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An IoT-Based Edge Computing Lossless Compression Approach for Enhancing Energy Efficiency in Networks

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As the Internet of Things (IoT) maintains to increase the inexperienced control of the huge amounts of records generated becomes increasingly more crucial. One of the major issues is big energy intake associated with transmitting records throughout networks. Addressing this issue is vital for the sustainability and feasibility of IoT infrastructures, mainly in packages stressful actual-time records processing and assessment. This paper targets to introduce a completely unique, energy-green technique for IoT compression that minimizes strength intake at some stage in records transmission. By leveraging edge computing, that seeks the machine data closer to its supply, thereby decreasing transmission distances and related electricity costs. A three-layered framework is introduced to achieve lossless compression by capturing network packets of different data sizes. The framework comprises IoT layer, Edge layer and Cloud layer. The framework is carried out at the brink of the community, enhancing statistics, decreasing power consumption, and ensuring security from cyber threats. The results are evaluated using metrics affecting data compression such as Root Mean Squared Error (RMSE) and Peak Signal to Noise Ratio (PSNR). The experimental results show that the proposed compression approach achieves the lowest power consumption rate as 80%, 85%, 90% and 88% in case of image, sensor, financial and textual data types respectively. Furthermore, the proposed framework achieves the highest PSNR value (92.14) and the lowest RMSE value (0.6653) thereby validating the performance of the given IoT-based framework. It shows that the proposed approach is better than existing compression techniques and recent review studies.

Keywords: Cloud layer, Data compression, Edge computing, Energy efficiency, Internet of Things (IoT)

Introduction

In the generation of digital transformation, the Internet of Things (IoT) is reshaping industries with the useful resource of permitting the mixing of bodily gadgets into virtual ecosystems, generating exceptional volumes of facts.[1] This information proliferation needs strong control techniques to maximise IoT machine efficiencies, specifically regarding statistics transmission and strength consumption. Traditionally, statistics processing in IoT structures has relied carefully on cloud computing structures, which frequently outcomes in excessive latency and large strength usage due to the widespread information conversation necessities. With the advent of factor computing, there may be a paradigm shift towards processing facts in the path of its deliver, which not only enhances reaction instances but furthermore significantly decreases the bandwidth desired for statistics transmission.[2–3] However, regardless of vicinity computing, the challenge of handling the electricity intake associated with data transmission stays important. Addressing this mission is crucial, now not most effective to beautify the operational common overall performance of IoT systems however additionally to growth the battery lifestyles of the brink devices, plenty of which may be constrained by way of the usage of their electricity capacities. Moreover, with the growing deployment of IoT in vital programs collectively with healthcare, transportation, and industrial automation, ensuring facts integrity and minimizing power consumption without sacrificing normal ordinary performance turns into paramount. This study introduces an innovative method to facts compression internal IoT frameworks, aiming to lessen the energy footprint of these structures whilst keeping excessive data utility for analytical responsibilities.

While aspect computing improves the scalability and performance of IoT networks, massive gaps continue to be in powerful data compression strategies that appropriately balance power conservation with information integrity.[4–6] Current answers often compromise statistics excellent or fail to scale

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efficaciously with growing statistics volumes and tool networks.[7–9] Additionally, the impact of information compression on the accuracy of system reading models in IoT packages is not sufficiently explored, raising troubles about the practical deployment of compression strategies in touchy real-time environments. *This research seeks to fill these gaps with the resource of developing an energy-green records compression technique that maintains excessive records constancy particularly tailored for component-based totally device getting to know packages.* Furthermore, there's a loss of a cohesive framework that seamlessly integrates superior compression algorithms proper away into IoT device firmware to optimize every power standard performance and information processing pace.[10–11]

Literature Review and Gap Analysis

The integration of the Internet of Things (IoT) into numerous sectors has necessitated green information manage strategies, especially in terms of transmission and storage. Anderson *et al.*[12] shows that at the equal time as traditional cloud-based totally fashions provide robustness in handling enormous statistics masses, they frequently causes latency issues and immoderate power consumption. As a remedy, edge computing has been proposed as a probable solution that techniques records close to its supply, considerably decreasing transmission distances and improving reaction times. Khaled *et al.*[13] focused on techniques to restrict the energy on the course of facts transmission. Poongodi *et al.*[14] discussed numerous lossless and lossy compression strategies, highlighting their ability to reduce facts duration notably however also noting the variable impact on facts constancy and processing overhead. Lossless strategies, at the equal time as maintaining information integrity, offer limited compression ratios, which might not be enough for huge-scale IoT deployments that generate large quantities of facts. Rao *et al.*[15] On the alternative hand, lossy compression strategies, which permit for better compression ratios thru sacrificing a controllable degree of information accuracy, were examined in contexts requiring plenty lots much less precision in records.

Park *et al.*[16] witnessed these techniques are in particular relevant in real-time monitoring structures in which the sheer number of statistics necessitates aggressive compression strategies to make certain well timed information processing and response. However, the software of these compression techniques in IoT, particularly at the same time as blended with place computing, has been less explored. Pandey et. *al.*[17] has started out to cope with this via implementing easy adaptive compression algorithms on factor devices however have no longer fully explored the trade-offs among compression common basic overall performance and computational call for in limited environments. Furthermore, at the same time as there can be a growing fashion to make use of device getting to know algorithms to beautify preference-making in IoT networks, the impact of data compression at the overall performance of those algorithms stays beneath-researched. Compression shown by Zhang *et al.*[18] can modify information developments, possibly primary to decreased version accuracy or reliability. Siemens *et al.*[19] introduce dynamic compression schemes that modify primarily based totally on community conditions, that could drastically optimize IoT communications. Moreover, Liu *et al.*[20] have contributed insights into the algorithmic performance of records compression techniques, specializing in their scalability in multi-node IoT networks. Moreover, the literature furthermore lacks comprehensive studies at the implementation challenges of integrating advanced data compression algorithms at once into IoT devices. These include hardware barriers, power constraints, and the need for actual-time processing talents. Barina *et al.*[21] additionally, most modern studies specialize in theoretical fashions and simulations with less emphasis on area trials or real-global implementations, which might be vital for validating the proposed solutions underneath practical going for walks conditions**.** Lempel *et al.*[22] has validated that even minor losses in statistics quality can substantially affect the general performance of deep studying fashions carried out in predictive analytics. The modern-day procedures furthermore often forget about the safety implications of compressed data transmission. With IoT devices an increasing number of being focused with the resource of cyber-assaults, making sure the integrity and security of compressed statistics streams is paramount, a gap no longer sufficiently covered in current studies. Nasif *et al.*[23] applied deep learning techniques to reduce size of Huffman tree using pooling. However, the given study failed to achieve lossless and secured compression due to shortest bit size. Chang *et al.*[24] introduced lossless compression approach for medical IoT systems by monitoring data based on heart rate, heart signals and electrocardiograph (ECG) scans.

Still, the given approach is unable to compress financial as well as textual data. Tosoni *et al.*[25] used sparse matrix-vector multiplication approach to investigate time, space and energy efficiency among IoT devices. Data parallelism improved execution time, energy consumption and space efficiency but the approach failed to validate the matrix variables in achieving data compression. Qiu *et al.*[26] introduced robust topology generation scheme for IoT systems to prevent loss of data bits. Its olive-like topology is only suitable for medium degree nodes and did not validate images for compression.

Novelty and Contributions

- Develops a unique lossless compression set of policies optimized for IoT devices, imparting better compression ratios with minimal loss of critical facts, thereby extending device battery life, and decreasing transmission costs.
- Seamlessly integrates the compression set of policies with facet computing frameworks, permitting network processing and garage of compressed facts, which drastically decreases power consumption.
- Ensures that the compression set of rules maintains the integrity of facts to a degree that lets in effective software of device gaining knowledge of fashions at the edge, addressing the mission of keeping version accuracy with compressed information.
- Incorporates sturdy protection protocol to guard the integrity and confidentiality of the compressed information, ensuring the answer's applicability in sensitive and important IoT programs.

Overview of Existing Data Compression Algorithms

(a) Adaptive Data Compression Algorithm (ADCA)[27]

This set of policies dynamically adjusts the compression degree based totally on actual-time community bandwidth and processing velocity at the brink node. It starts off evolved with the aid of using way of amassing information from IoT sensors, measuring modern community and processor situations, and then making use of an appropriate compression stage.

Algorithm 1: Adaptive Data Compression Algorithm[27]

Input: Raw data from IoT devices, Network bandwidth (NB), Processor speed (PS)

Output: Compressed data ready for transmission

1. Start
2. Collect raw data from IoT sensors.
3. Measure current network bandwidth (NB) and processor speed (PS) at the edge node.
4. Set compression level:
   a. If NB high and PS high, set compression level low.
   b. If NB low and PS high, set compression level medium.
   c. If NB low and PS low, set compression level high.
5. Apply the appropriate compression algorithm based on the determined level:
   a. For low compression, use fast lossless compression.
   b. For medium compression, use moderate lossy compression.
   c. For high compression, use aggressive lossy compression.
6. Compress data according to selected algorithm.
7. Transmit compressed data to the edge node.
8. End.

(b) Real-Time Compression Quality Adjustment (RCQA)[28]

This set of rules adjusts the mistake bounds of information compression in actual time, based totally completely on the sensitivity of the information being processed. It guarantees that critical statistics is compressed with higher constancy, keeping crucial accuracy for machine learning programs. By monitoring tool remarks and adjusting errors bounds consequently, it balances records integrity with compression performance, enhancing the usability of compressed records in sensitive or vital applications.

Algorithm 2: Real-Time Compression Quality Adjustment [28]

Input: Data to be compressed, Data sensitivity index (DSI)

Output: Compressed data with controlled quality loss

1. Start
2. Input statistics to be compressed and Data Sensitivity Index (DSI).
3. Determine initial mistakes bounds:
   a. If DSI is excessive (vital facts), set low mistakes bounds.
   b. If DSI is medium, set medium mistakes bounds.
   c. If DSI is low (non-vital data), set immoderate mistakes bounds.
4. Apply lossy compression with the determined blunders bounds.
5. Monitor actual-time device comments:
   a. If information high-quality is below great thresholds, decrease mistakes bounds.
   b. If device performance is impacted, growth errors bound slightly.

6. Adjust compression settings dynamically primarily based on tool remarks.
7. Output compressed information.
8. End

(c) Steam Control Transmission Protocol (SCTP)[29]

This relaxed protocol compresses after which encrypt IoT facts earlier than transmission, ensuring facts integrity and confidentiality. After compression, records are encrypted the use of uneven cryptography and signed with a virtual signature for integrity verification. At the receiving quit, the threshold node verifies the signature and decrypts the information, making sure that the facts remain comfortable at some point of transmission and is only on hand to crook entities.

***Algorithm 3:* Stream Control Transmission Protocol**[29]

Input: Data to be compressed

Output: Securely compressed data ready for transmission

1. Start
2. Input data to be compressed.
3. Compress data using the chosen compression algorithm.
4. Encrypt compressed data using an asymmetric encryption algorithm:
   a. Generate key pairs.
   b. Use the public key for data encryption.
5. Attach a digital signature using the private key to ensure data integrity.
6. Transmit the encrypted and signed data to the edge node.
7. On receipt at the edge node:
   a. Verify digital signature.
   b. Decrypt data using the private key.
8. Process decrypted data for further analysis.
9. End

Proposed Framework

The proposed framework is meticulously designed to beautify the electricity overall performance and protection of IoT structures running inside a facet computing paradigm. It strategically carries superior information compression and real-time adjustment mechanisms to address important disturbing conditions of excessive facts volumes, transmission costs, and stringent safety requirements. The structure of the proposed framework consists of three layers: IoT devices layer, Edge layer, and Cloud layer.

(a) IoT Devices Layer: This layer comprises data collection component as follows:

- Data collection: - It is used for gathering information from numerous IoT sensors and gadgets. It guarantees that information should be captured and transmitted to the edge nodes for similarly processing. Collection of data requires capturing of network packets which are to be compressed without affecting the system. Fig. 1 shows screenshot of data collection (network packets).

(b) Edge Layer: This layer consists of following components:

- Adaptive Compression**:** At the coronary heart of the framework, this module dynamically adjusts the facts compression price based totally on actual-time community situations and thing node

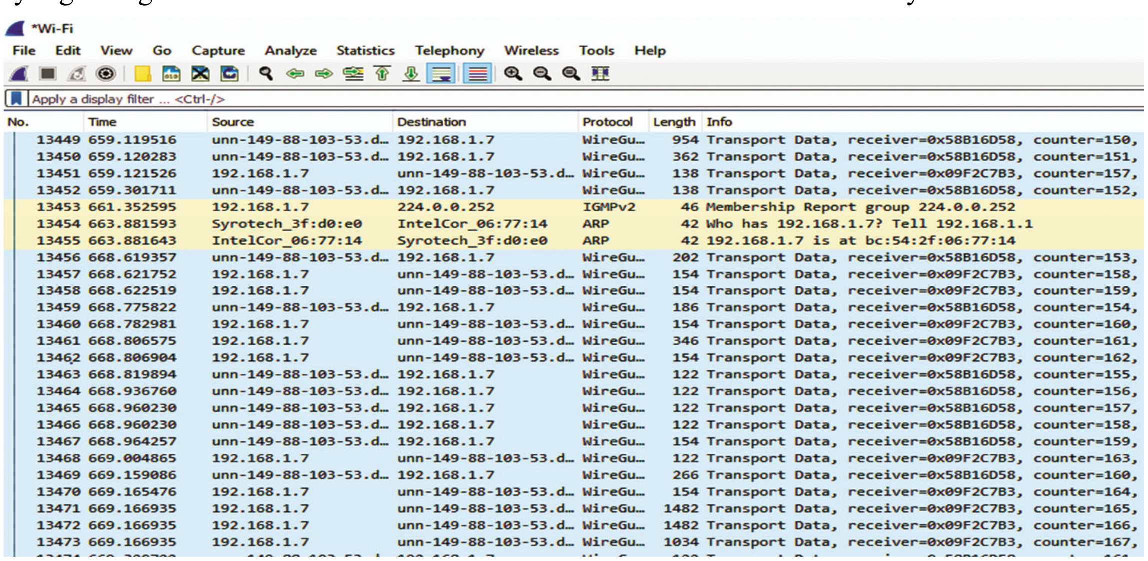

Fig. 1 — Data collection for compression

talents. It makes use of a complex set of policies that determines the most stability among compression efficiency and processing load, consequently maintaining strength, and decreasing bandwidth utilization.

- Quality Adjustment Control**:** Integrated in the edge layer, this factor video display units the integrity and accuracy of the compressed statistics the use of gadget studying algorithms. It adjusts the compression parameters in real-time to ensure that the facts superb is maintained, for vital packages requiring excessive records fidelity.
- Security Protocol**:** To shield statistics integrity and confidentiality, a strong protection protocol is implemented across all layers of the framework. It includes encryption, data anonymization, and use of digital signatures to get rid of cyber threats.

(c) Cloud Layer: It is used for storing massive portions of data and acting complex processing duties that cannot be treated at the threshold due to useful aid constraints. The components are:

- Data Transmission**:** It manages the green switch of processed and compressed facts between the IoT gadgets, thing nodes, and the cloud. It ensures that statistics flow seamlessly inside the course of the framework, optimizing each pace and aid utilization.
- Analytics and Processing: It plays actual-time information analytics to derive actionable insights without delay on the records deliver. It allows selection-making techniques and triggers automated actions without tremendous latency.

The layout of the proposed IoT-based framework is shown in Fig. 2.

Results and Discussion

This section evaluates the proposed framework based on the findings derived from compression strategies across distinctive IoT devices, and safety protocol effectiveness under several compression settings.[30] The metrics used to validate the proposed approach are as follows:

- *Root Mean Squared Error (RMSE):* It is used to check the accuracy of the given results. It is computed by the square of the difference between the proposed and actual values taken square root divided by N. Mathematically, it is given as:

$$\text{RMSE}=\sqrt{\sum_i \frac{(\textbf{Proposed value}-\textbf{Actual packet size})(\textbf{Proposed value}-\textbf{Actual packet size})}{\textbf{N}}} \quad \ldots (1)$$

where, N denotes number of bits or size of original packet

- *Peak Signal to Noise Ratio (PSNR):* It measures the quality between original data and compressed data. The higher the value of PSNR, the better will be quality of compression. It is given as:

$$\text{PSNR} = 10 \log_{10} (\text{Original file size / RMSE}) \quad \ldots (2)$$

In Table 1, we collate the proposed framework results with the existing compression algorithms[27–29] and recent studies.[23–26]

Table 1 shows comparison of average RMSE and average PSNR of recent studies and existing compression algorithms with the proposed approach. The results depict average RMSE of the recent studies (**1.8562, 1.7433, 1.5341 and 1.4873**) and existing compression algorithms **(1.4567, 1.3612 and 1.2583)**

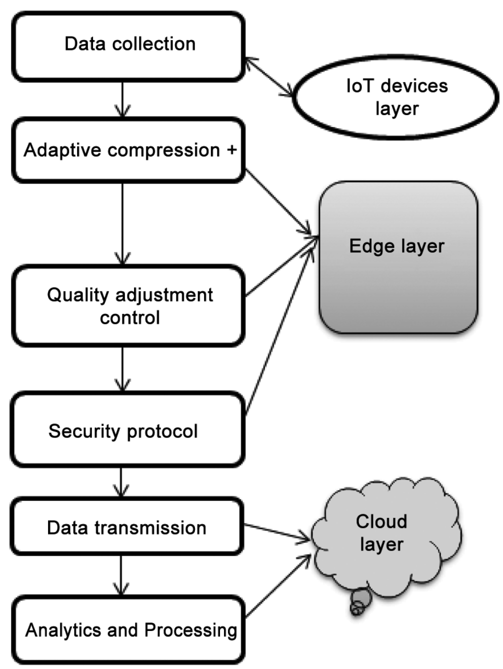

Fig. 2 — Layout of the proposed IoT-based edge computing framework

Table 1 — Comparative analysis of the proposed approach with existing compression algorithms and recent studies

Approaches / Algorithms/ Recent studies	Avg. RMSE	Avg. PSNR
Nasif *et al.*[23]	1.8562	80.02
Chang *et al.*[24]	1.7433	86.43
Tosoni *et al.*[25]	1.5341	84.45
Qiu *et al.*[26]	1.4873	88.09
ADCA [27]	1.4567	79.12
RCQA [28]	1.3612	83.76
SCTP [29]	1.2583	82.35
Proposed lossless compression	0.6653	92.14

Table 2 — Power consumption analysis of the proposed approach based on compression level

Data Type / Compression	No compression	Moderate compression	Lossless compression (proposed)
Image data	92%	89%	80%
Sensor data	95%	91%	85%
Financial data	98%	95%	90%
Text data	94%	92%	88%

is much higher than the proposed approach (**0.6653**). Lesser value of RMSE indicates that the proposed approach is prone to fewer errors and proves to be the most suitable for data compression. Since RMSE is inversely proportional to PSNR, therefore the proposed approach has the highest PSNR (**92.14).**
Individual analysis of the proposed lossless compression approach on several data types is shown in Table 2. The results are achieved by taking three aspects into consideration- no compression, moderate compression and lossless compression.

The "Proposed Compression" column in table 2 shows dramatic reductions thus indicating a large decrease in power consumption. It gives a clear and quantifiable demonstration that the proposed compression approach notably reduces the energy intake of IoT gadgets. The findings highlight the trade-off among data types and power consumption percentage. Image data type sees a reduction in power consumption from **92% to 80%** after applying the proposed lossless compression approach. Similarly, sensor data type ranges from **95% to 85%** decrease in power consumption. Financial data type compression also achieves the least power consumption (90%) on applying the proposed lossless scheme Textual data attains power consumption of **94% (no compression), 92% (moderate) and 88% (lossless compression).**

Security Protocol Effectiveness

The proposed framework meets the requirements of security protocol in terms of information sensitivity levels. When compression is done, especially advanced lossy strategies, safety integrity ratings decorate from 'Medium' to 'Maximum' at the identical time due to increase in records sensitivity. This development is pivotal, especially for noticeably sensitive data in which protection breaches can result in severe consequences. The better safety with better compression degrees can be attributed to fewer facts points being transmitted, which reduce the attack floor for capacity information breaches and simplify encryption and integrity verification strategies. A threshold related to information sensitivity levels are used to prevent data loss while compression.

Applications of the Proposed IoT-based Lossless Compression Approach

- It is used in ZIP file format to compress data and make it available to users in an efficient and secured manner.
- It will also be used to encode patients' record in healthcare systems which require compression and encoding of images.
- It may also lead to integration of several IoT devices for minimizing load on data centres thereby enhancing energy consumption in networks.

Limitations of the Current Study

- Lossless compression may not perform well when the data is subjected to entropy and uncertainties. It is hard to find exact value of entropy within bits of data.
- The quality of images used for compression may deteriorate due to lack of optimization parameters. The parameters must be selected optimally to preserve compression rate.

Conclusions

The study introduces an IoT-based framework to achieve lossless compression in given networks by exploring the effects of numerous data compression strategies. It seamlessly integrates the compression set of policies with facet computing frameworks, permitting network processing and garage of compressed facts, which drastically decreases power consumption across all device types, thereby improving operation, overall performance and sustainability. The proposed framework achieves the highest PSNR value (92.14) and the lowest RMSE value (0.6653) thereby validating the performance of the given IoT-based framework proving its superiority to the existing compression techniques.

Future research on actual-time adaptive structures is needed that modify compression parameters in response to converting community situations and processing skills. Additionally, the integration of system mastering techniques for maximum compression needs to be explored for ensuring efficacy of IoT systems. Ultimately, advancing those adaptive compression strategies will assist the broader adoption of IoT generation, making sure they meet the rigorous desires of modern-day digital infrastructures on the identical time as retaining excessive requirements of performance, safety, and facts integrity.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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