

Novel framework for downsizing the massive data in internet of things using artificial intelligence

Salma Firdose¹, Shailendra Mishra²

¹School of Information Science, Presidency University, Bengaluru, India

²College of Computer and Information Science, Majmaah University, Al Majma'ah, Saudi Arabia

Article Info

Article history:

Received Mar 27, 2024

Revised Feb 21, 2025

Accepted Mar 15, 2025

Keywords:

Artificial intelligence

Cloud

Data compression

Internet of things

Voluminous data

ABSTRACT

The increasing demands of large-scale network system towards data acquisition and control from multiple sources has led to the proliferated adoption of internet of things (IoT) that is further witnessed with massive generation of voluminous data. Review of literature showcases the scope and problems associated with data compression approaches towards massive scale of heterogeneous data management in IoT. Therefore, the proposed study addresses this problem by introducing a novel computational framework that is capable of downsizing the data by harnessing the potential problem-solving characteristic of artificial intelligence (AI). The scheme is presented in form of triple-layered architecture considering layer with IoT devices, fog layer, and distributed cloud storage layer. The mechanism of downsizing is carried out using deep learning approach to predict the probability of data to be downsized. The quantified outcome of study shows significant data downsizing performance with higher predictive accuracy.

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Corresponding Author:

Salma Firdose

School of Information Science, Presidency University

Itgalpur Rajanakunte, Yelahanka, Bengaluru, Karnataka 560064, India

Email: salma.firdose@presidencyuniversity.in

1. INTRODUCTION

With a targeted deployment of large scale environment towards data acquisition, internet of things (IoT) has been generating a staggering size of voluminous data [1]. The prime reason for generation of such massive data in IoT can be reasoned by proliferation of devices [2], continuous data generation [3], high granularity [4], diverse data types [5], and global reach [6]. Therefore, managing such massive streams of generated data poses a significant challenges towards performing robust analytical operation, distributed data storage, and security as well [7]. However, there are various preferred approaches evolved towards managing such challenging size of data. The primary solution evolved is to adopt edge computing in IoT that can not only conserve bandwidth but also minimize latency [8]. Various operations e.g. preliminary analysis, aggregation, data filtering can be carried out effectively by edge devices prior to forwarding the data to cloud. Another significant solution is towards adopting filtering and prioritization of data at the gateway or edge node by considering only essential information and discarding less effective information [9]. Such approach can minimize the data traffic to a large extent and emphasize towards resource management in IoT. The third essential approach towards traffic management is associated with compression or reduction of data while transmitting over the network [10]. Adopting various approaches e.g. data deduplication [11], lossless compression [12], delta encoding [13] is reported to accelerate the data transmission and minimizes the consumption of channel capacity. Apart from above three approaches, other frequently adopted approaches are distributed architecture, quality of service (QoS) management, constructing scalable infrastructure, and

adopting effective security measures. However, these are less frequently adopted compared to the other three approaches discussed above. The prominent research challenges associated with all the above approaches are associated with bandwidth constraint, scalability, data latency, data security, data storage management, data quality and reliability, interoperability and standardization, and energy efficiency [14].

Out of all these approaches, data compression approaches are commonly preferred as a candidate solution towards downsizing the data in IoT. However, there are various significant research problems associated with it as follows: i) compression approaches that claims of higher compression ratio is witnessed to consume extensive computational resources that poses as a bigger challenges for restricted processing capability of edge devices as well as IoT nodes; ii) adoption of compression and decompression process is also associated with inclusion of additional latency that affects data transmission performance especially for the applications that demands real-time functionalities with instantaneous response system; iii) energy consumption is another critical challenges in existing compression approaches that can eventually reduce the sustainable operations of IoT devices; iv) adoption of lossy compression schemes offers maximized compression ratio but at the cost of data quality thereby affecting certain applications in IoT that demands accurate representation of data; v) overhead in data compression is another significant challenges especially when metadata is compressed or additional synchronization takes place or to manage the decompression dictionaries; and vi) the demands of a compression algorithm to be adaptable as well as compatible while working with diversified protocols, platforms, and devices in IoT is truly challenging. Addressing these challenges requires careful consideration of the specific requirements, constraints, and trade-offs associated with compression in IoT and cloud deployments. The major gap identified is towards selection of an appropriate compression algorithms, optimizing compression parameters, and implementing efficient compression techniques tailored to the characteristics of the data and the underlying infrastructure, which is not much reported in existing system targeting towards maximizing the benefits of data compression in IoT and cloud environments.

The related work in the area of larger-sized IoT data management are as follows: Nwogbaga *et al.* [15] have presented discussion of data minimization approaches considering cloud environment, fog computing, and IoT. The idea of the work is towards downsizing the massive data to reduce the offloading delay. The work presented by Rong *et al.* [16] have constructed a collaborative model using cloud and edge computing for converging IoT with artificial intelligence (AI) in order to generate a data-driven approach for supporting IoT applications. Similar line of discussion has been carried out by Bourechak *et al.* [17]. Such types of studies with an inclusion of machine learning applied on edge computing in IoT is also advocated in work of Merenda *et al.* [18]. Heavier traffic management in IoT has been attempted to control using data minimization scheme as presented by Elouali *et al.* [19] using a unique information dissipation framework. Karras *et al.* [20] have presented a machine learning approach which is meant for performing management of big data where the idea of the work is – to perform anomaly detection after cleaning the data using federated learning, to integrate self-organizing map with reinforcement learning for clustering, and to use neural network to compress the data. Similar line of work is also carried out by Signoretti *et al.* [21]. Neto *et al.* [22] have designed a dataset that can be used for real-time investigation on IoT ecosystem. The study overcomes the issues of limited real-time data for analyzing IoT performance that acts as an impediment towards researching data management in IoT. Nasif *et al.* [23] have implemented deep learning approach along with lossless compression in IoT in order to address the memory and processing limitation of an IoT nodes. The study towards lossless compression was also witnessed in work of Hwang *et al.* [24] where a bit-depth compression technique has been adopted to witness optimal resource utilization. Sayed *et al.* [25] have presented a predictive model for traffic management in IoT in order to address the congestion problems using both machine and deep learning approaches. Zhang *et al.* [26] have presented a data minimization approach using adaptive thresholding and dynamic adjustment. Bosch *et al.* [27] have presented a data compression scheme especially meant for event filtering by sensors with a target of minimizing the data throughput.

Therefore, the contribution of the proposed study is towards developing a novel computational framework that can perform an effective management of streaming the raw data in IoT using layer-based architecture harnessing the potential of AI. The value added contribution of the proposed study different from existing system are as follows: i) the study model presents an optimal modelling of data minimization for a large scale of IoT traffic for facilitating an effective and quality data management; ii) the layer-based interactive architecture is designed considering IoT devices, fog layer, and cloud storage units that facilitates a unique filtering and transformation of raw and complex data to reduced and quality data; iii) a deep neural network is adopted in order to facilitate downsizing of the data without affecting the quality of essential information within it; and iv) an extensive test environment is constructed with dual settings representing normal and peak traffic condition in order to benchmark the outcome of proposed system in contrast to conventional data encoding system and learning-based model. The next section illustrates the research methodology involved in proposed study.

2. METHOD

The prime aim of the proposed scheme is to presents a novel data management framework using AI towards an effective traffic control on IoT environment. Figure 1 highlights the proposed architecture where it is shown that the proposed scheme is designed considering three layers of operation considering IoT device, fog layer, and cloud layer. Out of all the three layers, the intermediate layer of fog plays the most important role as the proposed data management is carried out in this layer. On the other hand, the first layer of IoT device generates the massive set of streamed sensory data while the processed data is utilized by the last part of cloud layer. Unlike any existing system, the proposed system doesn't forward the raw data that could eventually degrade the performance of the network along with various adverse consequences e.g., device failures, and higher resource consumption. The core agenda of the proposed study model is towards offering a balance between data quality and assigning minimal data at the source IoT device. The proposed scheme also uses a conventional compression algorithm before transmitting the sensed data from device layer to edge layer.

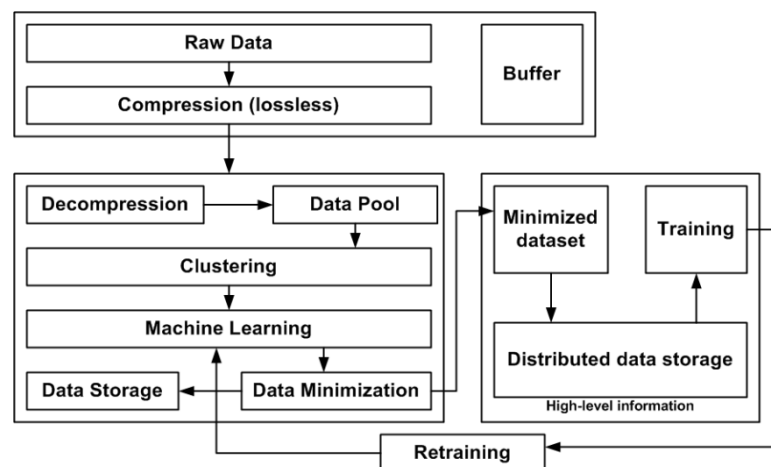


Figure 1. Proposed architecture

According to Figure 1, The proposed scheme implements a deep neural network approach in order to process the compressed data so that maximum data quality can be retained. The novelty of this approach is that it uses deep learning and not conventional signal compression algorithm which could leads to loss of significant information. Once the stream of data reaches the fog layer, it undergoes the process of decompression as the data at this point is usually unsuitable for analysis and storage owing to its unclear and ambiguous nature. These data are then retained in a temporary pool of data so that it can be systematically process to next sequence of operation. The proposed scheme applies unsupervised learning approach to the acquired data that is subjected to clustering process before applying learning operation. The proposed scheme considers that edge devices within the fog layer is the location which performs execution of the training operation of the learning model and hence the proposed model is trained on varied server as well as on cloud before applying it to the edge device.

While doing this, the scheme considers abundance deployment of resources and processing power present in cloud and varied servers in contrast to edge devices. This is because of the fact that training of the AI models can be suitably performed on potential and sustainable server compared to edge devices. The proposed model is also trained on edge devices too after that. It should be noted that deployment of the learning model is mainly directed towards accomplishing an objective of minimization of size of dataset considering triple attributes viz. correlation of context (CC), performance of distributed function (PDF), and ratio of minimization (RM). As the proposed system uses multiple data minimization algorithm, the solution of context actually switches among them on the basis of similarity with the apriori context, highlighted RM associated with each algorithm, and a segment of distorted data. The proposed learning model will select the best performing data minimization approach without performance declination. Apart from this, the scheme entitles the data stream to undergo check on its similarity of context prior to extract from the IoT devices.

The next step of implementation is associated with the extraction and minimization of IoT data streams. For this purpose, the configuration is required to be done by all owners of data on the basis of varying ranges of CC. With maximization of the level of correlation, the value of PDF keeps reducing, thereby representing the sustainable distortion present in the chunk of obtained data. The allocation of the CC

is carried out in form of percentile while the scheme assigns 0% to the score for PDF whose value is witnessed with much higher correlation value. Further, the parameter RM will offer a precise information of the maximum range to which the stream data can be subjected to minimization considering a specific data minimization technique is subjected to it. After this metric is predictively evaluated by the proposed study model than a precise data minimization approach is selected that finally results in minimization of the IoT traffic data prior to forward it to the cloud layer. It is quite possible for the IoT device to exhibit a fluctuating range of correlation owing to the heterogeneity of device and data. The data characterized by much lower fluctuating values are not demanded to be consistently stored while this type of the data can be subjected to data loss while performing data minimization without affecting any quality. The scheme applies both lossless and lossy minimization approach for all the data whose correlation is found to be very high. The proposed study applies lossless data minimization techniques for the values whose correlation is found to be very high.

The size of the data associated with the cluster is subjected to minimization in proposed approach in presence of varying approaches e.g. data sampling, compression, and filtering. on the basis of the characteristic of the data. In lossy data minimization approach, there is a possibility of loss of data while lossless retains all the essential information. The scheme also permits the retention of the data minimization technique within the local storage in order to facilitate the minimization of data chunk. Therefore, an edge device is used for storing this decision associated with the storage of local data. The data that is reduced is finally forwarded to the cloud layer while the cloud storage unit is responsible for retaining all the information of higher level. This is the potential novelty of proposed scheme where the raw data is not redirected to the cloud unlike any existing study models or commercially available cloud storage usage. Proposed system stores structured, processed, and error-free data that can be adapted easily for distributed cloud storage as well as for any future analytical operation. As the resource availability is more in cloud storage device compared to edge device, therefore, proposed scheme considers any possibilities of retraining of data to be carried out in cloud layer itself. The operations carried out in each layer are as following:

- IoT device layer: in this layer, there are varied number of sensing devices which works on the principle of time-slot based active and passive sensing for transmission and going to sleep state needed for energy conservation. When the device senses any new stream of data, it compares with the older data. In case of higher correlation, the device doesn't consider the newly arrived data to be transmitted and it goes to sleep state. Otherwise, it considers the unique and non-iterative incoming data stream and subject it towards evaluation for truncating any possibilities of errors followed by forwarding the data to next layer.
- Fog layer: all the stream of data from prior layer is forwarded to the edge device which decompresses the data and forward it to the storage pool followed by clustering the decompressed data. Further, learning approach is applied to estimate the PDF and RM score. If the correlation score is found to be very low than a lossy data minimization approach is applied or else it checks if the correlation is low. In case of low correlation, it suggests to apply lossy data minimization approach otherwise it checks if the correlation is moderate. In case of moderate correlation, it still suggests to apply lossy data minimization approach otherwise it checks for higher correlation. In case of higher correlation, it suggests for lossy data minimization like prior steps otherwise it checks for very high correlation. In case of absence of very high correlation, it aborts otherwise it applies lossless data minimization technique with maximized value of RM that can further reduce the decompressed clustered data. Finally, the obtained reduced data is transmitted to next layer.
- Cloud layer: when the reduced data form previous layer is received by the cloud node, it reevaluates the degree of reduced size and compared it with the reduced data that is already there within itself. In case of positive match, cloud node doesn't store this newly arrived data or else it stores it back. To improve the performance, it assesses if there is a requirement of retraining the model based on varying score of correlated reduced data. In case of the need, the cloud performs retraining of the model followed by updating the information to the prior layer of edge device otherwise it reevaluates if the newly arrived data is practically reduced.

3. RESULT

The development and scripting of the logic of implementation mentioned in prior section is carried out in python where a virtualized environment is constructed with deployment of sensors as IoT devices. The assessment of the proposed scheme is carried out considering two test environment where the primary test environment is meant for performing group-based data forwarding while the secondary test environment is meant for performing device-based individual data transmission. The prime reason of choosing sensory-based data format of an IoT device is because of the fact that it is characterised by time-series format where information is presented along with time involving instances and features. The proposed scheme chooses conventional compression scheme found in literature as follows:

- Exist₁: this data minimization approach was presented by Adedeji [28] which uses symbol that are structured in sequence ranging from maximal to minimal probabilities followed by classifying the two sets whose value of probability is in proximity of equalness to each other.
- Exist₂: this approach was presented by Abdo *et al.* [29] that performs specification of frequencies of iterativeness of signal followed by the score of the signal coefficient. The core agenda is to minimize the bits number for data set representation.
- Exist₃: this approach was discussed in work of Chowdary *et al.* [30] applied on edge computing which attempts to identify the iterative and longer phrases followed by encoding them. The individual phrases has prefix similar to prior phrase that has already been encoded along with one extra alphabetical character.
- Exist₄: this data minimization approach was presented by Zafar *et al.* [31] that evaluates the occurrences of appearance of specific symbols within a set of information thereby facilitating unambiguous and efficient code.
- Exist₅: this approach was implemented by Lee *et al.* [32] where the data minimization is carried out using less number of bits. The model of encoding was done specifically considering edge device to offer better coding performance.

The proposed system has been evaluated using standard dataset [33] with extensive sensory readings. Hence, a proper test-case has been designed considering two settings viz. Setting-1 consists of 10,526,380 bytes of data where each line of CSV file consists of ten sensory readings and setting-2 consists of 41,117,828 bytes of data where each line of CSV file consist of individual information. It is to be noted that the first setting is used for assessing normal traffic condition while second setting is used for assessing peak traffic condition. The numerical outcomes are exhibited in Tables 1 and 2 corresponding to both the primary and secondary settings.

Table 1. Numerical outcomes for setting-1

Approach	Compressed data (bytes)	Mean compressed file (bytes)	Compression ratio
Exist ₁	5,178,711	217.60	0.74
Exist ₂	11,085,434	511.83	0.85
Exist ₃	4,814,433	299.14	0.85
Exist ₄	4,184,031	157.20	1.18
Exist ₅	1,880,441	140.47	2.78
Prop	2,781,665	230.64	3.69

Table 2. Numerical outcomes for setting-2

Approach	Compressed data (bytes)	Mean compressed file (bytes)	Compression ratio
Exist ₁	23,616,330	184.35	0.49
Exist ₂	51,042,266	238.82	0.73
Exist ₃	24,286,087	188.18	0.36
Exist ₄	16,808,436	146.12	0.76
Exist ₅	17,815,801	151.75	0.79
Prop	29,815,832	251.87	0.93

The numerical outcome exhibited in Tables 1 and 2 showcase that proposed prop scheme offers better outcome for normal traffic (compression ratio=3.69) in contrast to peak traffic condition (compression ratio=0.93), which is quite aggregable in perspective of practical environment. A closer look into this numerical trend will show that proposed scheme has extensible capacity to offer highly optimal compression ratio. This is in contrast to all individual encoding approaches reportedly used in IoT and cloud environment.

In order to arrive at a conclusive outcome, a mean value of all the existing approaches is considered and compared to proposed scheme with respect to dual settings as exhibited in Figure 2. The size of the traffic is programmatically increased to 20% more to understand its impact on the outcome. The outcome showcases that the proposed system is found to offer approximately 17% and 39% of increased in compression ratio in setting-1 and setting-2 respectively. The prime reason behind the improvement of compression ratio in proposed system compared to existing system can be attributed by its involvement of learning-based approach. None of the existing system performs data minimizations in preemptive form and involves extensive algorithmic operation; however, proposed scheme exhibited a predictive-based methodology where the reduction is carried out on the sequential basis of observation of data within fog layer. Further, cloud layer too contributes towards data minimization unlike any of existing approaches. Further, the proposed study outcome has been compared with the existing AI-based models used for data

minimization. The existing AI-model considered for this purpose is that of convolution neural network (CNN) and conventional K-means clustering represented as exist₇ and exist₆ respectively in Figures 3 and 4.

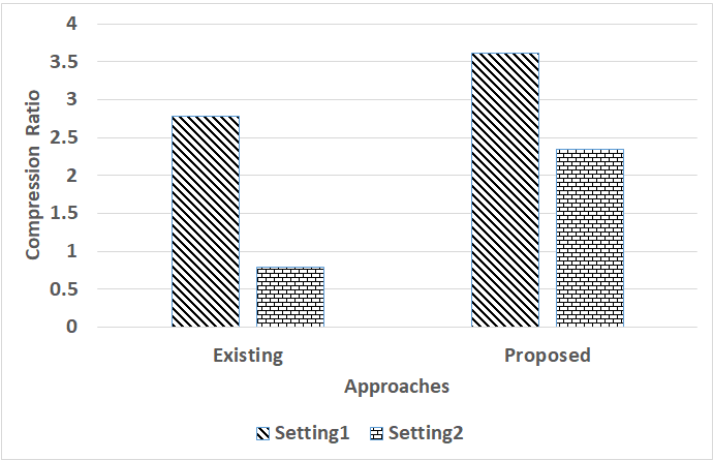


Figure 2. Comparative analysis of compression ratio

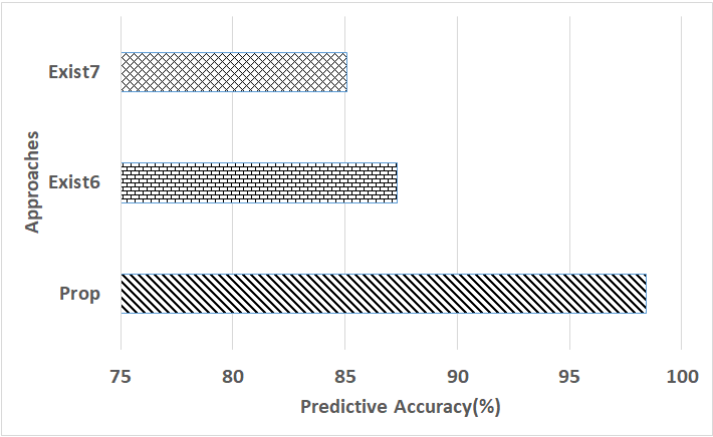


Figure 3. Comparative analysis of predictive accuracy

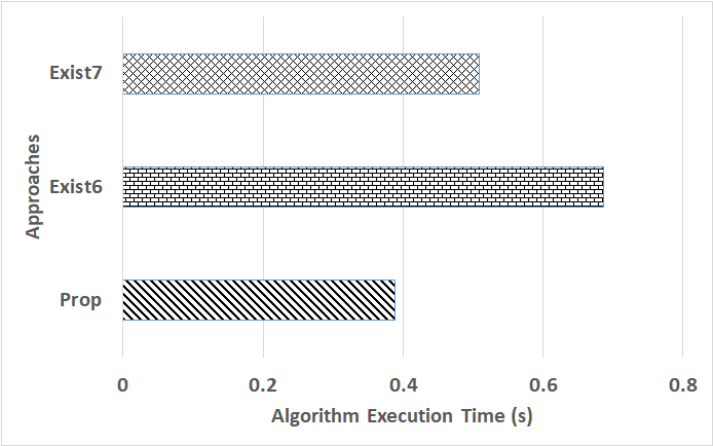


Figure 4. Comparative analysis of algorithm execution time

Figures 3 and 4 showcase that proposed scheme prop exhibits approximately 43% higher predictive accuracy and 32% reduced algorithm processing time in contrast to both the existing AI-models. While performing this extensive analysis, it was noted that CNN (exist₆) can suitably adept itself towards learning hierarchical representation of data. It also uses pooling layers in order to minimize the spatial dimension of feature maps without losing any essential information. However, training CNN (exist₆) is found to be computationally intensive especially when exposed to peak traffic condition. This results in extensive algorithm execution time while its interpretability is still limited. On the other hand, adoption of K-means clustering (exist₇) is seen to be quite faster than CNN (exist₆) as noted in Figure 4 as well as it is also found to adapt itself to larger dataset too. However, it suffers from higher sensitivity while initializing the cluster selection process. Further, exposure to non-linear structures of data cannot be handled well by this approach that leads to degraded accuracy score as seen in Figure 3.

These limitations as well as identified limitation of existing studies are addressed in proposed study model where it is seen that the proposed scheme doesn't encounter any such issues owing to its novel and yet streamlined flow of processed data within three layers involved in architecture. The presence of data pool also significantly assists in contributing better clustering performance within the fog layer. With involvement of dynamic PDF and RM values by the adopted learning schemes further offer better learning operation using deep neural network. The summarized key findings of proposed study are: i) better compression performance is exhibited by proposed system in contrast to existing system as exhibited in Tables 1 and 2 multiple varied test scenarios; ii) the compression performance of proposed system is 28% better than conventional scheme; iii) the accuracy score accomplished in proposed system is 43% improved than conventional methods; and iv) the algorithmic execution time is found to be 32% reduced than existing methods proving faster operation approaches in IoT environment.

4. CONCLUSION

The observation and study presented in proposed work showcase that the deployment of various applications of an IoT over cloud environments is usually characterized by generation of varied form of sensory data. Such form of data is not only bigger in size but also consists of various unnecessary information, which are quite challenging to identify and remove. The limitation of existing study reviewed can be summarized as: i) the adaptability of existing approaches towards larger decentralized environment of IoT and ii) existing learning schemes are over-burdened with analytical processing with raw data. Therefore, these issues are addressed in proposed study. The presented study model contributes towards offering following novel features: i) proposed study presents a layer-based architecture with an interactive and structured communication among IoT device, edge node, and cloud storage unit; ii) proposed scheme presents an unsupervised learning model for minimizing the data volumes without affecting the data quality; iii) the scheme performs compression in IoT device layer while decompression in fog layer while further data minimization is carried out in cloud layer; iv) a simplified clustering approach has been introduced which extracts data from pool followed by subjecting them to learning model for data minimization; and v) the analysis of the proposed model is carried out an extensive test environment where proposed scheme is witnessed with approximately 28% of maximized compression ratio performance, 43% of increased predictive accuracy, and 32% of minimized algorithmic processing time. However, the study model doesn't incorporate any means to safeguard the processing unit where the algorithm is executed. This is one of the limitation which will be addressed in future work. The possibility of future work will be towards securing the communication process as well as processing unit from being victimized by any adversaries. For this purpose, an ethereum blockchain based algorithm can be implemented. The implication of this direction of future work will balance both communication, computation, and security demands in IoT.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Salma Firdose	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Shailendra Mishra		✓				✓		✓	✓	✓	✓	✓		

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.




REFERENCES

- [1] A. Koohang, C. S. Sargent, J. H. Nord, and J. Paliszkievicz, "Internet of things (IoT): from awareness to continued use," *International Journal of Information Management*, vol. 62, 2022, doi: 10.1016/j.ijinfomgt.2021.102442.
- [2] B. Nagajayanthi, "Decades of internet of things towards twenty-first century: a research-based introspective," *Wireless Personal Communications*, vol. 123, no. 4, pp. 3661–3697, 2022, doi: 10.1007/s11277-021-09308-z.
- [3] J. L. Herrera, J. Berrocal, S. Forti, A. Brogi, and J. M. Murillo, "Continuous QoS-aware adaptation of cloud-IoT application placements," *Computing*, vol. 105, no. 9, pp. 2037–2059, 2023, doi: 10.1007/s00607-023-01153-1.
- [4] X. Zhang, G. Zhang, X. Huang, and S. Poslad, "Granular content distribution for IoT remote sensing data supporting privacy preservation," *Remote Sensing*, vol. 14, no. 21, 2022, doi: 10.3390/rs14215574.
- [5] A. Naghib, N. J. Navimipour, M. Hosseinzadeh, and A. Sharifi, "A comprehensive and systematic literature review on the big data management techniques in the internet of things," *Wireless Networks*, vol. 29, no. 3, pp. 1085–1144, 2023, doi: 10.1007/s11276-022-03177-5.
- [6] A. M. Rahmani, S. Bayramov, and B. K. Kalejahi, "Internet of things applications: opportunities and threats," *Wireless Personal Communications*, vol. 122, no. 1, pp. 451–476, 2022, doi: 10.1007/s11277-021-08907-0.
- [7] T. Alsoubi, Y. Qin, R. Hill, and H. Al-Aqrabi, "Distributed intelligence in the internet of things: challenges and opportunities," *SN Computer Science*, vol. 2, no. 4, 2021, doi: 10.1007/s42979-021-00677-7.
- [8] J. Pérez, J. Díaz, J. Berrocal, R. López-Viana, and Á. González-Prieto, "Edge computing: a grounded theory study," *Computing*, vol. 104, no. 12, pp. 2711–2747, 2022, doi: 10.1007/s00607-022-01104-2.
- [9] D. Ameyed, F. Jaafar, F. Petrillo, and M. Cheriet, "Quality and security frameworks for IoT-architecture models evaluation," *SN Computer Science*, vol. 4, no. 4, 2023, doi: 10.1007/s42979-023-01815-z.
- [10] A. A. Sadri, A. M. Rahmani, M. Saberikamarpashti, and M. Hosseinzadeh, "Data reduction in fog computing and internet of things: a systematic literature survey," *Internet of Things*, vol. 20, 2022, doi: 10.1016/j.iot.2022.100629.
- [11] P. G. Shynu, R. K. Nadesh, V. G. Menon, P. Venu, M. Abbasi, and M. R. Khosravi, "A secure data deduplication system for integrated cloud-edge networks," *Journal of Cloud Computing*, vol. 9, no. 1, 2020, doi: 10.1186/s13677-020-00214-6.
- [12] S. K. Idrees and A. K. Idrees, "New fog computing enabled lossless EEG data compression scheme in IoT networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 6, pp. 3257–3270, 2022, doi: 10.1007/s12652-021-03161-5.
- [13] S. Wielandt, S. Uhlemann, S. Fiolleau, and B. Dafflon, "TDD LoRa and Delta encoding in low-power networks of environmental sensor arrays for temperature and deformation monitoring," *Journal of Signal Processing Systems*, vol. 95, no. 7, pp. 831–843, 2023, doi: 10.1007/s11265-023-01834-2.
- [14] H. Omrany, K. M. Al-Obaidi, M. Hossain, N. A. M. Alduais, H. S. Al-Duais, and A. Ghaffarianhoseini, "IoT-enabled smart cities: a hybrid systematic analysis of key research areas, challenges, and recommendations for future direction," *Discover Cities*, vol. 1, no. 1, Mar. 2024, doi: 10.1007/s44327-024-00002-w.
- [15] N. E. Nwogbaga, R. Latip, L. S. Affendey, and A. R. A. Rahiman, "Investigation into the effect of data reduction in offloadable task for distributed IoT-fog-cloud computing," *Journal of Cloud Computing*, vol. 10, no. 1, 2021, doi: 10.1186/s13677-021-00254-6.
- [16] G. Rong, Y. Xu, X. Tong, and H. Fan, "An edge-cloud collaborative computing platform for building AIoT applications efficiently," *Journal of Cloud Computing*, vol. 10, no. 1, 2021, doi: 10.1186/s13677-021-00250-w.
- [17] A. Bourechak, O. Zedadra, M. N. Kouahla, A. Guerrieri, H. Seridi, and G. Fortino, "At the confluence of artificial intelligence and edge computing in IoT-based applications: a review and new perspectives," *Sensors*, vol. 23, no. 3, 2023, doi: 10.3390/s23031639.
- [18] M. Merenda, C. Porcaro, and D. Iero, "Edge machine learning for AI-enabled IoT devices: a review," *Sensors*, vol. 20, no. 9, 2020, doi: 10.3390/s20092533.
- [19] A. Elouali, H. Mora Mora, and F. J. Mora-Gimeno, "Data transmission reduction formalization for cloud offloading-based IoT systems," *Journal of Cloud Computing*, vol. 12, no. 1, 2023, doi: 10.1186/s13677-023-00424-8.
- [20] A. Karras *et al.*, "TinyML algorithms for big data management in large-scale IoT systems," *Future Internet*, vol. 16, no. 2, 2024, doi: 10.3390/fi16020042.
- [21] G. Signoretti, M. Silva, P. Andrade, I. Silva, E. Sisinni, and P. Ferrari, "An evolving tinyml compression algorithm for IoT environments based on data eccentricity," *Sensors*, vol. 21, no. 12, 2021, doi: 10.3390/s21124153.
- [22] E. C. P. Neto, S. Dadkhah, R. Ferreira, A. Zohourian, R. Lu, and A. A. Ghorbani, "CICIOT2023: a real-time dataset and benchmark for large-scale attacks in IoT environment," *Sensors*, vol. 23, no. 13, 2023, doi: 10.3390/s23135941.
- [23] A. Nasif, Z. A. Othman, and N. S. Sani, "The deep learning solutions on lossless compression methods for alleviating data load on IoT nodes in smart cities," *Sensors*, vol. 21, no. 12, 2021, doi: 10.3390/s21124223.
- [24] S. H. Hwang, K. M. Kim, S. Kim, and J. W. Kwak, "Lossless data compression for time-series sensor data based on dynamic bit packing," *Sensors*, vol. 23, no. 20, 2023, doi: 10.3390/s23208575.




- [25] S. A. Sayed, Y. Abdel-Hamid, and H. A. Hefny, "Artificial intelligence-based traffic flow prediction: a comprehensive review," *Journal of Electrical Systems and Information Technology*, vol. 10, no. 1, 2023, doi: 10.1186/s43067-023-00081-6.
- [26] H. Zhang, J. Na, and B. Zhang, "Autonomous internet of things (IoT) data reduction based on adaptive threshold," *Sensors*, vol. 23, no. 23, 2023, doi: 10.3390/s23239427.
- [27] R. E. Bosch, J. R. Ponce, A. S. Estévez, J. M. B. Rodríguez, V. H. Bosch, and J. F. T. Alarcón, "Data compression in the NEXT-100 data acquisition system," *Sensors*, vol. 22, no. 14, 2022, doi: 10.3390/s22145197.
- [28] K. B. Adedeji, "Performance evaluation of data compression algorithms for IoT-based smart water network management applications," *Journal of Applied Science and Process Engineering*, vol. 7, no. 2, pp. 554–563, 2020, doi: 10.33736/jaspe.2272.2020.
- [29] A. Abdo, T. S. Karamany, and A. Yakoub, "A hybrid approach to secure and compress data streams in cloud computing environment," *Journal of King Saud University - Computer and Information Sciences*, vol. 36, no. 3, 2024, doi: 10.1016/j.jksuci.2024.101999.
- [30] K. M. R. Chowdary, V. Tiwari, and M. Jebarani, "Edge computing by using LZW algorithm," *International Journal of Advance Research, Ideas, and Innovations in Technology*, vol. 5, no. 1, pp. 228–230, 2019.
- [31] S. Zafar, N. Iftikhar, A. Yadav, A. Ahilan, S. N. Kumar, and A. Jeyam, "An IoT method for telemedicine: lossless medical image compression using local adaptive blocks," *IEEE Sensors Journal*, vol. 22, no. 15, pp. 15345–15352, 2022, doi: 10.1109/JSEN.2022.3184423.
- [32] J. H. Lee, J. Kong, and A. Munir, "Arithmetic coding-based 5-bit weight encoding and hardware decoder for CNN inference in edge devices," *IEEE Access*, vol. 9, pp. 166736–166749, 2021, doi: 10.1109/ACCESS.2021.3136888.
- [33] L. M. Candanedo, V. Feldheim, and D. Deramaix, "Data driven prediction models of energy use of appliances in a low-energy house," *Energy and Buildings*, vol. 140, pp. 81–97, 2017, doi: 10.1016/j.enbuild.2017.01.083.

BIOGRAPHIES OF AUTHORS



Salma Firdose    working as an Assistant Professor in the School of Information Science at Presidency University, Bangalore. She completed her Doctor of Philosophy (Ph.D.) in Software Engineering from Bharathiar University, in 2019. She has 15+ years of teaching experience in the national and international universities. She has published several national and international papers. Her area of specialization is in software engineering, networking, and operating systems. She can be contacted at email: salma.firdose@presidencyuniversity.in.



Shailendra Mishra    working as a Professor in the College of Computer and Information Science, Majmaah University, Majmaah, Kingdom of Saudi Arabia. He received Ph.D. degrees in Computer Science and Computer Science and Engineering in the years 2007 and 2011 from Gurukul Kangri University Utrakhnad, India, and Utrakhnad Technical University, Dehradun, India respectively. He received the Young Scientist Award in 2006 and 2008 from the Department of Science and Technology, UCOST Government of Utrakhnad, India. He has published and presented 76 research papers in international journals and international conferences and wrote more than 10 articles on various topics in national magazines. He can be contacted at email: s.mishra@mu.edu.sa.