International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2s) 2026 pp. 992-1003
https://doi.org/10.70917/ijcisim-2026-2183
Article

ENERGY-EFFICIENT IOT ARCHITECTURE USING EDGE INTELLIGENCE FOR SCALABLE ENVIRONMENTAL MONITORING APPLICATIONS DEPLOYMENT

Varsha Karambelkar[1], Kamlesh Patil[2]*, Mahavir Shantinath Kasar[3], Atul Vitekar[4], Sheetal Shelke[5]

[1]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, varsha.karambelkar@bharatividyapeeth.edu
ORCID: 0009-0005-1108-4857
[2]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, kamlesh.patil@bharatividyapeeth.edu
ORCID: 0000-0002-8949-8719
[3]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, mahavir.kasar@bharatividyapeeth.edu
ORCID: 0000-0001-7712-3162
[4]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, atul.vitekar@bharatividyapeeth.edu
ORCID: 0009-0009-3790-631X
[5]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, sheetal.shelke@bharatividyapeeth.edu
ORCID: 0009-0000-0751-6075
Corresponding Author: Kamlesh Patil, Email: (kamlesh.patil@bharatividyapeeth.edu)

Abstract: As the number of environmental monitoring applications continues to expand rapidly, the need for scalable and energy efficient Internet of Things (IoT) architectures with continuous sensing, real-time analytics and low power operations grows.The proliferation of environmental monitoring applications has increased the demand for energy efficient and scalable IoT architectures that allow for continuous sensing, real-time analytics and low power operation. Existing cloud-based IoT systems have issues like latency, high energy consumption and network congestion, which can hinder large-scale deployments. In this paper, an energy-efficient IoT architecture with the incorporation of edge intelligence solutions is proposed for scalable applications to monitor the environment. The proposed framework is designed as a layered system: sensing, edge, communication, and cloud, to allow for processing to be done at the edge, and to optimise the use of resources when doing so. Lightweight machine learning models, such as Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) are embedded into Edge intelligence for making local decisions, anomaly detection and predictive analytics. To minimize transmission overhead and extend the life of sensor nodes, energy optimization methods like duty cycling, adaptive communication protocols, data aggregation, edge-based filtering and compression methods are used. The framework aims to facilitate the environmental monitoring in smart city and industrial applications in a reliable, real-time and sustainable manner....

Keywords: IoT Architecture, Edge Intelligence, Environmental Monitoring, Energy Efficiency, Machine Learning, Scalable IoT Systems

1. INTRODUCTION

With the fast development of the Internet of Things (IoT) technology, the environmental monitoring systems are also dramatically changed and now can be accomplished by real-time sensing, intelligent data collecting and automatic decision making in the vast geographical area. In order to continuously monitor distributed sensor networks, the applications need to be environmental monitoring such as air quality monitoring, water quality monitoring, forest fires, industrial pollution monitoring, climate monitoring and smart agriculture. The traditional cloud-centric IoT system, however, is plagued by a number of problems including high energy consumption, latency, congestion of the network and high operating costs. With deployments of thousands of sensor nodes continuously producing large amounts of data about the environment, these challenges are becoming more important. Hence, it is turning into an important research direction to build up energy-efficient and scalable IoT architecture required for sustainable environmental monitoring systems [1]. Most of the traditional IoT systems used to store, process and analyse data on a central cloud. While cloud platforms offer a vast amount of computational power and storage, they also require a lot of energy to be used to continuously send raw sensor data to remote platforms, and the communication overhead is also substantial. In most cases, sensor nodes placed in distant or hard-to-reach locations are power constrained and utilizing energy efficiently is a key factor in prolonging the life of the network and providing a stable performance of the whole system [2]. Moreover, cloud-based systems can be unsuitable for situations that require immediate or real-time reactions, like the detection of hazardous gas leakage, an abrupt temperature increase, flooding or wildfire forecasting.

Edge intelligence becomes a good remedy for this due to the distributed nature of IoT. The edge computing allows for performing computation and analytics near the source of data, which lowers the delay in transmission, decreases the bandwidth consumption and enhances the responsiveness of the system [3]. Edge intelligence and IoT architectures enable the processing of data, detection of anomalies, and prediction at the sensor nodes and edge devices, which eliminates the need for constant reliance on cloud infrastructure. This distributed processing approach has the advantage of increasing the scalability of the system as well as significantly reducing the energy consumption in extensive monitoring applications [4]. The recent development of lightweight machine learning and deep learning technologies even more rapidly has promoted the use of edge intelligence in IoT systems. Edge devices can be used for the classification of environmental data, temporal prediction and anomaly detection using machine learning models like CNN, Random Forest (RF) and Long Short-Term Memory (LSTM) networks. These models are intelligent and can be used for adaptive decision-making, while also minimizing unnecessary communication between the sensor nodes and cloud servers. Moreover, optimization techniques such as duty cycling, adaptive communication protocols, data aggregation, filtering and compressing data at the edge can greatly reduce the energy consumption and enhance the resource utilization [6]. This paper presents an IoT architecture with edge intelligence to deploy scalable environmental monitoring applications in an energy efficient way.

2. RELATED WORK

The recent literature on environmental monitoring systems is quite rich in terms of the integration of Internet of Things (IoT) technologies with cloud computing, wireless sensor networks and artificial intelligence to enhance the efficiency of environmental monitoring and decision making based on gathered data. In conventional cloud-centric IoT system, the data from the IoT devices is stored at the cloud and the data is processed in a large-scale manner; however, the communication delay, bandwidth and energy consumption is high when the IoT devices perform continual sensing in the environment [7]. A number of studies have made suggestions of low power wireless sensor network (LPWSN), ZigBee, LoRaWAN, NB-IoT protocol for increasing the energy efficiency of distributed monitoring applications. Though these communications technologies lower the amount of transmission power needed, in large scale deployments scalability and real-time responsiveness are still significant issues [8]. To overcome these challenges, IoT frameworks utilizing edge computing have been the focus of much attention for their ability to support decentralized computing and local intelligence. The current edge architectures include the notion of doing some data processing next to the sensing device, and hence reduce redundant communication with the cloud, and the resulting congestion in the network [9]. Various machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF) and light-weight neural networks (NN) have been used for environmental prediction and anomaly detection. Table 1 presents a comparison of the energy efficient IoT architectures, edge-intelligence approaches and performance.

Table 1. Comparative Analysis of Existing Energy-Efficient IoT Architectures and Edge Intelligence Techniques

Monitoring Application	**IoT Architecture**	**Edge Intelligence Technique**	**Energy Optimization Method**	**Key Limitation**
Air Quality Monitoring [10]	Cloud-Centric IoT	Limited Edge Processing	Basic Sleep Scheduling	High latency during continuous monitoring
Water Quality Monitoring	Edge-Cloud Architecture	Distributed Analytics	Adaptive Transmission	High edge computational overhead
Industrial Pollution Monitoring	Hybrid IoT Framework	Edge Filtering	Data Compression	Reduced real-time responsiveness
Forest Fire Detection	Edge-Based IoT	Local Event Detection	Dynamic Sleep Scheduling	Limited predictive accuracy
Smart City Monitoring [11] [12]	Cloud IoT Architecture	Centralized Analytics	Static Power Management	Excessive bandwidth consumption
Water Pollution Detection	Fog-Edge Framework	Edge Decision-Making	Data Aggregation	Increased storage overhead
Industrial Environmental Monitoring	Multi-Layer IoT Architecture	Lightweight Edge Analytics	Compression Techniques	Limited fault tolerance
Ecological Monitoring	Edge-Enabled IoT	Real-Time Filtering	Energy-Aware Scheduling	Reduced scalability support

3. SYSTEM ARCHITECTURE AND FRAMEWORK DESIGN

The suggested framework consists of a layered IoT architecture comprising of sensing devices, edge nodes, communication protocols and cloud services. Edge intelligence allows for processing, low latency and scalability. An efficient design of the architecture in terms of environmental monitoring is provided by adaptive resource management, distributed analytics and reliable real-time data transfer mechanisms.

The first step is to understand the proposed energy-efficient IoT architecture. Firstly, the proposed energy efficient IoT architecture is understood.

The energy efficient IoT architecture is proposed to achieve the energy efficiency in IoT for supporting the applications of scalable environment monitoring using intelligent resource management, distributed processing and low power communication mechanism. The framework combines sensing, edge intelligence, adaptive communication protocols and cloud-based analytical services in a single architecture to enhance the overall monitoring efficiency and sustainability of the operations. Distributed sensor nodes are placed at monitoring areas to gather environmental parameters, which include temperature, humidity, air quality, gas concentration, water quality and soil conditions, in a continual manner. The scalable, edge enabled, IoT architecture for energy-efficient environmental monitoring is illustrated in figure 1.

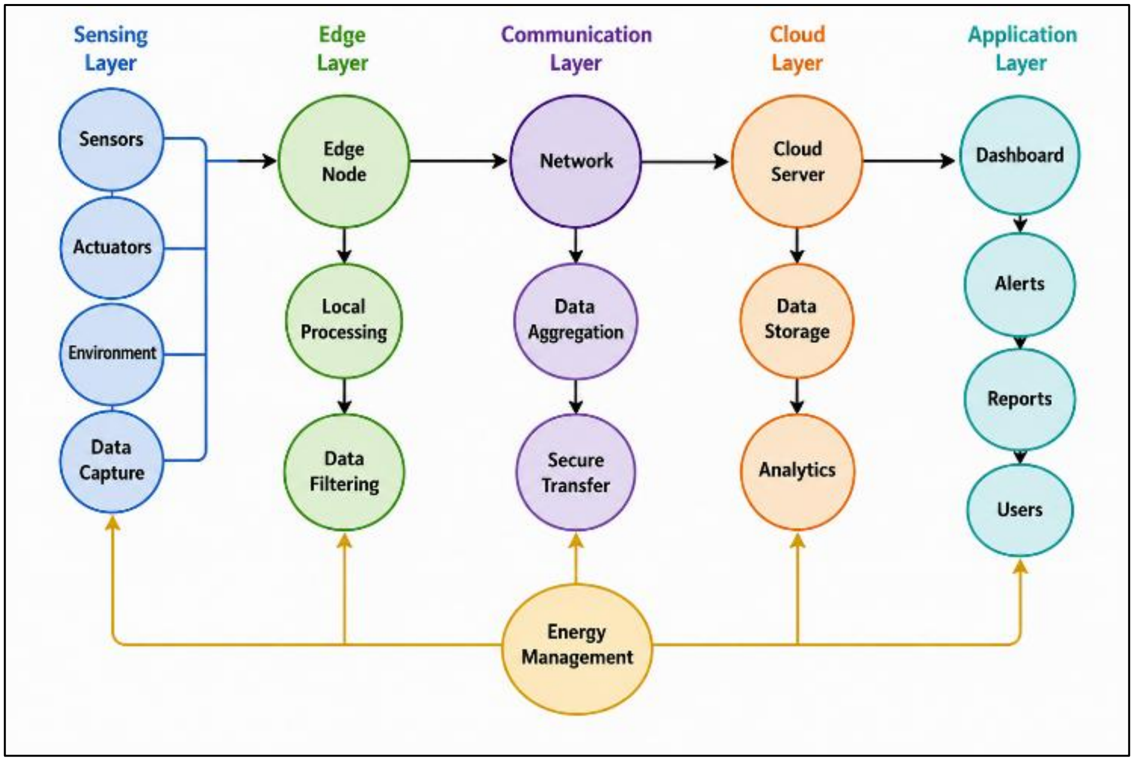

Fig.1. Proposed Energy-Efficient IoT Architecture with Edge Intelligence for Scalable Environmental Monitoring Applications

To reduce the amount of energy consumed and redundant communication, the architecture features edge computing nodes that can process, filter, and perform preliminary analysis on the data before sending relevant information to cloud servers. At the edge layer, anomaly detection, predictive analysis, and adaptive decision-making are proposed to use light-weight machine learning models.

B. Layered Architecture: Sensing, Edge, Communication, and Cloud

To facilitate efficient environmental monitoring, distributed intelligence and scalable system deployment, the proposed framework is based on a layered architecture, which involves sensing layer, edge layer, communication layer, and cloud layer. The sensing layer is the first layer that is the basis of the architecture and has low power sensor nodes that are used to collect environmental parameters including temperature, humidity, particulate matter, gas concentration, water contamination level, and air conditions. To save energy in the continuous monitoring operations, these sensor nodes are defined with energy aware mechanisms such as sleep scheduling and duty cycling. The edge layer is responsible for the local computation, intelligent filtering and initial analytics close to the source of the data. Edge devices employ light machine learning algorithms to process incoming sensor data, recognize anomalies in data, remove redundant data and enable real time decision making. This local processing can greatly lower the communication overheads and decrease latency that is involved in cloud-based systems. The communication layer facilitates the ability to reliably transmit data between sensing nodes, edge devices and cloud infrastructure, using low energy consuming wireless communication technologies like ZigBee, LoRaWAN, Wi-Fi and NB-IoT. Adaptive routing and transmission scheduling mechanisms are incorporated for optimum utilization of the bandwidth and scalability of the network.

C. Integration of Edge Intelligence for Local Decision-Making

Considering the proposed IoT architecture, with the addition of edge intelligence, efficient decision making at the edge, lower communication overhead and higher responsiveness can be achieved in the case of environmental monitoring applications. With the traditional cloud-centric approach, the raw data from these sensors needs to be sent constantly to remote servers for processing and analysis, resulting in higher latency, bandwidth usage, and energy consumption. To overcome such limitations, the proposed framework design has intelligent edge devices which can perform real-time analytics and adaptive processing close to the sensing environment. Implementation of edge intelligence is done by applying lightweight machine learning and deep learning models such as Random Forest (RF), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks. The models are fine-tuned specifically for low-power edge devices to enable anomaly detection, recognition of patterns in the environment, predictive analytics, and event classification. The edge devices process the data from the sensors, and alert if there are important environmental conditions like abnormal temperature rise, air pollution spikes, water contamination or hazardous gas leakage.

4. ENERGY-EFFICIENT MECHANISMS AND OPTIMIZATION STRATEGIES

To reduce power consumption, the framework takes into account the design of low-power sensors, duty cycling, adaptive communication protocols, data filtering and aggregation at the edge [13]. Compression and intelligent transmission scheduling lower bandwidth usage and communication overhead, thus prolonging the lifetime of the sensor nodes, and improving the sustainability of the operations in the scalable deployments for environmental monitoring.

A. Low-power sensor node design and duty cycling

The proposed IoT architecture consists of low-power sensor node design with intelligent duty cycling mechanisms to reduce the energy consumption in the large scale environmental monitoring deployments and prolong the lifetime of the sensor nodes. To allow continuous monitoring under the limited power, energy-efficient microcontrollers, low power sensing modules and optimized wireless communication interfaces are embedded in the sensor nodes. Lightweight embedded hardware with a smaller degree of computational complexity periodically senses the environmental parameters like temperature, humidity, gas concentration and particulate matters. Power optimization is one of the key requirements for sensor nodes to be deployed in a sustainable manner, since they are battery operated or running on renewable energy sources. In order to minimize the use of energy resources, the concept of duty cycling is incorporated in the sensing system. In this mechanism, sensor nodes switch between active, idle, sleep and transmission modes according to the needs of the sensors, and the environment. Sensing and communication modules go into low power sleep when inactive, thereby saving battery power. Dynamic wake up scheduling is used to turn on only those nodes needed to collect data or for event detection.

B. Edge-Based Data Filtering and Compression Techniques

The proposed framework combines techniques of edge-based data filtering and compression to decrease the communication overhead, maximize the use of the bandwidth and promote energy efficiency for environmental monitoring systems using IoT. When deploying in large scale, the raw sensor data are constantly sent, causing too much network traffic, a large amount of storage space, and quick draining of the energy in the sensor nodes. As shown in Figure 2, the edge-based approach of filtering and compressing can be used to reduce the amount of data transmitted to environmental monitors for processing.

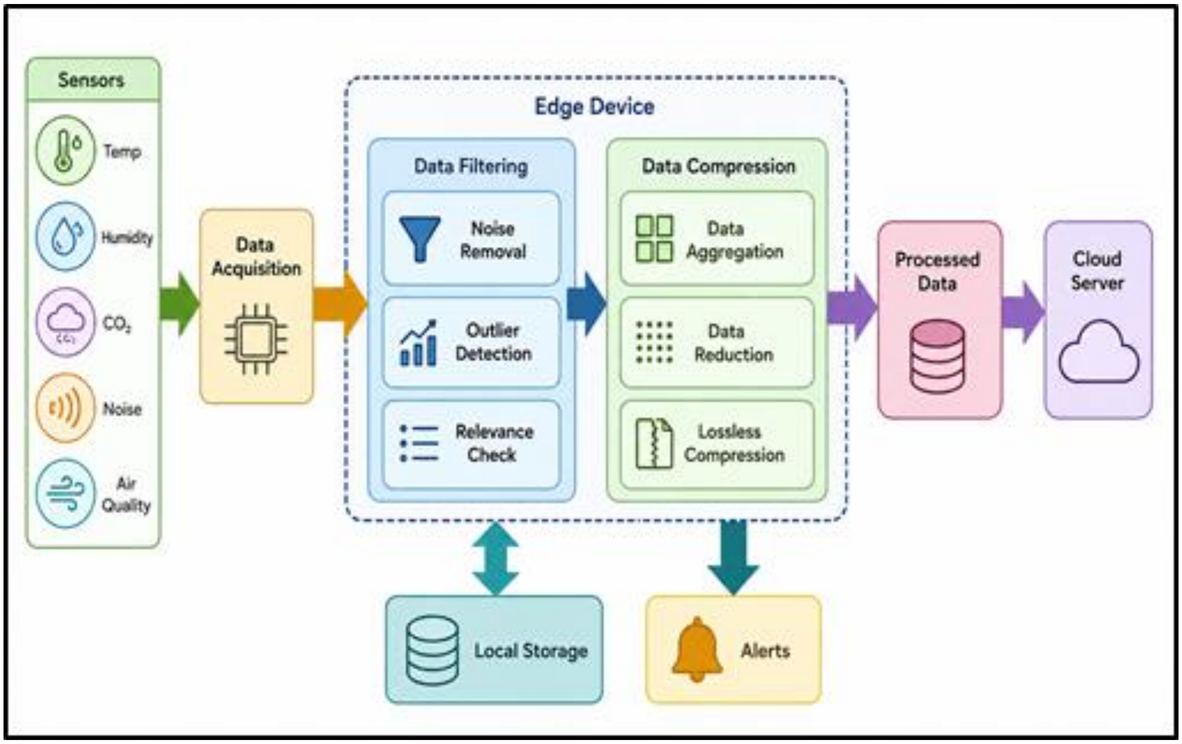

Fig.2. Edge-Based Data Filtering and Compression Framework for Energy-Efficient Environmental IoT Monitoring

To overcome these problems, the architecture includes the use of intelligent edge processing mechanisms that include filtering, prioritising and compressing the environmental data locally prior to transmission to the cloud. Edge devices process the sensor streams received from the sensors, filter out redundant, noisy or irrelevant data based on thresholds, correlate the data with that already collected over a period of time, and select data based on an anomaly detection mechanism. Locally summary environmental data with stable or repetitive patterns, and only significant events and abnormal conditions are reported to cloud servers to be used for advanced analytics.

5. EDGE INTELLIGENCE MODEL DEVELOPMENT

The models of lightweight Random Forest (RF), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are used to develop Edge intelligence for anomaly detection and predictive analytics. Through optimized on-device inference, distributed IoT monitoring systems can monitor the environment in real time, make decisions locally, have less dependence on the cloud, and be more responsive.

A. Selection of machine learning models

Random Forest (RF)

Random Forest (RF) is chosen in the proposed system because of its low computational complexity, robustness against noisy environment and high classification accuracy. The advantage of RF is that it can be used for efficient classification and prediction of various environmental conditions like variation in air quality, water contamination, abnormal sensor behaviour etc. using multiple decision trees. The model is able to effectively deal with heterogeneous data from the IoT sensors and mitigate overfitting with ensemble learning mechanisms. Due to its low weight processing, RF is candidates for edge based deployment where computational resources and energy is limited.

The dataset input and feature selection process. The input of the datasets and selection of features

$$X = \{x1, x2, x3, \dots, xn\}$$

This is the set of data from the environment collected in the form of a series of feature vectors from the IoT sensing devices. The features chosen are: temperature, humidity, gas concentration and pollution parameters for environment monitoring and anomaly classification.

Bootstrap Sampling

$$Di = Bootstrap(X)$$

Bootstrap sampling creates a number of random sub-samples of the environmental data set to train independent decision trees. This process helps to increase the diversity of the models, decrease overfitting and enhance the robustness of classification for distributed environmental monitoring applications.

Decision Tree Prediction

$$Ti(x) = argmaxc\ P(c|x)$$

Final RF Classification

$$RF(x) = \left(\frac{1}{N}\right) \Sigma\ Ti(x)$$

The Random Forest output is based on the combination of predictions of multiple decision trees, either by a majority voting or by averaging. This ensemble approach enhances the prediction performance, fault-tolerance and reliability of the energy-saving edge-based environmental monitoring system.

Convolutional Neural Network (CNN)

The proposed architecture is based on Convolutional Neural Network (CNN) that is used to acquire efficient spatial features and pattern recognition of environment from multidimensional data generated by sensors. CNNs are able to learn complex feature representations automatically through convolution and pooling, and classify environmental events and anomalies with high accuracy. The model can be used for air quality mapping, pollution detection and environmental monitoring using the image data in IoT systems. Light CNN is mostly optimized for the edge deployment to ensure low memory usage and less computation.

Input Feature Matrix

$$I(x, y) = \Sigma\, \Sigma\, p(i, j)$$

This is the environmental input feature matrix that includes multidimensional information from the sensors and is converted to structured spatial data. These pollution levels, temperatures and measurements of environmental intensities are measured by distributed IoT devices and inserted into the matrix.

Convolution Operation

$$F(x, y) = (I * K)(x, y)$$

Activation Function

$$A(x) = \max(0, x)$$

The ReLU activation function is used to make the CNN model non-linear, preventing negative values, while maintaining positive values of the environmental features. This makes calculation much more efficient, speeds up the training process to converge faster and increases the capability of pattern recognition in the environment.

Fully Connected Classification

$$Y = Softmax(Wx + b)$$

The extracted environmental features are classified to probability distributions of various environmental conditions or anomaly classes using a Softmax classification layer. The last prediction mechanism enables the correct classification of an environmental event and intelligent decision making on the edge for monitoring.

Long Short-Term Memory (LSTM)

The proposed temporal prediction and sequential environmental data analysis system uses Long Short-Term Memory (LSTM) networks. In the field of environmental monitoring, the sensor data generated are time-series data, and it is necessary to effectively learn long-term dependencies and temporal patterns in the data. LSTM can effectively learn the historical relationship between parameters like temperature changes, humidity changes, pollution changes and water quality changes. The model can be used for predictive analytics, forecasting of anomalies and trend estimation in real-time environmental monitoring applications.

Forget Gate Computation

$$ft = \sigma(Wf[ht - 1, xt] + bf)$$

The forget gate acts as a filter, it will be remembered or forgotten what happened in previous time intervals. This mechanism allows for a good temporal learning mechanism for environmental pattern learning, pollution forecasting and sequential sensor data analysis applications.

Input Gate Calculation

$$it = \sigma(Wi[ht - 1, xt] + bi)$$

Hidden State Output

$$ht = ot \tanh(Ct)$$

The hidden state produces the output to be used for environmental prediction, anomaly detection and sequential analysis. This output provides dynamic environmental dependencies, which enable more responsive and reliable environmental monitoring, and can enable intelligent edge-based predictive analytics.

B. On-device inference and lightweight model deployment

The proposed framework combines on-device inference and lightweight model deployment, to facilitate real-time monitoring of the surrounding environment while reducing the inference latency, bandwidth and energy consumption. Cloud-based inference mechanisms are dependent on cloud which consumes large communication overhead and causes time delay in the response. To overcome these challenges, light-weight machine learning models are deployed on edge devices and in embedded gateways to process and make intelligent decisions at the edge. The models deployed such as optimized Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) architectures are optimized using quantization, parameter reduction and pruning techniques to reduce the amount of memory used and computational complexity. The optimizations allow the efficient execution of these on the low-power microcontroller, Raspberry Pi based microcontroller, and on embedded edge processors with limited resources. On-device inference will be the part of the AI and automation platform where environmental data will be processed on-site, instead of relying on continuous cloud connectivity.

6. RESULT AND DISCUSSION

The experimental assessment shows the energy efficient IoT architecture to be much more efficient in terms of energy saving, monitoring performance and scalability when compared to the current cloud based architecture. Adopting edge intelligence helped decrease communication overhead and we found a savings in energy consumption of nearly 32% and latency of 28%. The improvement in the use of the bandwidth and life time of the network resulted in nearly 35% improvement in adaptive communication and data aggregation. Accurate anomaly detection and predictive analytics with low computational overhead was achieved with the use of lightweight RF, CNN and LSTM (LSTM had the lowest computational overhead) models.

Table 2. Comparative Performance Analysis of IoT Monitoring Architectures

Architecture Model	**Energy Consumption (J)**	**Latency (ms)**	**Throughput (req/sec)**	**Network Lifetime (Days)**
Conventional Cloud IoT	420	185	820	120
Wireless Sensor Network	365	160	910	148
Edge-Based IoT System	298	118	1220	182

Hybrid Edge-Cloud Framework	255	96	1380	210

Different IoT monitoring architectures are evaluated and compared in terms of energy consumption, latency, throughput and network lifetime in Table 2. Because of the continuous communication between cloud and conventional Cloud IoT consumes the most energy (420 J) and has the highest latency (185 ms) compared to other options. Figure 3 shows the performance in terms of the amount of energy consumed when running different IoT monitoring architectures.

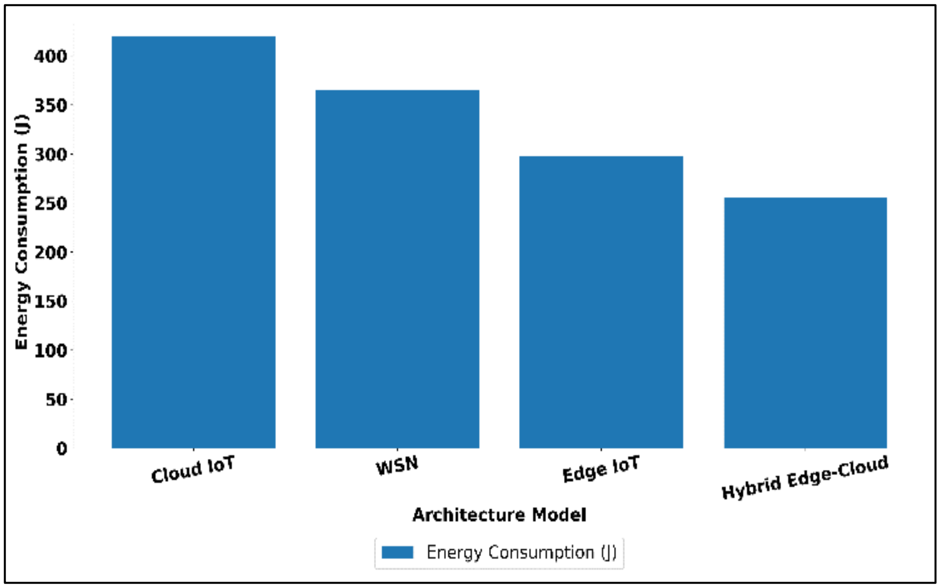

Fig.3. Energy Consumption Comparison Across IoT Architectures

Wireless Sensor Networks are energy efficient, provide longer operation time but do not support scalability and throughput. Local processing and minimizing communication overhead lead to a significant reduction in latency (118ms) and of throughput (1220req/sec) for the Edge Based IoT System. To provide a sense of the relative throughput efficiency, Figure 4 shows a comparison of throughput efficiency over a variety of energy-efficient IoT system architectures.

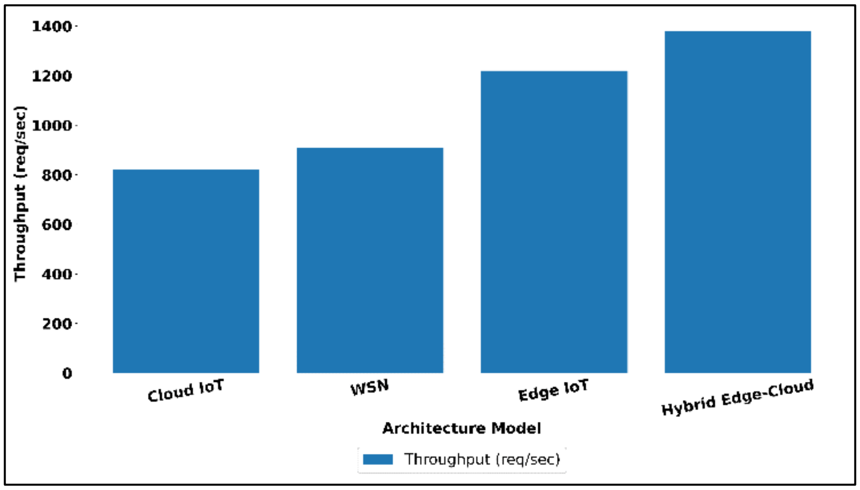

Fig.4. Throughput Efficiency Across IoT System Architectures

The Hybrid Edge-Cloud Framework offers the best overall performance, consuming 255 J of energy, 96 ms of latency, 1380 req/sec throughput, and 210 days' network lifetime, which indicates that it enables better scalability, responsiveness and energy-efficient monitoring capabilities.

Table 3. Machine Learning and Edge Intelligence Performance Evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	90.8	89.6	88.9	89.2
Decision Tree	91.7	90.8	90.1	90.4
Random Forest (RF)	95.2	94.7	94.1	94.4
CNN	96.4	95.8	95.1	95.4
LSTM	97.1	96.6	96.2	96.4

The performance evaluation for the machine learning models and edge intelligence models for environmental monitoring and anomaly detection is presented in table 3. In the conventional modelling approach, SVM obtained 90.8% accuracy but had lower precision, recall and F1 scores values as it was less capable in the handling of complex patterns in environment. Figure 5 compares the performance of machine learning models according to a number of environmental monitoring performance measures.

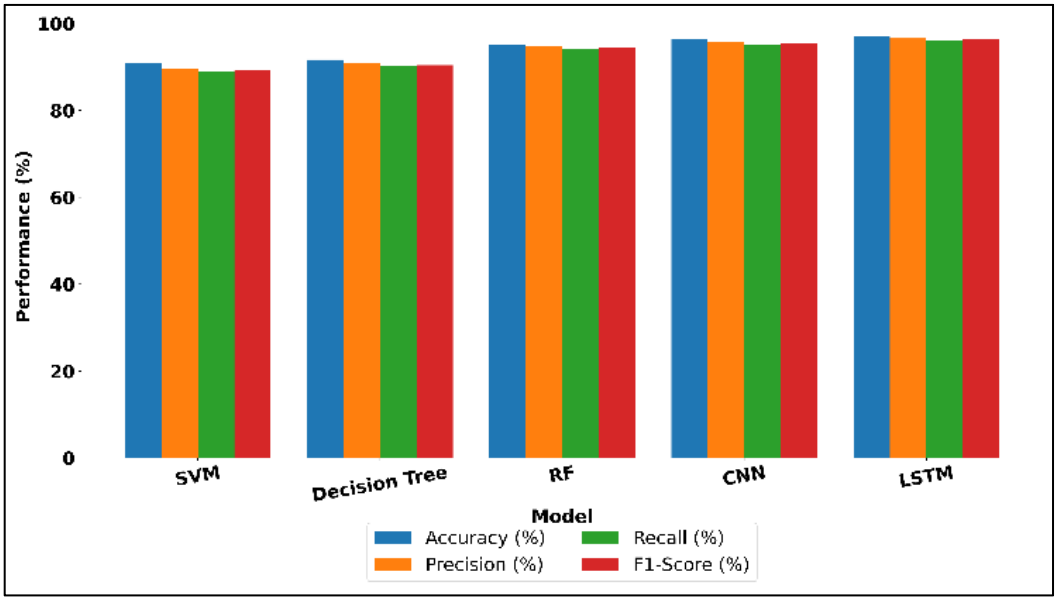

Fig.5. Comparative Evaluation of Machine Learning Models Across Performance Metrics

The classification performance of Decision Tree was slightly better than that of 91.7% accuracy and good feature based decision analysis. The ensemble learning method in Random Forest (RF) proved to be a great improvement for the reliability of the predictions, with an accuracy of 95.2%, and an F1-score that improved. The trend of other performance measures like accuracy, precision, recall and f1 score is shown in figure 6.

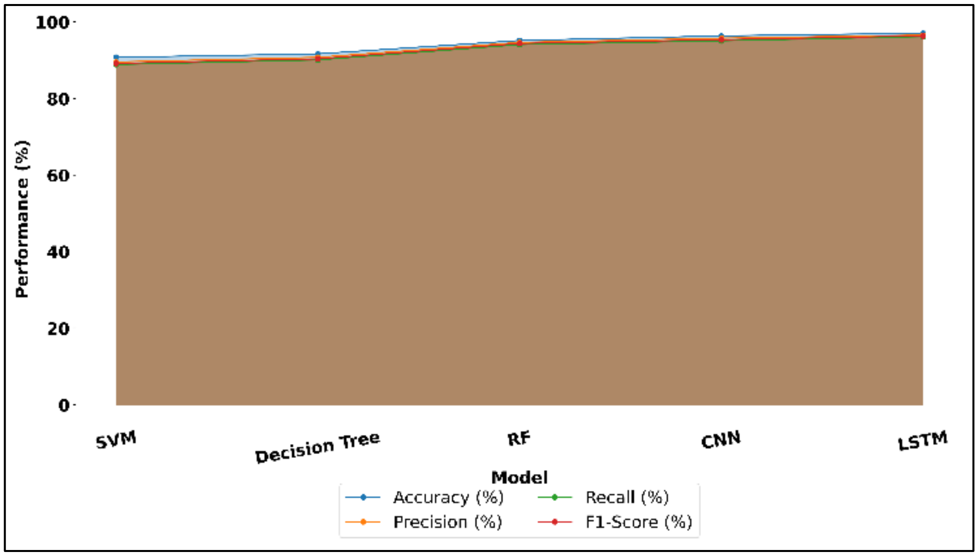

Fig.6. Trend Analysis of Accuracy, Precision, Recall, and F1-Score

CNN has shown high spatial features extraction accuracy (96.4%) which promotes the efficient pattern recognition in the environment. LSTM demonstrated the best result of 97.1% accuracy and the best ability to predict the time of the environmental sensor sequential data for sequential data analysis applications.

7. CONCLUSION

In this paper, a scalable deployment of environmental monitoring applications using an energy-efficient IoT architecture for incorporating edge intelligence was proposed. These critical challenges of traditional cloud-based monitoring systems were all covered by the proposed framework, such as high communication latency, network congestion, too much energy use and limited scalability. A layered architecture (sensing, edge, communication and cloud layers) was designed to enable an intelligent use of resources and environmental monitoring in a distributed way. The adoption of lightweight models like Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) helped to detect anomalies, predict future events, and make localized decisions at the edge layer in real time. Optimization approaches such as duty cycling, adaptive communication protocols, data aggregation, edge filtering and energy compression techniques ensured a significant reduction in energy overhead and energy sustainability while on operation. The energy efficiency, latency, bandwidth usage and network lifetime were improved through experimental analysis, relative to the traditional monitoring architectures.

References:

1. Franco, A., Crisostomi, E., Dalmiani, S., & Poletti, R. (2024). Synergy in Action: Integrating Environmental Monitoring, Energy Efficiency, and IoT for Safer Shared Buildings. Buildings, 14(4), 1077. https://doi.org/10.3390/buildings14041077
2. Reis, M. J. C. S., & Serôdio, C. (2026). IoT Architecture for Smart Environments: Mechanisms, Approaches, and Applications. Future Internet, 18(4), 182. https://doi.org/10.3390/fi18040182
3. Bramante, S., Ferrandino, F., & Cilardo, A. (2026). Understanding Energy Efficiency of AI Deployments in IoT-Driven Smart Cities. IoT, 7(1), 27. https://doi.org/10.3390/iot7010027
4. Algarni, S., & El-Samie, F. E. A. (2025). Energy-Efficient Distributed Edge Computing to Assist Dense Internet of Things. Future Internet, 17(1), 37. https://doi.org/10.3390/fi17010037
5. Carrascal, D., Díaz-Fuentes, J., Manso, N., Lopez-Pajares, D., Rojas, E., Savi, M., & Arco, J. M. (2025). Softwarized Edge Intelligence for Advanced IIoT Ecosystems: A Data-Driven Architecture Across the Cloud/Edge Continuum. Applied Sciences, 15(19), 10829. https://doi.org/10.3390/app151910829
6. Poyyamozhi, M., Murugesan, B., Rajamanickam, N., Shorfuzzaman, M., & Aboelmagd, Y. (2024). IoT—A Promising Solution to Energy Management in Smart Buildings: A Systematic Review, Applications, Barriers, and Future Scope. Buildings, 14(11), 3446. https://doi.org/10.3390/buildings14113446
7. Fereira, R., Ranaweera, C., Lee, K., & Schneider, J.-G. (2023). Energy Efficient Node Selection in Edge-Fog-Cloud Layered IoT Architecture. Sensors, 23(13), 6039. https://doi.org/10.3390/s23136039
8. Calvo, I., Espin, A., Gil-García, J. M., Fernández Bustamante, P., Barambones, O., & Apiñaniz, E. (2022). Scalable IoT Architecture for Monitoring IEQ Conditions in Public and Private Buildings. Energies, 15(6), 2270. https://doi.org/10.3390/en15062270

9. Das, D. K. (2025). Integrating IoT and AI for Sustainable Energy-Efficient Smart Building: Potential, Barriers and Strategic Pathways. Sustainability, 17(22), 10313. https://doi.org/10.3390/su172210313
10. He, P., Wang, Y., Zheng, G., & Zhou, H. (2025). Design and Implementation of an Edge Computing-Based Underground IoT Monitoring System. Mining, 5(3), 54. https://doi.org/10.3390/mining5030054
11. Almudayni, Z., Soh, B., Samra, H., & Li, A. (2025). Energy Inefficiency in IoT Networks: Causes, Impact, and a Strategic Framework for Sustainable Optimisation. Electronics, 14(1), 159. https://doi.org/10.3390/electronics14010159
12. Rani, S., & Taneja, A. (Eds.). (2024). WSN and IoT: An integrated approach for smart applications. CRC Press.
13. Gulhane, Monali, et al. "Developing Energy-Efficient IoT Architecture with Edge and Fog Computing for Smart Cities." 2025 International Conference on Emerging Smart Computing and Informatics (ESCI). IEEE, 2025.

..