AI-based Wireless Sensor IoT Networks for Energy-Efficient Consumer Electronics using Stochastic Optimization

Fahad Masood, Muhammad Abbas Khan, Mohammed S. Alshehri, Wad Ghaban, Faisal Saeed, Hussain Mobarak Albarakati, *Member IEEE*, Ahmed Alkhayyat

***Abstract*—Wireless Sensor Networks (WSNs) integration with the Internet of Things (IoT) expands its potential by providing ideal communication and data sharing across devices, allowing more considerable monitoring and management in Consumer Electronics (CE). WSNs have an essential limitation in terms of energy resources since sensor nodes frequently run on limited power from batteries. This limitation necessitates the consideration of energy-efficient techniques to extend the network's lifetime. In this article, an integrated approach has been presented to improve the energy efficiency of Wireless Sensor IoT Networks (WSINs) by leveraging modern machine learning algorithms with stochastic optimization. Recursive Feature Elimination (RFE) is utilized for the feature selection thus optimizing the input features for various machine learning models. These models are rigorously evaluated for their aptness to predict and mitigate energy consumption concerns inside WSINs. Subsequently, the stochastic optimization technique utilizes the uniform and normal distributions to model energy consumption situations. The results show that RFE-driven feature selection has significant effects on model performance and that Random Forest is effective at reaching higher accuracy. This research provides valuable perspectives for the design and implementation of WSINs in CE, supporting sustainable smart devices, by addressing energy consumption concerns using an optimized approach.**

***Index Terms*—WSINs, IoT, RFE, Energy Efficiency, Consumer Electronics**

I. Introduction

Wireless sensor networks (WSNs) are a type of wireless communication network in which sensors serve as the primary backbone [1]. The importance of WSN in the context of the Internet of Things (IoT) cannot be emphasized, as these networks provide the framework for automated processes, intelligent decision-making, and improved user experiences. WSNs based on IoT provide the unparalleled potential for real-time data gathering, monitoring, and control, making them essential components of smart cities, healthcare, industrial automation, and environmental sensing [2], [3].

Sensors are used in smart home applications to detect temperature changes, monitor energy consumption, and collect different environmental signals. This inflow of data enables the network to adapt intelligently to changing conditions, optimizing energy use and increasing overall efficiency [4]. The WSN communication paradigm prioritizes energy efficiency. As sensors convey data to other nodes or central processing units, the energy spent during transmission has a direct impact on the network's overall lifetime and performance. The entire potential of these networks is dependent on their energy efficiency, which is crucial given the frequently distant and resource-constrained deployment sites of IoT devices [5]. As a result, optimizing the mode of communication becomes critical to ensuring continuous functioning and long service life.

Machine learning (ML) is a critical component in improving WSN energy efficiency. ML adds a dynamic and adaptable layer to WSNs, enabling systems to learn and optimize their behavior through historical data as well as real-time inputs [6]. WSNs may modify their operations using machine learning, reducing wasteful energy use and increasing total network longevity. The combination of ML and WSN may create durable, self-optimizing networks, which are critical for the long-term deployment of IoT applications—especially in areas where energy conservation is a concern [7], [8].

Recursive Feature Elimination (RFE) is an important feature selection approach that contributes to the optimization and refining of the WSN frameworks implemented. RFE examines the importance of each feature systematically, iteratively deleting those having the least significance, hence improving the computational efficiency of the machine learning models [9]. RFE helps to mitigate the risk of overfitting, improve model interpretability, and perhaps identify latent patterns in sensor data by deliberately picking relevant features. Its use is especially important in the context of WSNs, where resource restrictions dictate intelligent feature selection to improve model performance and ease the deployment of energy-efficient sensor networks.

The incorporation of uniform and normal distributions emphasizes the significance of the research as well. Strategic adoption of these distributions can optimize sensor node deployment, assuring balanced coverage while minimizing

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Fahad Masood and Muhammad Abbas Khan are with the Department of Computing Abasyn University Peshawar, Pakistan (e-mail: fahad.masood@abasyn.edu.pk, abbas.khan@abasyn.edu.pk).
Mohammed S. Alshehri is with the Department of Computer Science, College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia (e-mail: msalshehry@nu.edu.sa).
Wad Ghaban is with Applied College, University of Tabuk, Tabuk, 47512, Saudi Arabia (e-mail: wghaban@ut.edu.sa).
Faisal Saeed is DAAI Research Group, College of Computing and Digital Technology, Birmingham City University, Birmingham, UK (e-mail: faisal.saeed@bcu.ac.uk).
Hussain Mobarak Albarakati is with the Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah 24382, Saudi Arabia (e-mail: hmbarakati@uqu.edu.sa).
Ahmed Alkhayyat is with the Islamic University, 54001 Najaf, Iraq (e-mail: ahmedalkhayyat85@iunajaf.edu.iq).

energy usage. Uniform distributions, by nature, encourage equitable sensor placement, while normal distributions may be customized to specific environmental factors, optimizing the network for energy-efficient transmission and data collecting.

In the ever-evolving environment of Consumer Electronics (CE), consumer interest in innovative and energy-efficient products is increasing, and this research assumes supreme importance. CE, from cell phones to smart home devices, are now vital components of daily life, influencing how we interact, work, and navigate our environment. However, the never-ending desire for greater capability frequently results in increasing energy consumption, causing issues with battery capacity and environmental sustainability. This research focuses on the critical convergence of technology and customer needs, to optimize energy utilization in WSIN integrated into CE. It provides a precise way to perform feature selection, model training, and optimization, resulting in more sophisticated and energy-efficient sensor nodes. Incorporating these approaches into the research framework represents a commitment to not just enhancing the efficiency of specific sensor nodes in addition optimizing the overall performance of the network. This approach also aligns with the larger objectives of developing resilient and adaptable WSNs that can perform at their best in a variety of evolving IoT contexts. The relevance thus rests in the ability to transform WSN implementation and operation, making them more sensitive to the energy restrictions associated with IoT applications and smart home environments in CE.

The organization of this paper is as follows, Section II presents the literature review of the previous studies, the detailed methodology is discussed in Section III, results have been presented in Section IV, and the conclusion has been given in Section V.

II. LITERATURE REVIEW

Wireless Sensor Internet of Things Networks (WSINs) have received substantial interest in recent years due to their potential to revolutionize a variety of areas such as routing[10], [11], [12], [13], [14], and energy efficiency [15], [16], [17]. The ongoing research of energy-efficient solutions to handle the inherent problems of resource-constrained sensing devices is a critical component of this convergence. Several studies have investigated the potential synergy between IoT-based WSN and machine learning (ML) approaches to improve energy efficiency. Savaglio et al. suggested a well-known artificial intelligence approach for designing an energy-saving medium access control (MAC) protocol to extend the network lifetime [18]. QL-MAC self-adjusts the duty cycle of WSN nodes, lowering energy usage without affecting other network characteristics. This is accomplished by altering the radio sleeping and active times based on traffic projections and neighboring node transmission states.

Mehmood proposed an energy-efficient and resilient routing strategy for WSNs based on artificial neural networks [19]. It employs a group-based approach to extend the overall network's life, with groups of varying sizes. Based on the backpropagation approach, an artificial neural network delivers effective threshold values for selecting a group's CN and cluster head, allowing intelligent, efficient, and resilient group organization. The possibility of energy reduction at the fog level using smart sleep and wake-up phases of context-aware fog nodes has been suggested in [20]. It provides a virtual machine management strategy for successfully assigning service requests with a small number of operational fog nodes utilizing a genetic algorithm (GA), followed by a reinforcement learning (RL) approach to optimize the duty cycle of fog nodes.

A deep learning-based distributed data mining (DDM) model for WSN fusion center energy efficiency and efficient load balancing has been proposed in [21]. The suggested model decreases the fusion center's overhead as well as the amount of data transmissions. The energy usage problem with a huge IoT system model with adaptive network architecture or cluster utilizing a multiagent system (MAS) in industrial 6G applications has been studied in [22]. The study uses distributed artificial intelligence (DAI) for arranging the sensor nodes in the system to locate and anticipate the main node. The simulation results demonstrate that the suggested strategy lowers resource waste due to redundant data, increases network energy efficiency, and preserves information.

The novel 'Monkey Tree Search-based Location-Aware Smart Collector (MTS-LASC)' exploits a Monkey Tree Search (MTS) behavioral model inspired by fauna [23]. Results show that increasing the delivery ratio while eliminating redundant transmission of packets and preserving fidelity yields promising outcomes. Radhika et.al. proposed a solution that decreases data transmission by cluster member nodes using machine learning and reduces the energy consumption for each sensor node by adopting an appropriate active/sleep schedule [24]. An ant colony optimization-based QoS aware energy balancing secure routing (QEBSR) technique for WSNs has been proposed by Rathee et.al. [25]. Improved heuristics for determining transmission end-to-end latency and node trust factor on the routed path are presented. The suggested technique is evaluated in comparison to two previous algorithms. The simulation results reveal that the suggested QEBSR method outperformed the other two techniques. A deep-reinforcement-learning (DRL) based intelligent routing method for IoT-enabled WSNs has been proposed that reduces latency and increases network lifespan [26]. NS3 is used to do thorough tests on the suggested method. The experimental findings are compared to state-of-the-art algorithms to illustrate the suggested scheme's efficiency in terms of the number of living nodes, energy efficiency, packet delivery, and network communication latency.

A theoretical hypothetic model based on ML has been examined as an effective way for constructing a power-efficient green routing system which may circumvent the constraints of standard green routing methods [27]. An energy-efficiency (EE) allocation of resources technique for the amplify-and-forward (AF) protocol, which is utilized to send data to the destination, is examined in [28]. Deep reinforcement learning (DRL) is used to establish resource allocation strategies in the subnetwork under the model built as a Markov decision process [29]. Based on energy harvesting, causal knowledge of battery condition, and channel gains, an actor-critic technique is used to locate the best solution in continuous phase and activity space and automatically attain the optimum performance of this network. The integration of the Energy Efficient and Secure Weighted Clustering Algorithm (EES-WCA) of EE-WCA with a centralized intrusion detection system (IDS) is proposed based on machine learning [30]. Researchers from various fields have utilized the adaptability of uniform and normal distributions to solve a wide range of problems. The applicability of these distributions in different domains has been presented in the literature [31], [32], [33].

III. Materials and Methods

The focus of our work is to optimize energy usage in WSINs. Figure 1 shows the system architecture. The dataset, which includes sensor readings from different locations, is first preprocessed to extract significant features. The Recursive Feature Elimination (RFE) approach is used to carefully choose relevant input features. Following feature selection, a variety of machine learning models, such as LR [34], DT [35], RF, [36], NB [37], SVM [38], and KNN [39] are trained and assessed using the selected features. The approach includes a component of energy modeling, extending within the domain of machine learning. Uniform and normal distributions are used in the model to add variety and authenticity. Uniform distributions, which represent actual variation, are given to parameters that include packet size and distance, whereas normal distributions manage uncertainties in sensor data. The resulting energy model outputs are then retrieved and thoroughly contrasted for comparison study. This detailed method additionally examines the prediction abilities of machine learning models and reaches into the energy dynamics, providing a thorough knowledge of the IoT network's operating features.

A. Dataset Collection

The dataset has been collected for this research from five unique locations inside a residential place. The Lounge, Porch, Living Room 1, Guest Room, Living Room 2, and Kitchen—each fitted with a set of six sensors monitoring CO2 levels, humidity, temperature, light, occupancy, and smoke for the selected features listed in Table I. The water tank, in particular, uses only a water sensor. The dataset includes 24 hours, with sensors programmed to provide an alert if their readings exceed predetermined threshold values, indicating excessive energy use. An approach that uses RFE with uniform/normal distributions is put into practice to reduce energy inefficiency. This model maximizes sensor performance and promotes energy-efficient behaviors in a variety of environmental scenarios. The dataset used in this research can be accessed at (https://github.com/fahads757/WSIN.git).

TABLE I
Features List.

Sr. No	Feature
1	Usage Duration (min)
2	On/Off Freq
3	EnergyConsum (kWh)
4	Power Consum (W)
5	Sensor Reading
6	Op Voltage (Volts)
7	Sleep Mode Duration (sec)
8	Sig Strength Range (meters)
9	Data Trans Freq

B. Recursive Feature Elimination

RFE is a feature selection technique commonly used in machine learning to improve the accuracy of models and interpretability. It works by deleting features recursively and ranking them depending on their influence on model correctness [9]. The least significant traits are trimmed in each iteration until the optimum subset is found. RFE alleviates the scourge of dimensionality by concentrating on the most important characteristics, lowering computing complexity, and perhaps increasing model generalization to new data. This procedure assists in finding essential factors that have the greatest impact on predicting accuracy, resulting in a more effective and interpretable model. A p-value is a probabilistic metric used in hypothesis testing to assess the hypothesis. If an input feature's p-value is smaller than the significance threshold (α), a statistical link exists between it and the output feature. The threshold value for RFE is 0.05 (α) [40]. The RFE algorithm begins with the whole feature set Ds, which includes the feature inputs p1, p2,... pN, and subsequently recursively prunes irrelevant features at every iteration based on the hypothesis statement stated in equations unless the p-value of features is smaller than the threshold value (α). RFE chooses the best features from the input dataset Ds by employing two types of hypotheses: null hypothesis and alternative hypothesis. The null hypothesis states that there is no association between the selected input feature and the output feature whenever the p-value associated with the chosen input feature is larger than or equal to the threshold value. According to the alternative hypothesis, there is a strong association between the i/o characteristics when the p-value of the input feature is less than the threshold values.

$$H_o = \mu \geq a \tag{1}$$

$$H_a = \mu < a \tag{2}$$

Where H_o represents a Null Hypothesis, μ is the p-value of an input feature, H_o, is an alternate Hypothesis, and α is the threshold value.

C. Stochastic Optimization using uniform and normal distributions

The uniform distribution, represented as U(a,b), is a situation in which all values between a and b are equally probable. It is used to simulate packet size (l) and distance (d). The uniform distribution's probability density function (PDF) is given as [32],

$$f(x) = \frac{1}{b-a} \tag{3}$$

where a, and b are the minimum and maximum permitted values, respectively.

The normal distribution, often known as the Gaussian distribution, has a bell-shaped curve. Its mean *(μ)* and standard

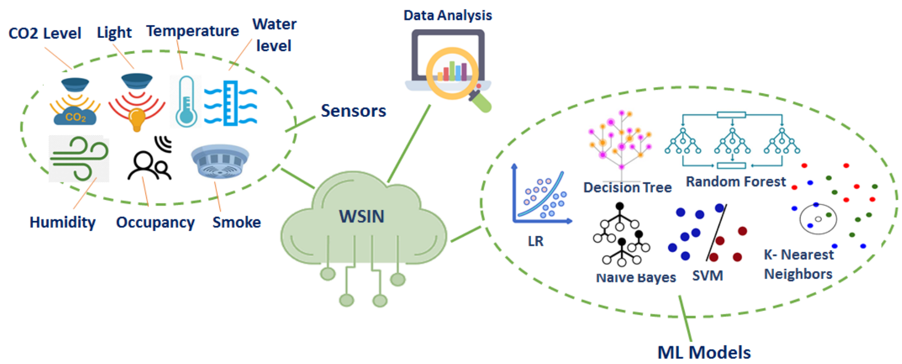


Fig. 1. WSIN Architecture

deviation *(σ)* characterize it completely. The normal distribution's probability density function is given as,

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \tag{4}$$

For characteristics such as packet size *(l)*, aggregated packet size *(l_{agg})*, and distance *(d)*, the uniform distribution introduces randomness within a given range and the normal distribution adds variability based on mean (μ) and standard deviation (σ).

1) Energy Model using uniform and normal distributions: The fundamentals of the energy model within the proposed architecture have been presented. The mathematical description includes the energy utilized during different stages of data transmission, reception, and aggregation. The first-order model proposed in [41] has been utilized to characterize the energy model of WSNs. It is employed to calculate the consumption of energy in both transmitting and receiving modes. When a sensor node sends data, the energy use is as follows,

$$E_{tx}(l, d) = l \times (E_{elect} + E_{amp} \times d^m) \tag{5}$$

The energy used for receiving data is given as,

$$E_{rx}(l) = l \times E_{elect} \tag{6}$$

The energy used for data aggregation and transmission is given as,

$$E_{agg}(l, d) = l_{agg}(E_{elect} + E_{amp} \times d^m) \tag{7}$$

where E_{tx}, E_{rx}, and E_{agg} represent the energy consumed for transmission, reception, and data aggregation and transmission respectively while E_{elect}, and E_{amp} is to power the transmitter/receiver, and the amplifier while *m* is the propagation attenuation exponent. The mathematical expressions of the energy usage for uniformly distributed packet size(l_u) and distance(d_u) of transmitting data are given as,

$$E_{tx}(l, d)_u = l_u \times (E_{elect} + E_{amp} \times d_u^m) \tag{8}$$

$$E_{rx}(l)_u = l_u \times E_{elect} \tag{9}$$

$$E_{agg}(l, d)_u = l_{u(agg)} \times (E_{elect} + E_{amp} \times d_u^m) \tag{10}$$

The mathematical expressions of the energy usage for normally distributed packet size(l_N) and distance(d_N) of transmitting data are given as,

$$E_{tx}(l, d)_N = l_{N(\mu,\sigma)} \times (E_{elect} + E_{amp} \times d^m_{N(\mu,\sigma)}) \tag{11}$$

$$E_{rx}(l)_N = l_{N(\mu,\sigma)} \times E_{elect} \tag{12}$$

$$E_{agg}(l, d)_N = l_{aggN(\mu,\sigma)} \times (E_{elect} + E_{amp} \times d^m_{N(\mu,\sigma)}) \tag{13}$$

By including uniform and normal distributions in the equations, we address and model the inherent variability and inconsistencies common to real-world WSIN environments. This statistical method improves the durability of the proposed model, enabling it to adapt to an extensive variety of conditions.

D. ML Performance Metrics

The following equations are used for the evaluation of the performance metrics.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{17}$$

IV. Results and Discussion

In this section, we simulate the performance of the suggested work provided in the previous section. The main objective of this study was to create an AI-based energy-efficient model for WSIN to transmit data in the network with the least amount of energy consumption and the longest lifetime of the network. We have compared the proposed scheme for the energy consumption of the sensors before and after the model implementation. The simulation parameters for the model implementation are presented in Table II

A. Implementation Details

The MATLAB implementation for the study executes high-performance computer resources, including an Intel Core i7-1165G7 CPU and a DDR4 memory of 16GB. The computational performance of this hardware configuration benefits simulations and analyses, ensuring quick execution of complicated WSN models and ML techniques. Furthermore, the CY22 Intel i7-1165G7, when combined with Integrated Intel Iris

TABLE II
SIMULATION PARAMETERS.

Sr. No	Parameter	Value
1	Size of Network	10x24 metre
2	Number of Sensors	37
3	Number of Locations	6
4	Transmission Range	30 metres
5	Initial Energy	0.4-0.5 J
6	Data Collection	24 hours
7	Communication Protocol	Standard IoT

Xe graphics, improves simulation utility and speed, providing an ideal foundation for analyzing the complex interactions between sensor data, ML models, and energy-efficient WSN designs.

B. Results Analysis

Various assessment measures including accuracy, recall, precision, and F1 score, given in Equations (14)-(17), were utilized to evaluate the models' performance, as shown in Table III and Table IV. The DT and RF models, in particular, perform more accurately than the other ML models. Figure 2 presents a comparative analysis of all the ML models. It has been noticed that the RF and DT models have better results across all of the parameters, which indicates their ability to categorize data effectively. The LR and NB models have low performance in comparison to the KNN and SVM models, which consequently perform less well in comparison to the RF and DT models.

Figure 3 shows the ROC curve for the ML models. LR has a decent capacity to differentiate between classes, NB has a good capability. SVM outperforms KNN with a high AUC, suggesting good identifying abilities. RF outperforms the other models, with an AUC of 0.87 indicating efficient categorization. With an AUC of 0.84, the Decision Tree (DT) also performs well.

TABLE III
COMPARISON OF THE ML MODELS IN TERMS OF ACCURACY FOR UNIFORM AND NORMAL DISTRIBUTIONS.

Model	Accuracy$_{uni}$	Accuracy$_{norm}$	Accuracy$_{mean}$
LR	0.84	0.86	0.85
NB	0.86	0.88	0.87
KNN	0.92	0.95	0.93
SVM	0.93	0.95	0.94
DT	0.97	0.98	0.98
RF	0.99	0.99	0.99

TABLE IV
COMPARISON OF THE ML MODELS IN TERMS OF VARIOUS PERFORMANCE METRICS.

Model	Accuracy	Precision	Recall	F1- Score
LR	0.85	0.77	0.59	0.61
NB	0.87	0.90	0.61	0.65
KNN	0.93	0.82	0.85	0.83
SVM	0.94	0.96	0.83	0.88
DT	0.98	0.97	0.95	0.96
RF	0.99	0.99	0.95	0.97

The box plot observations for every feature are shown in Table V and Figures 4. The box plot analysis provides useful

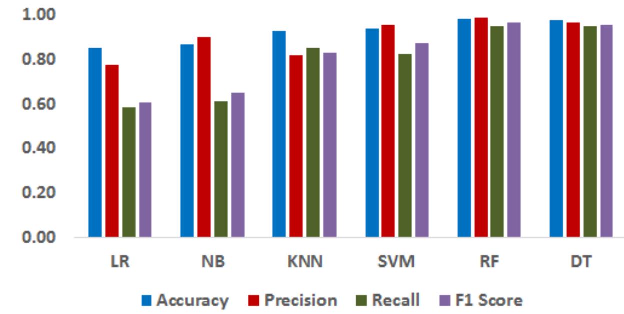


Fig. 2. Comparison of the ML models in terms of various performance metrics.

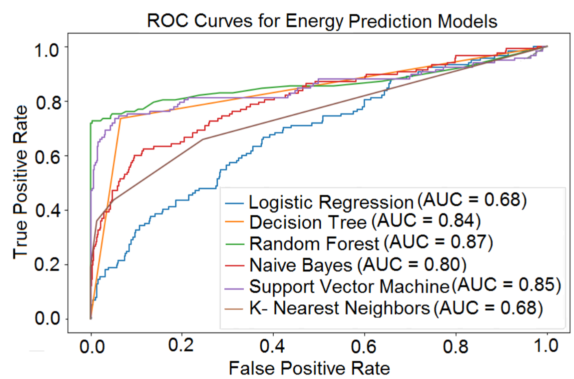


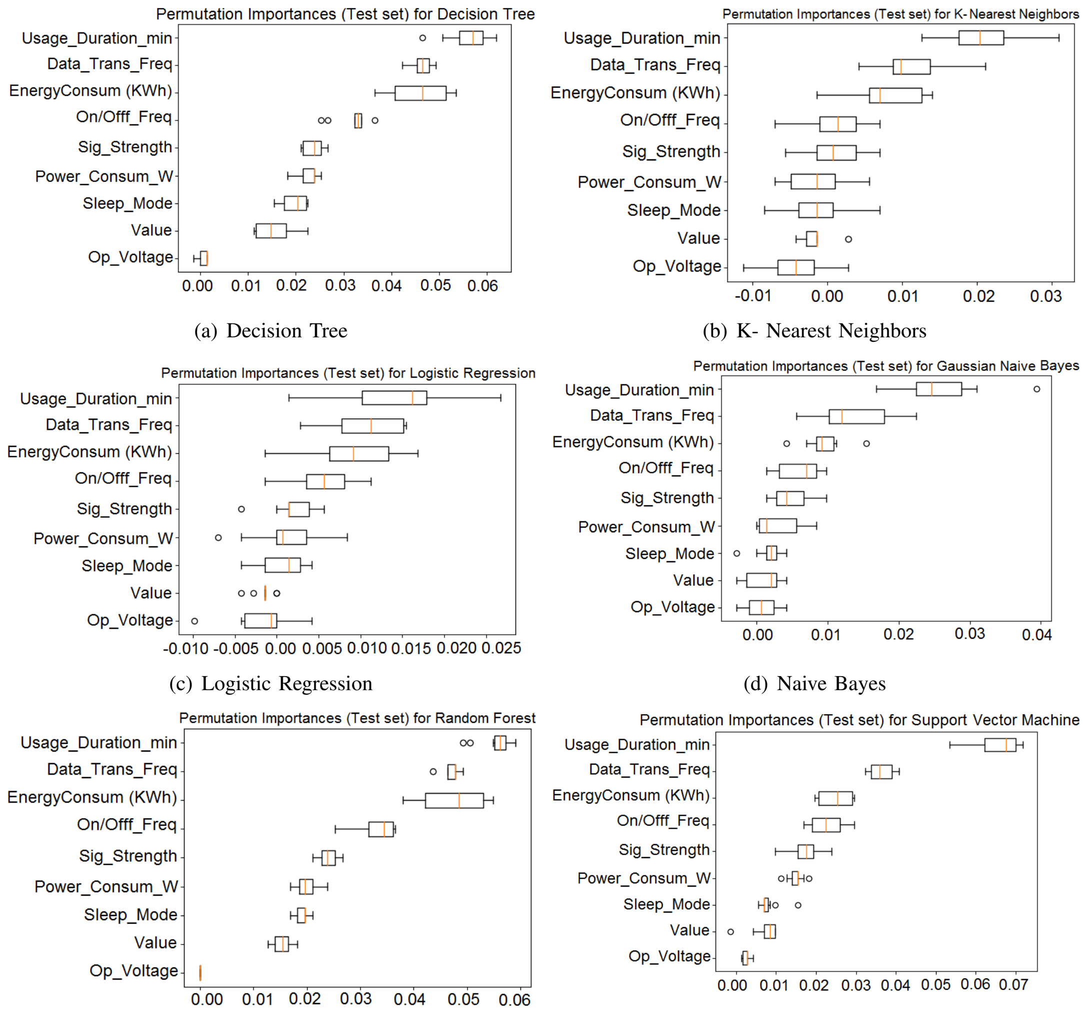
Fig. 3. ROC curve of the ML models.

information about the distributional properties of important features in the dataset. Notably, usage length has a very regular distribution with a median of 60.5 minutes, but on/off frequency has considerable variation with a median of 3.0 and a significant number of outliers. Energy and power usage are gradually increasing, having medians around 0.5 kWh and 0.15 W, respectively. The operating voltage has a wide range, with a median of 4.2 volts. The medians for data transmission frequency and sleep mode duration are 7.0 and 181.0 seconds, respectively. The signal strength range is quite variable.

TABLE V
COMPARISON OF THE DATA DISTRIBUTION FOR VARIOUS FEATURES.

Features	Min Value	Median	Max Value	IQR
Usage Duration	30	60.5	100	31
On/Off Freq	1	3	5	1
Energy Consum	0.1	0.5	1	0.4
Power Consum	0.1	0.15	0.39	0.1
Op Voltage	3	4.2	5	1.2
Data Tran Freq	4	7	15	4
Sleep Mode Duration	80	181	265	60
Sig Strength Range	30	75	119	26

Figure 5 shows the average battery life of all the sensors. The observed decrease in sensor battery usage with the adoption of ML models represents a considerable increase in energy efficiency. Sensors were using more batteries before model adoption, indicating a less optimized and perhaps inefficient use of energy resources. It demonstrates how machine learning may be used to improve energy management in sensor net-



(a) Decision Tree (b) K- Nearest Neighbors

(c) Logistic Regression (d) Naive Bayes

(e) Random Forest (f) Support Vector Machine

Fig. 4. Data distribution of various features for DT, KNN, LR, NB, RF, and SVM models.

works, causing them to be more robust and resource-efficient.

Figure 6 shows the effect of various energy distribution techniques on the overall consumption of energy of the sensor network within 24 hours. E$_{uni}$, which represents a uniform distribution of energy, exhibits a progressive increase in energy consumption, peaking at 0.62 J. E$_{norm}$, which uses a normal distribution, has a better energy consumption curve having a peak of 0.59 J. E$_{mean}$, which is calculated using the mean energy consumption, shows a constant increase, indicating stability throughout the observed period and peaking at 0.61. Notably, without the suggested technique, the E$_{simple}$ exhibits a steeper and less optimized energy consumption trend, peaking at 0.78 J.

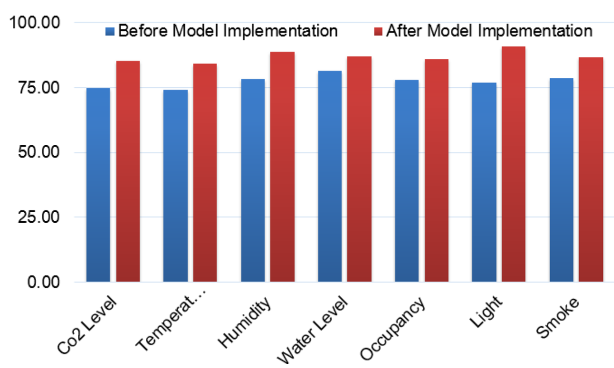


Fig. 5. Comparison of 24-hour average battery life of various sensors before and after the model implementation.

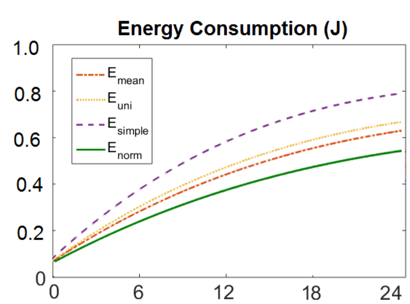


Fig. 6. Comparison of energy consumption for Simple, Uniform distribution, Normal distribution, and Mean results.

The residual energy data for sensors during 24 hours are shown in Figure 7. E$_{uni}$ and E$_{norm}$ represent situations with uniform and normal energy distributions, with both beginning at 0.40. The mean result, E$_{mean}$, shows a slight drop from the original 0.40. In contrast, E$_{simple}$ drops rapidly without the suggested technique, reaching 0.08 after 24 hours. These findings highlight the efficacy of the suggested technique E$_{mean}$ in keeping a more consistent and efficient energy consumption behavior when compared to the rapid fall observed in the absence of the proposed method E$_{simple}$.

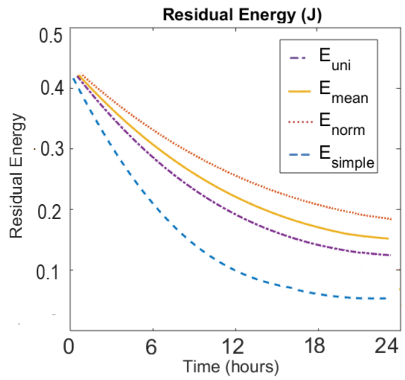


Fig. 7. Comparison of residual energy for Simple, Uniform distribution, Normal distribution, and Mean results.

V. Conclusions

This research addressed the complex terrain of Wireless Sensor Internet of Things Networks (WSINs), focusing on the fundamental aspects that characterize their functioning in Consumer Electronics (CE). A multidimensional strategy integrating Recursive Feature Elimination (RFE), machine learning models, and stochastic optimization approaches was used to solve the inherent issues of energy limits in sensor nodes. We discovered and prioritized significant features using RFE, lowering the complexity of the dataset and improving the performance of further machine learning models. The use of multiple machine learning methods yielded encouraging results in terms of accuracy, recall, precision, and F1 score. These models not only help to forecast notifications accurately, but they additionally serve an important role in optimizing energy use inside the WSIN. Incorporating uniform and normal distributions into energy models created a probabilistic framework for modeling and optimizing energy consumption patterns. This stochastic optimization method, when combined with machine learning perspectives, helps to create energy-efficient WSINs. The study provides the way for the advancement of CE with much-increased energy efficiency, resulting in devices that are not just smarter but also more sustainable and cost-effective in the long term. In the future, these results will be applied in the field of 6G communication. Machine learning models may be customized and developed to handle the particular problems and possibilities presented by terahertz frequencies, opening the door for breakthroughs in high-frequency communication technology in CE. This study is a step towards more sustainable and intelligent WSINs, having implications for both existing sensor networks and upcoming terahertz communication systems.

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References

[1] M. A. Matin and M. Islam, “Overview of wireless sensor network,” *Wireless sensor networks-technology and protocols*, vol. 1, no. 3, 2012.

[2] K. Gulati, R. S. K. Boddu, D. Kapila, S. L. Bangare, N. Chandnani, and G. Saravanan, “A review paper on wireless sensor network techniques in internet of things (iot),” *Materials Today: Proceedings*, vol. 51, pp. 161–165, 2022.

[3] S. Lavanya, A. Prasanth, S. Jayachitra, and A. Shenbagarajan, “A tuned classification approach for efficient heterogeneous fault diagnosis in iot-enabled wsn applications,” *Measurement*, vol. 183, p. 109771, 2021.

[4] C. S. Abella, S. Bonina, A. Cucuccio, S. D’Angelo, G. Giustolisi, A. D. Grasso, A. Imbruglia, G. S. Mauro, G. A. Nastasi, G. Palumbo, *et al.*, “Autonomous energy-efficient wireless sensor network platform for home/office automation,” *IEEE Sensors Journal*, vol. 19, no. 9, pp. 3501–3512, 2019.

[5] R. Deepa, M. Sankar, R. Rathiya, C. Sankari, R. Kalaivani, *et al.*, “Iot based energy efficient using wireless sensor network application to smart agriculture,” in *2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*. IEEE, 2023, pp. 90–95.

[6] P. Yadav and S. C. Sharma, “A systematic review of localization in wsn: Machine learning and optimization-based approaches,” *International Journal of Communication Systems*, vol. 36, no. 4, p. e5397, 2023.

[7] V. Prakash, P. K. Tripathi, S. Pandey, and R. K. Shukla, “A perspective on impact of machine learning in wsns: Applications and research challenges,” in *2023 1st International Conference on Intelligent Computing and Research Trends (ICRT)*. IEEE, 2023, pp. 1–7.

[8] K. Belsare, M. Singh, A. Gandam, P. K. Malik, R. Agarwal, and A. Gehlot, “An integrated approach of iot and wsn using wavelet transform and machine learning for the solid waste image classification in smart cities,” *Transactions on Emerging Telecommunications Technologies*, p. e4857, 2023.

[9] S. Pande, A. Khamparia, and D. Gupta, “Feature selection and comparison of classification algorithms for wireless sensor networks,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–13, 2021.

[10] F. Masood, W. U. Khan, S. U. Jan, and J. Ahmad, “Ai-enabled traffic control prioritization in software-defined iot networks for smart agriculture,” *Sensors*, vol. 23, no. 19, p. 8218, 2023.

[11] A. A. Siddique, N. Alasbali, M. Driss, W. Boulila, M. S. Alshehri, and J. Ahmad, “Sustainable collaboration: Federated learning for environmentally conscious forest fire classification in green internet of things (iot),” *Internet of Things*, vol. 25, p. 101013, 2024.

[12] M. S. Alshehri, J. Ahmad, S. Almakdi, M. Al Qathrady, Y. Y. Ghadi, and W. J. Buchanan, “Skipgatenet: A lightweight cnn-lstm hybrid model with learnable skip connections for efficient botnet attack detection in iot,” *IEEE Access*, 2024.

[13] S. Ullah, J. Ahmad, M. A. Khan, M. S. Alshehri, W. Boulila, A. Koubaa, S. U. Jan, and M. M. I. Ch, “Tnn-ids: Transformer neural network-based intrusion detection system for mqtt-enabled iot networks,” *Computer Networks*, vol. 237, p. 110072, 2023.

[14] B. Xu, J. Wang, Z. Zhao, H. Lin, and F. Xia, “Unsupervised anomaly detection on attributed networks with graph contrastive learning for consumer electronics security,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 4062–4072, 2024.

[15] M. Shahid, M. Tariq, Z. Iqbal, H. M. Albarakati, N. Fatima, M. A. Khan, and M. Shabaz, “Link-quality based energy-efficient routing protocol for wsn in iot,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 4645–4653, 2024.

[16] X. Huang, Y. Zhang, Y. Qi, C. Huang, and M. S. Hossain, “Energy-efficient uav scheduling and probabilistic task offloading for digital twin-empowered consumer electronics industry,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 2145–2154, 2024.

[17] A. Taneja and S. Rani, “A novel energy conservation scheme for iot based wireless networks: A use case of e-commerce systems for consumer electronics,” *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 1648–1655, 2024.

[18] C. Savaglio, P. Pace, G. Aloi, A. Liotta, and G. Fortino, "Lightweight reinforcement learning for energy efficient communications in wireless sensor networks," *IEEE Access*, vol. 7, pp. 29 355–29 364, 2019.

[19] A. Mehmood, Z. Lv, J. Lloret, and M. M. Umar, "Eldc: An artificial neural network based energy-efficient and robust routing scheme for pollution monitoring in wsns," *IEEE Transactions on Emerging Topics in Computing*, vol. 8, no. 1, pp. 106–114, 2017.

[20] K. H. K. Reddy, A. K. Luhach, B. Pradhan, J. K. Dash, and D. S. Roy, "A genetic algorithm for energy efficient fog layer resource management in context-aware smart cities," *Sustainable Cities and Society*, vol. 63, p. 102428, 2020.

[21] S. N. Mohanty, E. L. Lydia, M. Elhoseny, M. M. G. Al Otaibi, and K. Shankar, "Deep learning with lstm based distributed data mining model for energy efficient wireless sensor networks," *Physical Communication*, vol. 40, p. 101097, 2020.

[22] A. Mukherjee, P. Goswami, M. A. Khan, L. Manman, L. Yang, and P. Pillai, "Energy-efficient resource allocation strategy in massive iot for industrial 6g applications," *IEEE Internet of Things Journal*, vol. 8, no. 7, pp. 5194–5201, 2020.

[23] A. G. Soundari and V. Jyothi, "Energy efficient machine learning technique for smart data collection in wireless sensor networks," *Circuits, Systems, and Signal Processing*, vol. 39, pp. 1089–1122, 2020.

[24] S. Radhika and P. Rangarajan, "Fuzzy based sleep scheduling algorithm with machine learning techniques to enhance energy efficiency in wireless sensor networks," *Wireless Personal Communications*, vol. 118, pp. 3025–3044, 2021.

[25] M. Rathee, S. Kumar, A. H. Gandomi, K. Dilip, B. Balusamy, and R. Patan, "Ant colony optimization based quality of service aware energy balancing secure routing algorithm for wireless sensor networks," *IEEE Transactions on Engineering Management*, vol. 68, no. 1, pp. 170–182, 2019.

[26] G. Kaur, P. Chanak, and M. Bhattacharya, "Energy-efficient intelligent routing scheme for iot-enabled wsns," *IEEE Internet of Things Journal*, vol. 8, no. 14, pp. 11 440–11 449, 2021.

[27] Q. Ding, R. Zhu, H. Liu, and M. Ma, "An overview of machine learning-based energy-efficient routing algorithms in wireless sensor networks," *Electronics*, vol. 10, no. 13, p. 1539, 2021.

[28] Y.-Y. Guo, J. Yang, X.-L. Tan, and Q. Liu, "An energy-efficiency multi-relay selection and power allocation based on deep neural network for amplify-and-forward cooperative transmission," *IEEE Wireless Communications Letters*, vol. 11, no. 1, pp. 63–66, 2021.

[29] B. Zhao and X. Zhao, "Deep reinforcement learning resource allocation in wireless sensor networks with energy harvesting and relay," *IEEE Internet of Things Journal*, vol. 9, no. 3, pp. 2330–2345, 2021.

[30] P. Gulganwa and S. Jain, "Ees-wca: energy efficient and secure weighted clustering for wsn using machine learning approach," *International Journal of Information Technology*, vol. 14, no. 1, pp. 135–144, 2022.

[31] M. A. Fiaz, M. A. Ashraf, and A. A. Rizvi, "Average scattered field from a random pec cylinder buried below a slightly rough surface," *Waves in Random and Complex Media*, vol. 28, no. 1, pp. 60–75, 2018.

[32] F. Masood and M. A. Fiaz, "Evaluation of average cross-polarised scattered field from a pemc cylinder of the random radius with uniform/normal distribution," *IET Microwaves, Antennas & Propagation*, vol. 13, no. 6, pp. 804–812, 2019.

[33] F. Masood, W. U. Khan, K. Ullah, A. Khan, F. H. Alghamedy, and H. Aljuaid, "A hybrid cnn-lstm random forest model for dysgraphia classification from hand-written characters with uniform/normal distribution," *Applied Sciences*, vol. 13, no. 7, p. 4275, 2023.

[34] D. W. Hosmer Jr, S. Lemeshow, and R. X. Sturdivant, *Applied logistic regression*. John Wiley & Sons, 2013, vol. 398.

[35] J. R. Quinlan, "Induction of decision trees," *Machine learning*, vol. 1, pp. 81–106, 1986.

[36] L. Breiman, "Random forests," *Machine learning*, vol. 45, pp. 5–32, 2001.

[37] P. Domingos and M. Pazzani, "On the optimality of the simple bayesian classifier under zero-one loss," *Machine learning*, vol. 29, pp. 103–130, 1997.

[38] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, pp. 273–297, 1995.

[39] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE transactions on information theory*, vol. 13, no. 1, pp. 21–27, 1967.

[40] J. Miao and L. Niu, "A survey on feature selection," *Procedia computer science*, vol. 91, pp. 919–926, 2016.

[41] B. Abidi, A. Jilbab, and E. H. Mohamed, "Wireless body area network for health monitoring," *Journal of medical engineering & technology*, vol. 43, no. 2, pp. 124–132, 2019.

Fahad Masood is an Assistant Professor and Coordinator of the (BSAI) program at the Department of Computing, Abasyn University Peshawar, Pakistan. He received his Ph.D. degree in Electronics from Quaid-e-Azam University Islamabad Pakistan in 2021. He has several research publications in reputed International journals. He has served as general chair for various International conferences. His research interests include Artificial Intelligence, IoTs, Sensor and Adhoc Networks, and Intelligent Reflecting Surfaces.

Muhammad Abbas Khan received his MS degree in Telecomm Engineering from Blekinge Institute of Technology, Sweden in 2012. His research interest includes Internet of Things, and Wireless Sensor Networks.

Mohammed S. Alshehri received a B.S. degree in Computer Science from the King Khalid University, Abha, Saudi Arabia, M.S. degree in Computer Science from the University of Colorado Denver, Denver, USA, and a Ph.D. degree in Computer Science from the University of Arkansas, Fayetteville, USA, in 2021. Mohammed's areas of interest are Cybersecurity, Computer Networks, Blockchain, Machine Learning, and Deep Learning.

Wad Ghaban is an Assistant Professor in the applied college at the University of Tabuk, Saudi Arabia. Wad received her BSc in computer science from King Abdul-Aziz University, MSc. in Advanced Computer Science from the University of Birmingham in 2015, and PhD from the University of Birmingham in 2020. She worked on several projects related to Human-computer interaction, survival analysis, online learning, Natural language processing, and sentiment analysis. Wad also published and presented several papers in International Conferences and Indexed Journals.

Faisal Saeed is an Associate Professor at the College of Computing and Digital Technology, at Birmingham City University. He is leading the MSc Artificial Intelligence course, Research Summer School, and Smart Health Lab at the College. He obtained his BSc in Computers (Information Technology) from Cairo University, Egypt, in 2005, followed by a MSc in Information Technology Management and a PhD in Computer Science from UTM, in 2010 and 2013, respectively. Faisal's research interests include data mining, artificial intelligence, machine learning, information retrieval, and health informatics. He achieved an outstanding publication record in prestigious high-impact factor journals and presented papers at several international conferences. Moreover, Faisal has secured 21 research funds from various funders in Malaysia, Saudi Arabia, and the UK. Faisal served as General Chair of 12 International Conferences and Guest Editor of tens of indexed Journals.

Hussain Mobarak Albarakati is with the Department of Computer Engineering, College of Computer and Information Systems, Umm Al-Qura University, Makkah, Saudi Arabia. He is currently an Assistant professor at the university where he teaches courses related to AI, networks, and embedded systems. In addition, he is a senior AI researcher related to remote sensing and medicine. His research interests include artificial intelligence, machine learning, embedded systems, the Internet of Things, cloud computing, software engineering, and networks.

Ahmed Alkhayyat received a B.Sc. degree in Electrical Engineering from AL KUFA University, Najaf, Iraq, and an M.Sc. degree from the Dehradun Institute of Technology, Dehradun, India. He is currently Dean of International Relations and Manager of the world ranking at the Islamic University, Najaf, Iraq. His research interests include network coding, cognitive radio, efficient-energy routing algorithms, and efficient-energy MAC protocol in cooperative wireless networks.