Predicting Energy Efficiency in Healthcare IoT Systems and Cloud Storage Solutions

[1]Yashwant Kumar Kolli, [2]priyadarshini Radhakrishnan, [3]Vijai Anand Ramar, [4]Karthik Kushala, [5]Venkataramesh Induru, [6]Thanjaivadivel M
[1]Cognizant Technology Solutions Us Corp, College Station, Texas, USA
[2]ibm Corporation, Ohio, USA
[3]Delta Dental Insurance Company, Georgia, USA
[4]Taylor Corporation, Minnesota, USA
[5]Piorion Solutions Inc, New York, USA
[6]Nandha Engineering College, Erode, Tamil Nadu 638052, India,

ABSTRACT:
Energy savings while maintaining performance levels highly have turned into an emergent challenge considering that Internet of Things (IoT) devices in healthcare are growing at a very fast pace. The dramatic growth in health-related IoT data generation by these devices will typically make energy consumption sprawl, as well as processing time. The existing problem lies in the difficulty of managing energy consumption efficiently as the number of IoT devices and data size scale up. This study aims to predict the energy efficiency of healthcare IoT data and store it in the cloud for efficient management and analysis.The data is collected from IoT healthcare followed by pre-processing to clean the data, and then the data incorporates Cat Swarm Optimization (CSO) for feature selection, Fast Fourier Transform (FFT) for feature extraction, Autoencoders for predicting energy modelling, and Cloud Storage Optimization for efficient data management. The outcomes exhibit the elevation in a domain from energy usage of 0.10 (jule) to 0.30 (jule) and processing time from 20 seconds to more than 120 seconds with an increase in the number of devices and data size. This work will help develop optimization strategies for improving energy efficiency and system performance for large-scale IoT healthcare systems.
Keywords: Healthcare IoT Systems, Cloud Storage, Energy-Efficiency Modelling, Cat Swarm Optimization (CSO), Fast Fourier Transform (FFT)

I. INTRODUCTION

Increasing usages of the Internet of Things (IoT) devices in health care systems are beginning to leave great footprints on the monitoring, diagnostics, and management of patients in the health sector[1]. These devices do have challenges regarding energy consumption, so they may have a reduced life in terms of operation along with the overall performance of the system[2]. With the rapid proliferation of healthcare IoT devices, there will be an increasing need for energy efficiency which achieves the required performance level with low power consumption[3]. The framework has been devised with a view to optimizing the energy consumption of healthcare IoT systems while maintaining optimal performance at which healthcare devices can operate sustainably over time[4].

The energy optimization strategies employed in existing healthcare IoT systems often rely on standard approaches, such as Task Scheduling, Power Scaling, and Resource Allocation[5]. Common energy optimization strategies are Dynamic Voltage and Frequency Scaling (DVFS) and Task Offloading. However, they may not suit applications that process large sizes of data[6]. Although some researchers have attempted to use Reinforcement Learning (RL) to optimize energy consumption, the approach may consume a lot of computation resources and data for training[7]. Besides, cloud-based energy management strategies may not be efficient in compromising the energy requirements versus computational performance for real-time health monitoring[8].

Integrated with Cat Swarm Optimization (CSO) for feature selection, Autoencoders for energy inefficiencies detection, and Fast Fourier Transform (FFT) for feature extraction, the proposed framework would eventually enhance the accuracy and energy-efficiency of IoT devices and eliminate the problems faced by existing works[9]. Cloud storage optimization coupled within deep learning models provides a novel approach in this work, bringing about low power consumption without compromising system performance[10]. Both data compression techniques and optimization algorithms have been incorporated in this study to propose a very full approach, which serves to overcome the constraints that other ones have had in giving a better solution that can be built on like more robust and scalable solutions for emotions of IoT healthcare systems[11].

The framework focuses on energy optimization while reducing the computational load on IoT devices using clouds[12]. The IoT devices tend to consume lesser energies since they offload the extensive computations to the cloud[13]. With this, IoT devices can operate very efficiently without stressing local resources[14]. Thus, health care providers can handle larger volumes of real-time data without hampering their performance, which suffices for applications like continuous health monitoring and predictive analytics. This includes cloud storage optimization techniques at the framework, hence improving the efficiency of handling large data sets while ensuring scalability of health care IoT systems as the future unfolds.

Autoencoders provide the necessary artificial intelligence during energy modelling processes. Autoencoders introduce the possibility of alerting anomalies concerning the energy consumption of the system, causing adaptation of the system to changing conditions, whether that is through adjustment in the usage of some devices or possible environmental change. This adaptability allows adjustments in energy optimization techniques for long-term sustainability and reduced operational costs. The unique fabric of this framework consists of fusion between machine learning optimization techniques and cloud storage solutions[15].

The paper is organized as follows: A review of literature on the latest possibilities and challenges of energy efficiency for the healthcare sector IoT systems is provided in Section 2. The methodology, is discussed in detail in Section 3. Results are presented and analysed in Section 4 based on the experiments performed. Section 5 concludes the findings and future work.

II. LITERATURE SURVEY

As for cloud computing today, governments, big organizations, and institutions use it just like Jigsaw Mali. The major landmark dates included include the original papers written by Google in 2003 for this road map, followed by the original service commercial launch into Amazons EC2 in 2006[16]. The reason cloud computing today is not just a saving option to enterprises but also a revenue avenue. This is about the concept, history, pros and cons, various value chains as well as standardization initiatives down the years.

IIoT generates massive amounts of data which cannot depend on the local storage available on the IIOT devices because of energy and storage constraints[17].Self-organization and short-range IoOT networking help in outsourcing to cloud computing data from devices' constraints as a solution. This research tackles the hitches and computing techniques that are required for seamless integration of IoT with cloud computing, focusing on the efficiency of Cloud Solutions and the new trends in data storage[18].

Research on cloud computing technology as applied to organizations through case studies to provide insight into innovations and major aspects of the technology has been discussed. Besides, it also included cybersecurity and intrusion detection and prevention, as well as other avenues of future research with respect to challenges of cloud adoption in business environments [19].

PCT or Point Cloud Transformer proposes a promising new framework for point cloud learning based on the architecture of transformation that will directly deal with their irregular and unordered nature to conquer the aforementioned limitations. PCT processes in point sequences, is permutation invariant, and captures local context using far-point sampling and nearest-neighbor search [20].A disadvantage of PCT is that, no doubt, it gets cutting-edge results in shape classification and segmentation tasks, but its high resource-consumption slows down efficiency for larger point cloud datasets.

Cloud computing has become a must-have for service-providing companies and people. Its beauty was that it offered easy access and reduced costs for on-demand provision [21].Security is still to be settled with certainty, probably looked into in 2020, where three-layer security vulnerabilities came to bear: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). The present review intends to assess the status of cloud security over the last ten years; it comes with its disadvantages in that security challenges have evolved very rapidly with emerging cloud technologies, and quite a number of associated problems mushrooming toward counter-affording the growth of security threats over time. The present systematic review presents a short glimpse of the IoT-enabled Health Care System for evaluation of architecture, performance, and data management to monitor the healthy states and predict diseases of elderly patients in elderly care homes[22].

The primary focus of this study is on IoT capabilities for symptom detection and disease prediction. This leads to other two major drawbacks-high power consumption and resource depletion-and security issues since so many devices are concerned, all these afflict in a grave way the global performance and sustainability of IoT health care systems. There are many different kinds of Internet-of-Things devices, from smartwatches to health-monitoring wristbands, being used for tracking and transmitting physiological signals in real-time to aid remote health monitoring.

The IoT healthcare market is still giantleaping forward every year. Yet, privacy issues, external threats to security, and ramifications on health data regarding acts done among people left with each other are among challenges that remain consequential. This paper introduces some various recent approaches to looking at these problems, while many remain in securing IoT devices and ensuring that the users trust this data is safe.

2.1. PROBLEM STATEMENT

There are some outstanding issues in healthcare energy efficiency IoT settings. The energy consumption of IoT devices in health care systems is one of the major challenges. These devices continuously collect and transmit data, resulting in their consuming more power over time. The volume of data produced by IoT healthcare devices leads to complexity in data storage and management, which increases pressure on both local devices and cloud systems[23]. Unoptimized and excessive data transfer between the IoT devices and the cloud generates additional energy consumption especially when large chunks of data are sent through it. Lastly, solutions available would efficiently work more on one than the other, as with their performance and energy efficiency, an increase in performance generally translates into increased energy consumption particularly in limited resource environments such as healthcare IoT networks.

III. EXPERIMENTAL WORK

Optimizing energy consumption in healthcare IoT systems while ensuring high performance and operational efficiency is shown in figure 1. The datasets are collected from IoT healthcare devices and prepared/cleaned for ensuring good-quality data. Next, those features which are most relevant to energy consumption are identified by means of feature selection with Cat Swarm Optimization (CSO). After this, feature extraction is done by transforming the data into the frequency domain with the help of Fast Fourier Transform (FFT). Thereafter, cloud storage is essentially used for managing the data while energy efficiency modelling would be predicted using Autoencoders for the minimization of energy efficiencies.

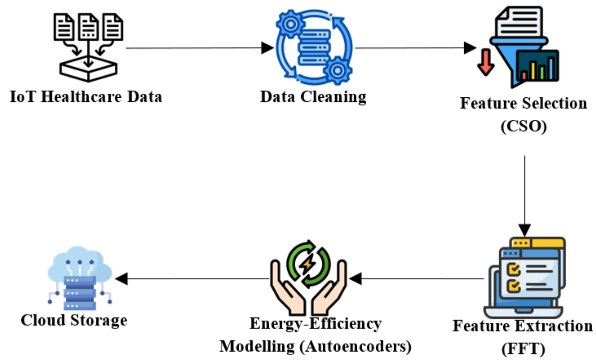

Fig 1: Energy-Efficiency Optimization for Healthcare IoT Systems

3.1. Data Collection

Data is collected from wearables and smart health gadgets based on patients' vital health metrics under continuous monitoring and recording. They record information ranging from heart rates to blood pressures, glucose levels, body temperatures, and activity status. Data so obtained is generated largely containing time-series data, which throw light on patients' health with time. After this, the data are transferred to a cloud system for further processing, storage, and analysis. Accuracy and completeness of data would ensure trustworthiness in health monitoring and hence future optimization in the energy sphere.

3.2. Data Pre-processing

Cleaning is the process conducted on the collected IoT healthcare data to match the accuracy and remove the inconsistencies that the data may have. Missing values will be imputed with a suitable imputation method, while noisy data will be filtered to preserve the whole data integrity. The data normalization will serve as the phenomenon in standardizing the different features of a dataset so that its values can be treated on a similar scale to better analysis and modelling. Data aggregation reduces complexity, summarizing information over the relevant time windows where necessary. This process cleans and prepares data for the various steps that follow: feature selection and extraction-from being available and reliable to analysis-ready data.

3.3. Feature Selection using CSO

Following pre-processing, which achieves data cleaning, normalization, and aggregation of loTgvc healthcare data, the next step is to effect feature selection through Cat Swarm Optimization (CSO). CSO is an optimization algorithm inspired by nature, and mimics the behaviour of cats in hunting for most relevant features. It reduces the dimensionality of data making sure that only the most influential features are kept for analysis. The fitness function for CSO is expressed in equation (1).

(1)

Were, represents the set of features selected, is the performance metric of the model with selected features, is the weight assigned to each feature.

3.4. Feature Extraction using FFT

Feature extraction using Fast Fourier Transform (FFT) involves converting time-domain data into the frequency domain, whereby frequency-based features, which otherwise are not clearly visible in the raw signal, can be detected. Using FFT, IoT healthcare data, such as heart rate or ECG signals, is decomposed into its frequency components, which in turn makes possible the achievements of crucial features such as signal peaks or power spectral density and frequency-related patterns. The FFT of a signal is given in equation (2).

(2)

Where is the Fourier transform of is the frequency, and is the imaginary unit.

3.5. Predicting Energy Efficiency using Autoencoders

When considering energy efficiency, autoencoders refer to training neural network models in such a way that they learn to represent data in a compressed, lower-dimensional representation, effectively minimizing processing and energy costs for storage and computation. In applications pertinent to IoT healthcare, autoencoders can assist in the selection and reconstruction of signature characteristics of a signal and discard irrelevant or redundant information in turn leading to energy efficiency. The autoencoder consists of two parts an encoder, which compresses the input into a lower-dimensional representation , and a decoder, which reconstructs the input from this representation. The autoencoder loss function is represented as equation (3).

(3)

Where is the original input, is the reconstructed input, and the objective is to minimize the reconstruction error .

3.6. Cloud Storage

- Cloud storage is required to store and manage large amounts of data transmitted from IoT healthcare appliances, after performing the necessary feature extraction.
- The processed data obtained from feature extraction techniques such as FFTs or autoencoders is stored in the cloud for later analysis or on long-term storage.
- Cloud storage keeps the extracted features in a scalable, energy-efficient manner reducing the load of local devices and centralizing the management of the data.
- Techniques such as data compression and deduplication help reduce the storage footprint and subsequently reduce energy consumption for storage and retrieval.
- Cloud storage optimizes the energy consumption by providing efficient access to relevant features for quick retrieval without overburdening local resources, hence supporting energy efficiency in IoT healthcare systems.

IV. RESULTS AND DISCUSSION

The corresponding summary results show that there is a direct relationship between the number of IoT devices and energy consumption, as more devices will require higher energy consumption to perform functions. This will further signify that the energy requirements attached to the healthcare IoT grow as it scales further. Although one can use techniques such as Autoencoders in reducing data complexity and optimizing power consumption, the cumulative increase in the number of devices will result in high energy use. This highlighted a need for more energy optimization strategies for dealing with large IoT systems more effectively.

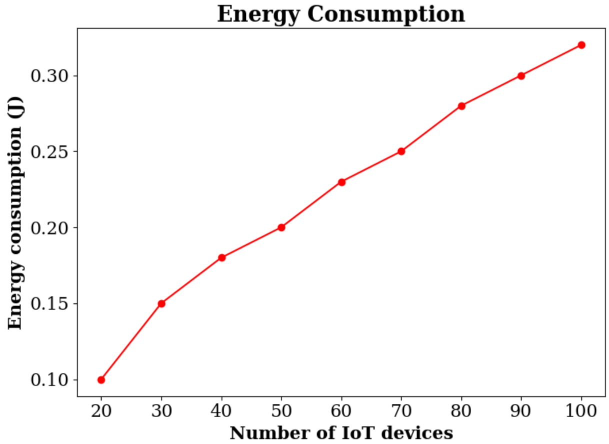

Fig 2**:** Energy Consumption in IoT Devices

The linkage between energy consumption and the number of IoT devices in a system is revealed in figure 2. When the number of IoT devices festers from 20 to 100, energy consumption increases strictly in a linear manner, beginning from around 0.10 till 0.30 (jule). This curve exhibits when adding IoT devices within a network contributes to increased energy needs. Such Autoencoders can be used to manage and compress data from these devices, but, inevitably, augmenting the number of devices would still increase overall energy consumption in proportion. This trend indicates the requirements of requiring further optimization to control efficient energy consumption commensurate with the number of connected devices.

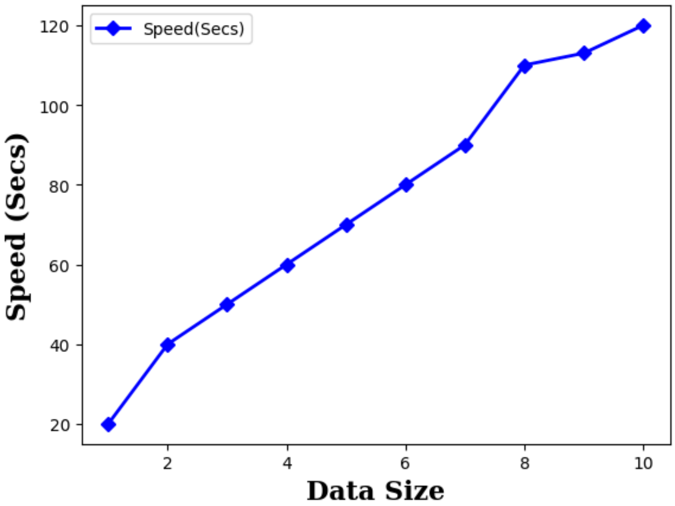

Fig 3: Impact of Data Size on Processing Time

Figure 3 depicts the linkage along the size of the data against the time spent in seconds in the process. From one to unto ten, the data volume continues to grow, so does the time of processing from an average of 20 seconds to well above 120 seconds. The data points are quite regressive; therefore, they indicate that larger data sets take longer to process. This shows that as more information is handled, the time required for computations or for possible optimization reaches higher levels. The results, therefore, establish a need for optimizing algorithms or their options to handle bigger datasets without greatly increasing processing time.

CONCLUSION

An open research investigation proposes an energy consumption prediction framework for healthcare IoT systems, according to which an increase in the number of IoT devices may double the energy consumption and triplicate the processing time, just like scaling the data size. It shows about a near-linear relationship between increasing devices and energy use rising from 0.10 to 0.30 (jule) as devices increase from 20 to 100, with processing time getting spiked from 20 seconds to over 120 seconds as data size increases. While such methods as Autoencoders and Cloud Storage optimization reduce data complexity and improve energy efficiency, architecture-wide increases in devices and data significantly increase energy demands and processing times. Future prospective research attempts will focus on novel paths into energy optimization strategy, especially dynamic resource allocation, Deep Reinforcement Learning, Federated Learning, energy-aware scheduling algorithms, and other more advanced optimization paradigm for effective large IoT system management while sustaining high performance.

REFERENCES

1. Saba, T., Haseeb, K., Ahmed, I., & Rehman, A. (2020). Secure and energy-efficient framework using Internet of Medical Things for e-healthcare. Journal of Infection and Public Health, 13(10), 1567-1575.
2. Guo, Y., Ganti, S., & Wu, Y. (2024). Enhancing energy efficiency in telehealth internet of things systems through fog and cloud computing integration: simulation study. JMIR biomedical engineering, 9(1), e50175.
3. Isa, I. S. B. M., El-Gorashi, T. E., Musa, M. O., &Elmirghani, J. M. (2020). Energy efficient fog-based healthcare monitoring infrastructure. IEEE Access, 8, 197828-197852.
4. Ghosh, A., Raha, A., & Mukherjee, A. (2020). Energy-efficient IoT-health monitoring system using approximate computing. Internet of Things, 9, 100166.
5. Kim, J. (2015). Energy-efficient dynamic packet downloading for medical IoT platforms. IEEE Transactions on Industrial Informatics, 11(6), 1653-1659.
6. Kang, J. J., Dibaei, M., Luo, G., Yang, W., Haskell-Dowland, P., & Zheng, X. (2021). An energy-efficient and secure data inference framework for internet of health things: a pilot study. Sensors, 21(1), 312.
7. Chakraborty, C., Othman, S. B., Almalki, F. A., &Sakli, H. (2024). FC-SEEDA: fog computing-based secure and energy efficient data aggregation scheme for Internet of healthcare Things. Neural Computing and Applications, 36(1), 241-257.
8. Akmandor, A. O., Hongxu, Y. I. N., & Jha, N. K. (2018). Smart, secure, yet energy-efficient, internet-of-things sensors. IEEE

Transactions on Multi-Scale Computing Systems, 4(4), 914-930.

9. El Kafhali, S., & Salah, K. (2019). Performance modelling and analysis of Internet of Things enabled healthcare monitoring systems. IET Networks, 8(1), 48-58.
10. Abirami, S., & Chitra, P. (2020). Energy-efficient edge based real-time healthcare support system. In Advances in computers (Vol. 117, No. 1, pp. 339-368). Elsevier.
11. Aqeel, I., Khormi, I. M., Khan, S. B., Shuaib, M., Almusharraf, A., Alam, S., & Alkhaldi, N. A. (2023). Load balancing using artificial intelligence for cloud-enabled internet of everything in healthcare domain. Sensors, 23(11), 5349.
12. Suryadevara, S. (2021). Energy-Proportional Computing: Innovations in Data Center Efficiency and Performance Optimization. International Journal of Advanced Engineering Technologies and Innovations, 1(2), 44-64.
13. Magsi, H., Sodhro, A. H., Al-Rakhami, M. S., Zahid, N., Pirbhulal, S., & Wang, L. (2021). A novel adaptive battery-aware algorithm for data transmission in IoT-based healthcare applications. Electronics, 10(4), 367.
14. Zekić-Sušac, M., Mitrović, S., & Has, A. (2021). Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities. International journal of information management, 58, 102074.
15. Al-Turjman, F., & Deebak, B. D. (2020). Privacy-aware energy-efficient framework using the internet of medical things for COVID-19. IEEE Internet of Things Magazine, 3(3), 64-68.
16. Kumar, K., Kumar, S., Kaiwartya, O., Cao, Y., Lloret, J., & Aslam, N. (2017). Cross-layer energy optimization for IoT environments: Technical advances and opportunities. Energies, 10(12), 2073.
17. Ruiz, D. P., Vasquez, R. A. D., & Jadan, B. V. (2023). Predictive Energy Management in Internet of Things: Optimization of Smart Buildings for Energy Efficiency. Journal of Intelligent Systems & Internet of Things, 10(2).
18. Shah, S. F. A., Iqbal, M., Aziz, Z., Rana, T. A., Khalid, A., Cheah, Y. N., & Arif, M. (2022). The role of machine learning and the internet of things in smart buildings for energy efficiency. Applied Sciences, 12(15), 7882.
19. Iwendi, C., Maddikunta, P. K. R., Gadekallu, T. R., Lakshmanna, K., Bashir, A. K., & Piran, M. J. (2021). A metaheuristic optimization approach for energy efficiency in the IoT networks. Software: Practice and Experience, 51(12), 2558-2571.
20. Ahmed, Q. W., Garg, S., Rai, A., Ramachandran, M., Jhanjhi, N. Z., Masud, M., & Baz, M. (2022). Ai-based resource allocation techniques in wireless sensor internet of things networks in energy efficiency with data optimization. Electronics, 11(13), 2071.
21. Jia, Z., Chen, J., Xu, X., Kheir, J., Hu, J., Xiao, H., ... & Shi, Y. (2023). The importance of resource awareness in artificial intelligence for healthcare. Nature Machine Intelligence, 5(7), 687-698.
22. Nandyala, C. S., & Kim, H. K. (2016). Green IoT agriculture and healthcare application (GAHA). International Journal of Smart Home, 10(4), 289-300.
23. Hartmann, M., Hashmi, U. S., & Imran, A. (2022). Edge computing in smart health care systems: Review, challenges, and research directions. *Transactions on Emerging Telecommunications Technologies*, *33*(3), e3710.