D. Kwak, M.H. Kabir, M. Hossain, K.S. Kwak, The internet of things for health care: a comprehensive survey, IEEE Access 3 (2015) 678–708.

[47] A.B. Jambek, N.A. Khairi, Performance comparison of Huffman and Lempel-Ziv Welch data compression for wireless sensor node application, Am. J. Appl. Sci. 11 (1) (2014) 119–126.

[48] M.A. Jan, F. Khan, M. Alam, M. Usman, A payload-based mutual authentication scheme for Internet of Things, Fut. Gener. Comput. Syst. 92 (2019) 1028–1039.

[49] L.K. Ketshabetswe, A.M. Zungeru, B. Mtengi, C.K. Lebekwe, S.R.S. Prabaharan, Data Compression Algorithms for Wireless Sensor Networks: A Review and Comparison, IEEE Access, 2021.

[50] M.J. Khani, Z. Shirmohammadi, UEELC: an ultra energy efficient lossless compression method for wireless body area networks, in: 2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), 2020, pp. 1–7.

[51] N. Kimura, S. Latifi, A survey on data compression in wireless sensor networks, in: International Conference on Information Technology: Coding and Computing (ITCC'05)-Volume II 2, IEEE, 2005, pp. 8–13.

[52] R. Krishnamoorthy, T. Jayasankar, S. Shanthi, M. Kavitha, C. Bharatiraja, Design and implementation of power efficient image compressor for WSN systems, Mater. Today: Proc. 45 (2021) 1934–1938.
[53] D. Laiymani, A. Makhoul, Adaptive data collection approach for periodic sensor networks, in: 2013 9th international wireless communications and Mobile computing conference (IWCMC), IEEE, 2013, pp. 1448–1453.
[54] H. Larochelle, I. Murray, The neural autoregressive distribution estimator, in: Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, 2011, pp. 29–37. JMLR Workshop and Conference Proceedings.
[55] M. Lewandowski, B. Płaczek, M. Bernas, Classifier-based data transmission reduction in wearable sensor network for human activity monitoring, Sensors 21 (1) (2020) 85.
[56] W. Li, Y. Chai, F. Khan, S.R.U. Jan, S. Verma, V.G. Menon, X. Li, A comprehensive survey on machine learning-based big data analytics for IoT-enabled smart healthcare system, Mobile Netw. Appl. (2021) 234–252, 1-19.
[57] X. Liang, S. Di, D. Tao, S. Li, S. Li, H. Guo, Z. Chen, F. Cappello, Error-controlled lossy compression optimized for high compression ratios of scientific datasets, in: 2018 IEEE International Conference on Big Data (Big Data), IEEE, 2018, pp. 438–447.
[58] P.S. Mathew, A.S. Pillai, V. Palade, Applications of IoT in healthcare. Cognitive Computing for Big Data Systems Over IoT, Springer, Cham, 2018, pp. 263–288.
[59] G. Mathur, P. Desnoyers, P. Chukiu, D. Ganesan, P. Shenoy, Ultra-low power data storage for sensor networks, ACM Trans. Sens. Netw. (TOSN) 5 (4) (2009) 1–34.
[60] S. Meckel, M. Lohrey, S. Jo, R. Obermaisser, S. Plasger, Combined compression of multiple correlated data streams for online-diagnosis systems, Microprocess. Microsyst. 77 (2020), 103184.
[61] N. Mittal, U. Singh, Distance-based residual energy-efficient stable election protocol for WSNs, Arab. J. Sci. Eng. 40 (2015) 1637–1646.
[62] H.A. Mohamed Shaffril, S.F. Samsuddin, A. Abu Samah, The ABC of systematic literature review: the basic methodological guidance for beginners, Qual. Quant. 55 (4) (2021) 1319–1346.
[63] M.B. Mohamed, A. Meddeb-Makhlouf, A. Fakhfakh, O. Kanoun, Secure and reliable ML-based disease detection for a medical wireless body sensor networks, Int. J. Biol. Biomed. Eng. 16 (2022) 196–206.
[64] H. Mohammadi, A. Ghaderzadeh, A. Sheikh Ahmadi, A novel hybrid medical data compression using Huffman coding and LZW in IoT, IETE J. Res. (2022) 1–15.
[65] M. Mohammadi, A. Al-Fuqaha, S. Sorour, M. Guizani, Deep learning for IoT big data and streaming analytics: a survey, IEEE Commun. Surv. Tutor. 20 (4) (2018) 2923–2960.
[66] R.K. Mondal, D. Sarddar, Data-centric routing protocols in wireless sensor networks: a survey, Compusoft 3 (2) (2014) 593.
[67] S. Movassaghi, M. Abolhasan, J. Lipman, Energy efficient thermal and power aware (ETPA) routing in body area networks, in: 2012 IEEE 23rd international symposium on personal, Indoor and Mobile Radio Communications-(PIMRC), IEEE, 2012, pp. 1108–1113.
[68] A.S. Nagdive, P.K. Ingole, Implementation of energy-efficient data compression & security mechanism in clustered wireless sensor network, in: 2015 International Conference on Advances in Computer Engineering and Applications, IEEE, 2015, pp. 375–380.
[69] U. Nandi, J.K. Mandal, Fractal image compression using fast context independent HV partitioning scheme and MRBH, MRBHM coding, in: 2014 First International Conference on Automation, Control, Energy and Systems (ACES), IEEE, 2014, pp. 1–5.
[70] V. Natarajan, A. Vyas, Power efficient compressive sensing for continuous monitoring of ECG and PPG in a wearable system. 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT), IEEE, 2016, pp. 336–341.
[71] W. Osamy, A. Salim, A.M. Khedr, A.A. El-Sawy, IDCT: Intelligent data collection technique for IoT-enabled heterogeneous wireless sensor networks in smart environments, IEEE Sensors J. 21 (18) (2021) 21099–21112.
[72] S. Pattar, R. Buyya, K.R. Venugopal, S.S. Iyengar, L.M. Patnaik, Searching for the IoT resources: Fundamentals, requirements, comprehensive review, and future directions, IEEE Commun. Surv. Tutorials 20 (3) (2018) 2101–2132.
[73] Y. Qu, G. Zheng, H. Wu, B. Ji, H. Ma, An energy-efficient routing protocol for reliable data transmission in wireless body area networks, Sensors 19 (19) (2019) 4238.
[74] M. Quach, G. Valenzise, F. Dufaux, Learning convolutional transforms for lossy point cloud geometry compression, in: 2019 IEEE international conference on image processing (ICIP), IEEE, 2019, pp. 4320–4324.
[75] R. Raju, M. Moh, T.S. Moh, Compression of wearable body sensor network data using improved two-threshold-two-divisor data chunking algorithms, in: 2018 International Conference on High Performance Computing & Simulation (HPCS), IEEE, 2018, pp. 949–956.
[76] M.A. Razzaque, C. Bleakley, S. Dobson, Compression in wireless sensor networks: a survey and comparative evaluation, ACM Trans. Sens. Netw. (TOSN) 10 (1) (2013) 1–44.
[77] A. Reinhardt, D. Christin, M. Hollick, R. Steinmetz, On the energy efficiency of lossless data compression in wireless sensor networks, in: 2009 IEEE 34th Conference on Local Computer Networks, IEEE, 2009, pp. 873–880.
[78] D. Rezende, S. Mohamed, Variational inference with normalizing flows, in: International conference on machine learning, PMLR, 2015, pp. 1530–1538.
[79] C.M. Sadler, M. Martonosi, Data compression algorithms for energy-constrained devices in delay tolerant networks, in: Proceedings of the 4th international conference on Embedded networked sensor systems, 2006, pp. 265–278.
[80] J. Sarma, R. Biswas, A VLSI-based hybrid ECG compression scheme for wearable sensor node, IEEE Sens. Lett. 6 (4) (2022) 1–4.
[81] Schoellhammer, T., Greenstein, B., Osterweil, E., Wimbrow, M. and Estrin, D., 2004. Lightweight temporal compression of microclimate datasets.
[82] E. Setyaningsih, A. Harjoko, Survey of hybrid image compression techniques, Int. J. Electr. Comput. Eng. 7 (4) (2017) 2206.
[83] D. Sharma, R.C. Tripathi, Technical report, 2020.
[84] N. Sharma, U. Batra, Performance analysis of compression algorithms for information security: a review, EAI Endorsed Trans. Scal. Inf. Syst. 7 (27) (2020).].
[85] R. Sharma, S. Bollavarapu, Data security using compression and cryptography techniques, Int. J. Comput. Appl. 117 (14) (2015).
[86] T. Sheltami, M. Musaddiq, E. Shakshuki, Data compression techniques in wireless sensor networks, Fut. Gener. Comput. Syst. 64 (2016) 151–162.
[87] G. Signoretti, M. Silva, P. Andrade, I. Silva, E. Sisinni, P. Ferrari, An evolving tinyml compression algorithm for IoT environments based on data eccentricity, Sensors 21 (12) (2021) 4153.
[88] I.M. Silva, L.A. Guedes, F. Vasques, Performance evaluation of a compression algorithm for wireless sensor networks in monitoring applications, in: 2008 IEEE International Conference on Emerging Technologies and Factory Automation, IEEE, 2008, pp. 672–678.
[89] S. Siripanadorn, W. Hattagam, N. Teaumroong, Anomaly detection using self-organizing map and wavelets in wireless sensor networks, in: Proceedings of the 10th WSEAS International Conference on Applied Computer Science, 2010, pp. 291–297. ACS'10.
[90] C. Şişman, H.Y. Özderya, İ. Kaya, Low complexity, lossless differential base data compression method for wireless body area networks, 2016, in: 24th Signal Processing and Communication Application Conference (SIU), IEEE, 2016, pp. 2221–2224.
[91] R. Somasundaram, M. Thirugnanam, Review of security challenges in healthcare internet of things, Wireless Netw. 27 (2021) 5503–5509.
[92] T. Srisooksai, K. Keamarungsi, P. Lamsrichan, K. Araki, Practical data compression in wireless sensor networks: a survey, J. Netw. Comput. Appl. 35 (1) (2012) 37–59.
[93] M. Suárez-Albela, T.M. Fernández-Caramés, P. Fraga-Lamas, L. Castedo, A practical evaluation of a high-security energy-efficient gateway for IoT fog computing applications, Sensors 17 (9) (2017) 1978.
[94] D. Takahashi, Y. Xiao, F. Hu, LTRT: Least total-route temperature routing for embedded biomedical sensor networks, in: IEEE GLOBECOM 2007-IEEE Global Telecommunications Conference, IEEE, 2007, pp. 641–645.
[95] D. Tang, S. Singh, P.A. Chou, C. Hane, M. Dou, S. Fanello, J. Taylor, P. Davidson, O.G. Guleryuz, Y. Zhang, S. Izadi, Deep implicit volume compression, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 1293–1303.
[96] G.B. Tayeh, A. Makhoul, D. Laiymani, J. Demerjian, A distributed real-time data prediction and adaptive sensing approach for wireless sensor networks, Pervasive Mob. Comput. 49 (2018) 62–75.

[97] Tuama, A.Y., Mohamed, M.A., Muhammed, A., Hanapi, Z.M., Mohamed, R.R. and Abu Bakar, K.A., 2018. Recent advances of data compression in Wireless Sensor Network.
[98] A. Ullah, G. Said, M. Sher, H. Ning, Fog-assisted secure healthcare data aggregation scheme in IoT-enabled WSN, Peer-to-Peer Network. Appl. 13 (1) (2020) 163–174.
[99] Vadori, V., 2015. Biometric signals compression with time-and subject-adaptive dictionary for wearable devices.
[100] A. Van den Oord, N. Kalchbrenner, L. Espeholt, O. Vinyals, A. Graves, Conditional image generation with pixelcnn decoders. Advances in Neural Information Processing Systems, 2016, p. 29.
[101] Y.C. Wang, Data compression techniques in wireless sensor networks, Pervas. Comput. 61 (1) (2012) 75–77.
[102] P.A. Williams, V. McCauley, Always connected: the security challenges of the healthcare Internet of Things. 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT), IEEE., 2016, pp. 30–35, 119.
[103] C.H. Wu, Y.C. Tseng, Data compression by temporal and spatial correlations in a body-area sensor network: a case study in pilates motion recognition, IEEE Trans. Mob. Comput. 10 (10) (2010) 1459–1472.
[104] Y. Xiao, M. Watson, Guidance on conducting a systematic literature review, J. Plann. Educ. Res. 39 (1) (2019) 93–112.
[105] L. Yadav, C. Sunitha, Low energy adaptive clustering hierarchy in wireless sensor network (LEACH), Int. J. Comput. Sci. Inf. Technol. 5 (3) (2014) 4661–4664.
[106] R. Yang, X. Sun, Z. Liu, Y. Zhang, J. Fu, A numerical analysis of the effects of equivalence ratio measurement accuracy on the engine efficiency and emissions at varied compression ratios, Processes 9 (8) (2021) 1413.
[107] Y. Yang, S. Mandt, L. Theis, arXiv preprint, 2022.
[108] J. Yick, B. Mukherjee, D. Ghosal, Wireless sensor network survey, Comput. Netw. 52 (12) (2008) 2292–2330.
[109] L. Yu, D. Xiong, L. Guo, J. Wang, A compressed sensing-based wearable sensor network for quantitative assessment of stroke patients, Sensors 16 (2) (2016) 202.
[110] A. Zeb, S. Wakeel, T. Rahman, I. Khan, M.I. Uddin, B. Niazi, Energy-efficient cluster formation in IoT-enabled wireless body area network, Computat. Intell. Neurosci. (2022) 2022.
[111] C. Zhang, C.F. Lai, Y.H. Lai, Z.W. Wu, H.C. Chao, An inferential real-time falling posture reconstruction for Internet of healthcare things, J. Netw. Comput. Appl. 89 (2017) 86–95.