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Feature Selection and Energy Management in Wireless Sensor Networks using Deep Learning

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Abstract—In wireless sensor networks, when the available energy sources and battery capacity are extremely constrained, energy efficiency is a major issue to be adressed. One of the main goals in the design of wireless sensor networks (WSNs) is to maximize longevity of battery life. Designers can benefit from the use of intelligent power utilization models to accomplish this goal. These models seek to decrease the number of chosen sensors used to record environmental measures in order to minimize power utilization while retaining the acceptable level of measurement accuracy. In order to simulate wireless sensor networks, we looked at real world datasets. Our simulation findings demonstrate that the suggested strategy can be used to accomplish significant goals by using the right number of sensors using deep learning, extend the lifespan of the wireless sensor networks.

Keywords-Wireless Sensor Networks, Data Sets, Deep Learning, Feature Selection, Accuracy, Life time

I. INTRODUCTION

A networked collection of sensor nodes is the definition of a wireless sensor network (WSN). The resources available to these tiny sensors are quite constrained. Each node in a typical sensor network is required to monitor a variety of environmental and physical factors, including temperature, sound, humidity, pressure, vibration, motion, and light. Due to a small battery capacity and numerous sensors dispersed over a big region, energy management in WSN is a significant problem. There is no power support with consistent power rate in sensor networks. A sensor's lifespan is severely constrained by its finite power supply. Consequently, reducing energy use is always a major concern. Several strategies have been devised to deal with this problem, but they have had only limited success in terms of dynamically regulating the energy requirements without sacrificing accuracy in the event of sensor failures. Depending on the sensor network's goal, sensors may work together to complete particular tasks. The natures of the monitored parameters and the numerous installed sensors have also resulted in a high degree of correlation in the collected data. Therefore, it is unnecessary to report each individual sensor reading; as a result, it is crucial to use intelligent network models with minimum power depletion algorithm that make use of information fusion [1].

It was underlined that in order to increase network lifetime, an energy-efficient management strategy must be used. The energy used for data transfer by sensor nodes is excessive. Therefore, avoiding energy waste and increasing network lifetime will be made possible by limiting the amount of useless communication [2]. The key problem facing WSNs is building an efficient power depletion system for sensor networks, especially those installed in remote places [3]. Significant research efforts have proposed intelligent models based on ML to address this issue [4]. The benefit of employing machine learning algorithms in WSNs was highlighted since they help remove needless redesign concerns. The authors also claim that machine learning techniques have aided in the creation of workable solutions that increase the network lifetime [5]. Additionally, a number of justifications were provided to highlight how crucial it is for WSN environmental monitoring applications to employ machine learning methods. First, due to unforeseen environmental behavior, sensor nodes might not function as planned.

In these situations, machine learning algorithms can get around these issues by modifying themselves to the newly learned information. Second, the resulting mathematical models for the network could be quite complicated because the environments where WSNs are installed are unpredictable [6]. Machine learning algorithms can help create appealing and less complicated solutions. Third, a lot of correlated and redundant data is produced by sensor nodes. Machine learning algorithms are strong tools that may be used to research and locate connected data, make judgments, forecasts, and categorize data [1, 6].

In the fields of machine learning, neural networks, and artificial intelligence, well-known algorithms like Naive Bayes, Multilayer Perceptron (MLP), and Support Vector Machine (SVM) are used and researched extensively. Beginning with the classification operation, MLP can successfully complete it. However, because of its intricate structure, MLP neural network training is challenging. SVM is regarded as a very potent algorithm in the data mining industry. In a large variety of scientific applications, it has been used with success [7-10].

Despite the significance of machine learning algorithms for WSN applications, there hasn't been much focus on comparing different algorithms, particularly when it comes to WSN energy management. Additionally, there have been few efforts to design a suitable intelligent energy management paradigm for these networks. Except for the one which is disclosed in prior work [11], authors are not aware of any previous work that supports the usage of a certain intelligent algorithm in comparison to others for WSNs. In that study, authors suggest use of MLP rather than Naive Bayes to create an intelligent and effective energy management model for WSNs. To assess their performance in terms of the percentages of accurate classification, a comparison between MLP and Naive Bayes was offered. According to simulation data, MLP significantly outperforms Naive Bayes in terms of selection accuracy given the same Lifetime Extension Factor. Due to its intricacy and the process of updating a sequence of weights, MLP, however, requires more time to train the network. As a result, during the deployment stage, sensor nodes could use a little bit more energy.

By conducting a thorough comparison of different classification methods to design power efficient model for WSNs, LSVM is found to be best among them due to its simplicity [11, 12, 13]. The application of LSVM with linear kernel is more and produces better accuracy [14, 15]. Additionally, Yuan et al. [16] were able to draw the conclusion that, in contrast to other classifiers like MLP, SVM classifier, especially with linear kernel, has the capacity to learn and construct the necessary knowledge from less training samples while still providing good classification accuracy.

According to authors, reducing the quantity of sensors for minimizing power depletion is comparable to reducing the quantity of features [2]. We employ deep learning technique for minimization of features, where features are rated according to the importance of their utilization in wireless sensor networks. That means, in order to achieve a certain level of accuracy, the sensors are first selected from the most to the least important.

We utilized various publicly accessible datasets related to WSNs from the Machine Learning repository [3] for validating the suggested strategy. Different numbers of sensors are included in each data set (features).

A. Motivation

In this research, we provide a novel pattern recognition-based formulation of energy-efficient WSNs that can still meet accuracy criteria when sensors fail. In this technique, features from data sets pertaining to various WSN application scenarios, such as human activity recognition system. For energy-efficient management, reducing the number of sensors is comparable to reducing the number of features in our formulation [2]. We employ a feature selection strategy for minimization, in which the characteristics are not prioritized in accordance with the importance of their application in the wireless sensor network. In order to create an intelligent model with deep learning and two activation functions for energy- efficient WSNs that meet certain accuracy, we first chose the sensors based on the criteria.

The rest of paper is organized as follows. Section II discusses the related works, Section III represents Preliminaries, Section IV is purposed system and experimental result. Section VI gives conclusion and future Work

II. RELATED WORK

To improve the energy efficiency of WSNs, a number of intelligent models have been put out. In [17], the authors suggested a method for choosing sensors that can aid in figuring out the ideal number of sensor nodes for the network. By doing this, the network's lifespan can be extended while the number of sensor nodes can be decreased without impairing the decision-making process. In order to choose the best sensors for the network, the Bayesian methodology was employed for sensor selection. Additionally, a classifier called the Self-Organizing Map (SOM) was employed. A selection strategy for reducing WSNs' energy consumption was put forth by the authors in [18]. Based on the importance of their use in the WSNs, the sensors in their scheme were ordered from the most to the least significant. Following that, the Naive Bayes classification algorithm was employed. On three well-known real sensor datasets, the methodology was tested. The findings indicated that using additional sensors will result in higher energy consumption and a shorter lifespan for the sensor network. However, if the sensors are ranked, the selection method is utilized first, then the intelligent classifier, lengthening the lifespan of the sensor network. This is as a result of using fewer carefully chosen sensors.

In [19], the authors suggested a plan to enhance the lifespan of the sensor network while minimizing energy consumption. Based on a feature/sensor selection that reduces the number of used sensors, this is the case. The K-Nearest Neighbor (KNN) classification algorithm and selection algorithm are different.

Richter [20] proposed a method that includes the following five steps: signal recording, pre-processing, feature extraction, feature reduction, and classification. For wireless systems where it is important to swap or hand off the communication link from one base station to another for two key reasons: to preserve the signal quality and avoid interference, Narasimhan and Cox [21] suggested a Handoff algorithm. To disrupt the frequency hopping spread spectrum patterns, Song and Allison [22] created algorithms. The transmitter uses a recognized switching mechanism known as hopping or hopping pattern to broadcast on one frequency for a brief period of time before switching to another in a frequency-hopping spread spectrum. Due to rigorous battery constraints, Walchi and Braun's [23] suggested office monitoring system can discern between abnormal and typical office access. Consequently, it is necessary to classify office access patterns.

The self-learning anomaly detection system for office monitoring with wireless sensor nodes' node-level decision unit is provided. The neural network-based resource reservation technique created by Yu and He [24] is simple to use and flexible for a variety of circumstances. When resources are scarce in wireless networks, it provides precise categorization about the user's erratic movement in tiny size cells and increased resource efficiency. Ongoing work on a distributed event detection system for WSNs was given by Dziengel, Wittenburg, and Schiller [25]. In contrast to other methods, their system is self-contained; for instance, it runs without the need for a central processing or coordinating component and actively utilizes the redundantly positioned sensor nodes in the network to increase detection accuracy. According to the experimental data in this work, distributed event detection is more accurate than local event detection on a single node. A solution for distributed event detection in WSNs was presented by Wittenburg [26] that enables a large number of sensor nodes to work together to determine which application-specific event has happened. In [27], the authors are designed an intelligent model using machine learning to forecast when mine fire hazards will occur in underground coal mines by taking data set for training and testing of the model. Compared to an offline monitoring system, this method is more trustworthy and sensitive to any threats. In [28], the authors have focused on wireless sensor networks (WSNs), sink mobility has gained popularity as a technique of data collecting since it dramatically enhances network performance. They have applied shark smell optimization method for designing mobile sink to collect data from different locations in shortest way.

III. PRELIMINARIES

A. *Machine Learning and deep Learning*

There are many intelligence techniques which are used to design intelligent model for wireless sensor networks. They are machine learning and deep learning [29].

Machine learning helps in analysis of data and trains the machine by data sets and solves different types WSNs issues like IoT applications and other applications using different techniques such as regression, decision tree, random forest etc.

Deep learning is subset of ANN. It is also layer based which is inspired by human nerve system. It is applied in various WSN applications like routing, energy harvesting, medical image processing, speech recognition etc.

B. *Dataset*

Here we have given a brief overview of the datasets used for the experimental comparison as well as the categorization algorithms. Three human activity reorganization datasets are used in this study and they are all briefly described in paper [30].

TABLE I. DATASET

Dataset	**No. of activities**	**Sensor (Accel.)**	**Sensor (Gyro.)**	**Sensor position**
ActiveMiles	7	Yes	Yes	All place
WISDM v1.1	6	Yes	No	Thigh
Daphnet FoG	2	Yes	No	Trunk, thigh, ankle
Skoda	10	Yes	No	Arms

IV. PROPOSED SYSTEM

With the aid of the deep learning, an intelligent neural network model for effective energy management in WSNs is proposed in this work. We have incorporated human activity reorganization datasets to accesses performance and accuracy. Additionally, the dataset is split into training and testing for each trial, with 70% of dataset for training and the remaining 30% being used for testing. According to [18] the Lifetime Extension Factor is given by

LTEF = Total number of sensors/Number of sensor used (1)

Our purposed model operates in four steps which are as below and shown in figure 2.

(1) Pre-processing.
(2) Processing: Feature Selection.
(3) Deep Learning.
(4) Performance evaluation.

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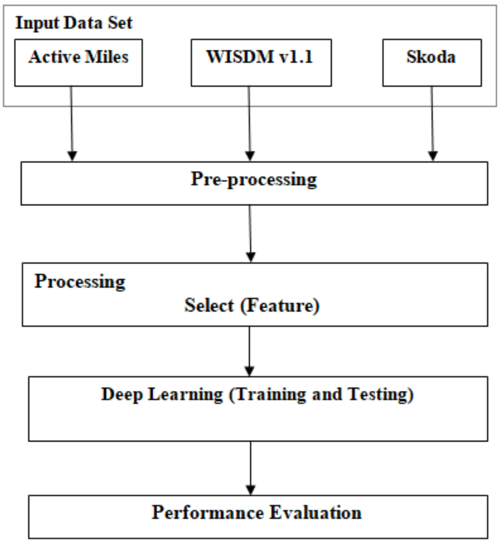

Figure 2. Proposed model.

A. Activate functions

Sigmoid:

It is one of the most popular non-linear activation functions. The sigmoid function changes values between 0 and 1. The sigmoid mathematical expression is given below.

$$F(x) = 1/e\text{-}x \quad (2)$$

It is important to remember that sigmoid is a non-linear function in contrast to the binary step and linear functions. This basically means that the output is also nonlinear when it has several neurons that have sigmoid function as their activation function.

ReLU (Rectified Linear Unit):

Another non-linear activation function that has grown in prominence in the deep learning field is the ReLU function. Rectified Linear Unit is referred to as ReLU. The ReLU function's primary advantage over other activation functions is that it does not simultaneously fire all of the neurons. This signifies that the neurons won't stop firing unless the linear transformation's result is less than 0. It has the following mathematical representation:

$$F(x) = \max(0, x) \quad (3)$$

B. Experimental Result

In this part, we will verify the performance of the proposed model by using three metrics. The metrics are energy consumption, accuracy and lifetime of networks.

C. Simulation Environment

The simulation works are done by using Python, an Intel core i5 with 2.00 GHZ CPU and 8GB RAM running on the platform Microsoft Windows10.

D. Performance Metrics

Energy consumption: For energy-efficient management, reducing the number of features.

Network lifetime and Accuracy: It depends on number of selected features.

E. Result Discussion

We have taken four different data sets for the simulation work. The data sets used for this paper are summarized in the table below.

The main goal is to demonstrate how the number of features chosen may impact accuracy and the life extension factor. The accuracy and lifespan of a sensor network depending on the total number of features employed across all sensor networks.

TABLE II. ACCURACY

Dataset	Approach	Window	Accuracy (%)
Active Miles	Cs1 Cs2	10s	98.0 99.0
WISDM v1.1	Cs1 Cs2 Cs3	10s	98.7 97.4 99.6
Skoda (Node 16)	Cs1 Cs2 Cs3 Cs4	10s	98.7 99.6 96.8 99.3

TABLE III. TABLE LIFETIME

Feature	Lifetime extension factor
10	102/10=10.2
20	102/20=5.1
30	102/30=3.4
40	102/40=2.55
50	102/50=2.04
60	102/60=1.7
70	102/70=1.45
80	102/80=1.27
90	102/90=1.13
102	102/102=1

We have observed from table II that the accuracy is not constant in all the cases due to different approaches and window size. The lifetime depends on the features selection because based on features we can able to identify the life time of WSNs. If we choose machine learning method then we all have taken individual parameters and experiments also increased more but, in our case, we have experimented only one experiment on every dataset because deep learning only able to identify the best parameters in every epoch. Deep learning can save the time compared to machine learning method.

From table III, it is clear that the life time of WSNs has increased when a smaller number of sensors are used. However, the selection of features plays major role for life time, power consumption and accuracy of WSNs.

V. CONCLUSION AND FUTURE WORK

Wireless sensor networks have a very small number of energy sources. In this paper, we have suggested a feature selection method and deep learning technique for wireless sensor network for energy management. Using more important sensors with fewer ones lengthen the network's lifespan. In the case of a sensor network, management failure occurs by raising the quantity of sensors to address the specific standards for accuracy. The suggested plan thorough experimental assessment was used to validate various datasets related to wireless sensors networks and utilized in many contexts for applications. In the future, we intend to examine other data sets to attain more precision.

REFERENCES

[1] E. F. Nakamura, A. A. F. Loureiro and A. C. Frery,"Information fusion for wireless sensor networks: methods, models, and classifications," ACM Computing Surveys, vol.39, 3, article 9 , Aug 2007. doi 10.1145/1267070.1267073.

[2] S. M. AlTabbakh, E. M. Elshahed, R. A. Ramadan and H. M. Elzahed," Energy management of wireless sensor network based on modeling by game theory approaches, " IEEE European Modelling Symposium(EMS '15), Madrid, Spain, Oct 2015, doi 10.1109/EMS.2015.62.

[3] J. A. Khan, H. K. Qureshi and A. Iqbal," Energy management in wireless sensor networks: a survey," Computers and Electrical Engineering,"vol. 41, Jan 2015, pp. 159–176.

[4] Y. Yu," A survey of intelligent approaches in wireless sensor networks for efficient energy consumption," Proceedings of the International Conference on Software and Computer Applications (ICSCA '12), Singapore ,2012.

[5] M. A. Alsheikh, S. Lin, D. Niyato, and H.P. Tan,"Machine learning in wireless sensor networks: algorithms, strategies, and applications," IEEE Communications Surveys and Tutorials, vol. 16, April 2014, pp. 1996– 2018.

[6] N. Enami, R. Moghadam,A. K. Dadashtabar, and M. Hoseini," Neural network based energy efficiency in wireless sensor networks: a survey," International Journal of Computer Science & Engineering Survey, vol.1, Aug., 2010, pp. 39–53.

[7] Y. M. M. Hassim and Ghazali, R. " Training a functional link neural network using an artificial bee colony for solving a classification problems. Journal of Computing, 2012, vol. 4, 9, pp. 110–115.

[8] A. K. Paland S. Pal," Classification model of prediction for placement of students," International Journal of Modern Education and Computer Science, vol. 5,11, Nov. 2013, pp. 49-56.

[9] S. W. Purnami, J. M. Zain and T. Heriawan," An alternative algorithm for classification large categorical dataset: k-mode clustering reduced support vector machine," International Journal of DatabaseTheory and Application, vol. 4,1, March 2011,pp. 19–30.

[10] Azhahudurai, K. ., & Veeramanikandan, V. . (2023). Artificial Flora Optimization with Deep Learning Enabled Air Pollution Monitoring System in IoT Environment. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 22–34. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2568

[11] A. T. Mitrokotsa, M. Tsagkaris and C. Douligeris,"Intrusion detection in mobile ad hoc networks using classification algorithms," Advances in Ad Hoc Networking, vol. 265,June 2008, pp. 133–144.

[12] A. Y.Barnawi and I. M.,"Energy management of wireless sensor networks based on multi-layer perceptrons," Proceedings of the 20th EuropeanWireless Conference, European Wireless, 2014, pp. 1–6.

[13] G. R. Gupta and P. Ramanathan," Level set estimation using uncoordinated mobile sensors," Ad- Hoc, Mobile andWireless Networks, vol. 4686, 2007, pp.101–114.

[14] M. Magno, D. Brunelli, P. Zappi and L. Benini," Energy efficient cooperative multimodal ambient monitoring," Smart Sensing and Context, November 2010, pp. 56–70.

[15] E. S. Sazonov and Fontana, J. M.," A sensor system for automatic detection of food intake through non- invasive monitoring of chewing", IEEE Sensor Journal, 12(5), pp. 1340-1348 (2012).

[16] M. Bal, M. F. Amasyali, H. Sever, G. Kose and A. Demirhan," Performance evaluation of the machine learning algorithms used in inference mechanism of a medical decision support system," The Scientific World Journal, Article ID 137896, pp.15

[17] S. Yuan, D. Liang, L. Qiu and M. Liu," Mobile multi-agent evaluation method for wireless sensor networks-based large scale structural health monitoring," International Journal of Distributed Sensor Networks, September 2012, Article ID 164527, pp.1-15.

[18] S. Thiemjarus, B. P. L. Lo, K. V. Laerhoven and G. Z. Yang," Feature selection for wireless sensor networks," Proceedings of the 1st International Workshop on Wearable and Implantable Body Sensor Networks (BSN '04), London, UK, April 2004.

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[19] M. Alwadiand G. Chetty," Feature selection and energy management for wireless sensor networks," IJCSNS International Journal of Computer Science and Network Security, vol.12, no 6, June 2012 pp. 46-51.

[20] Fatima Abbas, Deep Learning Approaches for Medical Image Analysis and Diagnosis , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[21] Mr. B. Naga Rajesh. (2019). Effective Morphological Transformation and Sub-pixel Classification of Clustered Images. International Journal of New Practices in Management and Engineering, 8(01), 08 - 14. https://doi.org/10.17762/ijnpme.v8i01.74

[22] J. Csirik, P. Bertholet and H. Bunke, " Pattern recognition in wireless sensor networks in presence of sensor failures," Proceedings of the 12th WSEAS International Conference on Neural Networks (NN '11), Bras, ov, Romania,April 2011.

[23] R. Richter," Distributed Pattern Recognition in Wireless Sensor Networks" 2008, pp. 1-5.

[24] R. Narasimhan and D.C. Cox, " A handoff algorithm for wireless systems using pattern recognition," IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), vol. 3, September 1998, pp. 8-11.

[25] M. Song and T. Allison," Frequency Hopping Pattern Recognition Algorithms for Wireless Sensor Networks, PDCS, 2005 .

[26] M. Wälchli and T. Braun, "Efficient signal processing and anomaly detection in wireless sensor networks," Applications of Evolutionary Computing, vol. 5484, 2009, pp. 81-86.

[27] W. Yu and C. He," Resource reservation in wireless networks based on pattern recognition," IEEE joint conference on neural networks proceedings, July 2001, pp. 2264-2269, doi.org/10.1109/IJCNN.2001.938519.

[28] Wanjiku, M., Ben-David, Y., Costa, R., Joo-young, L., & Yamamoto, T. Automated Speech Recognition using Deep Learning Techniques. Kuwait Journal of Machine Learning, 1(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/135

[29] N. Dziengel, G. Wittenburg and J. Schiller, "Towards distributed event detection in wireless sensor networks" Adjunct Proc. of 4th IEEE/ACM Intl. Conf. on Distributed Computing in Sensor Systems (DCOSS '08), June 2008.

[30] G. Wittenburg," A system for distributed event detection in wireless sensor networks,"IPSN '10: Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks, April 2010, pp. 94-104.

[31] L. Muduli, D. P. Mishra and P. K. Jana," Wireless Sensor Network Based Underground Coal Mine Environmental Monitoring Using Machine Learning Approach," Proceedings of 11th International Mine ventilation congress, 2019, pp. 776-786.

[32] R. Anwit, A. Tomar, and P.K. Jana," Tour planning for multiple mobile sinks in wireless sensor networks: A shark smell optimization approach. Applied Soft Computing, 97, Part A, 2020

[33] I. H. Sarkar, " AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. S. N. Computer Science, 3, 158, 2022.

[34] D. Ravi, C. Wong, B. Lo and G. -Z. Yang, "Deep learning for human activity recognition: A resource efficient implementation on low-power devices," 2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN), San Francisco, CA, USA, 2016, pp. 71-76, doi: 10.1109/BSN.2016.7516235.