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Efficient Energy Consumption in Wireless Sensor Networks using Multi Layer Perception Classifier

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Abstract

In recent years, the number of wireless sensor network deployme nts for real life applications has rapidly increased. Still, the energy problem remains one of the major barriers somehow preventing the complete exploitation of this technology. Sensor nodes are typically powered by batteries with a limited lifetime and, even when additional energy can be harvested from the external environment, it remains a limited resource to be consumed judiciously. Efficient energy management is thus a key requirement for a credible design of a wireless sensor network. Wireless sensor networks find great applications in radiation levels control, noise pollution control, atmospheric pollution control, structural health monitoring and smart vehicle parking. All sensors present in wireless sensor network are battery operated devices which have limited battery power. After the deployment of sensor devices it is impossible to replace each and every battery present in the network. Hence efficient energy management is an essential requirement in the design of Wireless Sensor Networks (WSNs). The main contribution of this paper is proposing an intelligent model for efficient energy management in WSNs by using the Multi-Layer Perceptrons (MLP) neural network as a classification algorithm.

Keyterms: Multilayer perceptron, Naive Bayes, SupportVector Machine, Neural Networks, Machine learning

1.Introduction

A wireless sensor network (WSN) can be defined as a networked collection of sensor nodes. These sensors are small-scale devices with very limited resources. In a typical sensor network, each node has to monitor environmental and physical conditions such as temperature, sound, humidity, pressure, vibration, motion, and light. Depending on the objective of the sensor network, sensors may cooperate to carry out specific tasks. Also, the generated data is highly correlated due to the nature of the monitored parameters anddue to the large number of deployed sensors. Therefore, it is a waste of resources to report each individual sensor reading; hence, energy-efficient protocols and network models, which utilize information fusion, are extremely important [1]. AlTabbakh et al. [2] emphasized that an energy-efficient management scheme has to be employed in order to extend network lifetime. Sensor nodes waste a lot of their energy in data communication. So, reducing the amount of unnecessary communication will help in minimizing energy waste and extending network lifetime. Also, Khan et al. [3] pointed out that designing an effective energy management scheme for sensor networks, especially those deployed in remote areas, is one of the main challenges facing WSNs. Noticeable research efforts have addressed this issue by proposing intelligent models based on machine learning [4]. For example, Abu Alsheikh et al. [5] emphasized the advantage of adopting machine learning algorithms in WSNs since they assist in eliminating unneeded redesign issues. The authors have also indicated that machine learning algorithms

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have contributed to the development of practical solutions that result in extending the network lifetime. In addition, several reasons were given to stress the importance of adopting machine learning algorithms in WSN environmental monitoring applications. First, sensor nodes might not operate as expected because of unexpected environmental behaviour. In such cases, machine learning algorithms can overcome such problems by adjusting themselves to the newly obtained knowledge. Second, due to the unpredictable environments where WSNs are deployed, the resulting mathematical models for the network might be very complex. Machine learning algorithms can assist in developing attractive and less complex solutions. Third, sensor nodes generate large amounts of correlated and redundant data. Machine learning algorithms are powerful tools that can be used to study and identify correlated data, making decisions, predictions, anddata classification.Algorithms such as Naive Bayes, Multilayer Perceptron (MLP), and Support Vector Machine (SVM) are examples of well-known algorithms that are also widely adopted and investigated in the area of machine learning, neural networks, and artificial intelligence. For starters, MLP can perform the classification operation with significant success [7, 8]. On the other hand, MLP neural network training is difficult due to the complexity of its structure [7]. SVM is also considered to be a very powerful algorithm in the field of data mining. It has been successfully applied in a wide range of scientific applications [9].

2.Related Work

Several intelligent models have been proposed in order to achieve better energy efficiency in WSNs. A sensor selection technique can help to determine the optimal number of sensor nodes in the network. By doing this, the number of sensor nodes can be reduced without degrading the decision process, and the lifetime of the network can be increased. The Bayesian approach was used for sensor selection, as this filter method helps to find the optimal sensors in the network. In addition, the Self-Organizing Map (SOM) was used as a classifier and a selection scheme for minimizing the energy consumption of WSNs. In that scheme, sensors were ranked from the most to the least significant, based on the significance of their use in the WSNs. Then, the Naive Bayes classification algorithm was used. This approach was tested on three well-known real sensor datasets. The results showed that more energy is consumed if more sensors are used and, subsequently, the lifetime of the sensor network is reduced. However, if the sensors are ranked, the lifetime of the sensor network can be increased, as the selection algorithm is used, followed by the intelligent classifier. This is because the number of selected sensors that are used is less. Similarly, a scheme was proposed to both minimize the energy consumption and maximize the lifetime of the sensor network. This is based on a feature/sensor selection that minimizes the number of the used sensors. However, it uses a different selection algorithm and K-Nearest Neighbour (KNN) classification algorithm.

In the clustering problem is viewed as a classificationproblem such that clusters are built by using Least Squares SVM (LS-SVM) with a hybrid kernel, which is a mixture of polynomial and Radial Basis Function (RBF) kernels. Results showed that the clustering process using LS-SVM with hybrid kernel had better results compared to LS-SVM with a single kernel. This was obvious in the case where we had a multiclass classification problem in the clustering problem. Also, Li et al. addressed the energy management in the WSNs at the architecture level by using SVM classifier. A clustering-based distributed Linear-SVM

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algorithm, called CDLSVM, was developed, which differs from other parallel SVM algorithms in its ability to obtain a global optimal classifier. The results showed that the proposed algorithm is efficient for large-scale WSN because it saves the information exchange and energy consumption. [11] discussed about a method, Optimality results are presented for an end-to-end inference approach to correct(i.e., diagnose and repair) probabilistic network faults at minimum expected cost. One motivating application of using this end-to-end inference approach is an externally managed overlay network, where we cannot directly access and monitor nodes that are independently operated by different administrative domains, but instead we must infer failures via end to-end measurements. We show that first checking the node that is most likely faulty or has the least checking cost does not necessarily minimize the expected cost of correcting all faulty nodes. In view of this, we construct a potential function for identifying the candidate nodes, one of which should be first checked by an optimal strategy. Due to the difficulty of finding the best node from the set of candidate nodes, we propose several efficient heuristics that are suitable for correcting fault nodes in large-scale overlay networks. We show that the candidate node with the highest potential is actually the best node in at least 95% of time, and that checking first the candidate nodes can reduce the cost of correcting faulty nodes as compared to checking first the most likely faulty nodes.

3.Preliminaries

This section provides a brief background about the classification algorithms

a) Naive Bayes Classifier. Naive Bayes is a well-known type of classifier that is based on the application of Bayes' theorem with strong independence assumptions. It is considered to be a simple probabilistic classifier that computes conditional class probabilities and then predicts the most probable class. In other words, it will assign a class for an object based on the values of the descriptive attribute probability model.

b) Multilayer Perceptron (MLP). MLP is composed of a large number of highly interconnected neurons that are working in parallel to solve a certain problem. It is organized in layers with a feed-forward information flow. The main architecture of an MLP network consists of signals that flow sequentially through the different layers from the input to the output layer. Between the input layer and the output layer are intermediate layers. They are also called hidden layers because they are not visible at the input or at the output. Each unit is first used to calculate the difference between a vector of weights and the vector given by the outputs of the previous layer. To generate the input for the next layer, a transfer function also called activation is applied to the result. The main steps of the training phase in an MLP network are as follows: first, given an input pattern of the dataset, this pattern is forward-propagated to the output of the MLP network andthen compared with the desired output; second, the error signal between the output of the network and the desired response is back-propagated to the network; and finally, adjustments are made on the synaptic weights. This process is repeated for the next input vector until all the training patterns are passed through the network.

C) Support Vector Machine (SVM). SVM splits the dataset into two classes, which are separated by placing a linear boundary between the normal and attack classes in such a way that the margin is maximized. SVM works to find the hyperplane that gives the maximum distance from the hyperplane to the closest positive and negative samples. The basic structure of an SVM network is similar to that of the ordinary RBF network, but instead of the exponential activating function (usually Gaussian activation

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functions), the kernel activating function is applied. The kernel activating function can be a polynomial kernel, Gaussian radial basis kernel, or two-layer feed-forward neural network kernels.

4. The Proposed System

In this work, an intelligent neural network model for efficient energy management in WSNs is presented with the use of the classification algorithm. For conducting experiment, 40% of the dataset is used for training data, and the remaining 60% is used for testing. This allows us to present a MLP classifier, by fixing the shared and common parameters. In addition, the Lifetime Extension Factor is given by

$$LTEF = \frac{\text{Total number of sensors}}{\text{Number of sensors used}} \qquad (1)$$

In [12], two important steps were carried out in order to minimize the energy consumption and extend the lifetime factor. These two steps are as follows: (1) the most dominant sensor nodes in WSNs were selected after ranking them based on the significance of use, from the most significant to the least, and (2) Naive Bayes and MLP classification algorithms were applied. It is important to emphasize that, in our research work, an intelligent model for efficient energy management in WSNs is introduced by means of the classification algorithm by using SVM with linear kernel which is a polynomial kernel with exponent 1. Our proposed scheme operates in four stages, which are as follows:

(1) Preprocessing.
(2) Processing:
  (a) Ranking:
    (i) Calculate significance level of feature/sensor.
    (ii) Sort in a descending order.
  (b) Selection.
(3) Machine learning.
(4) Performance evaluation.

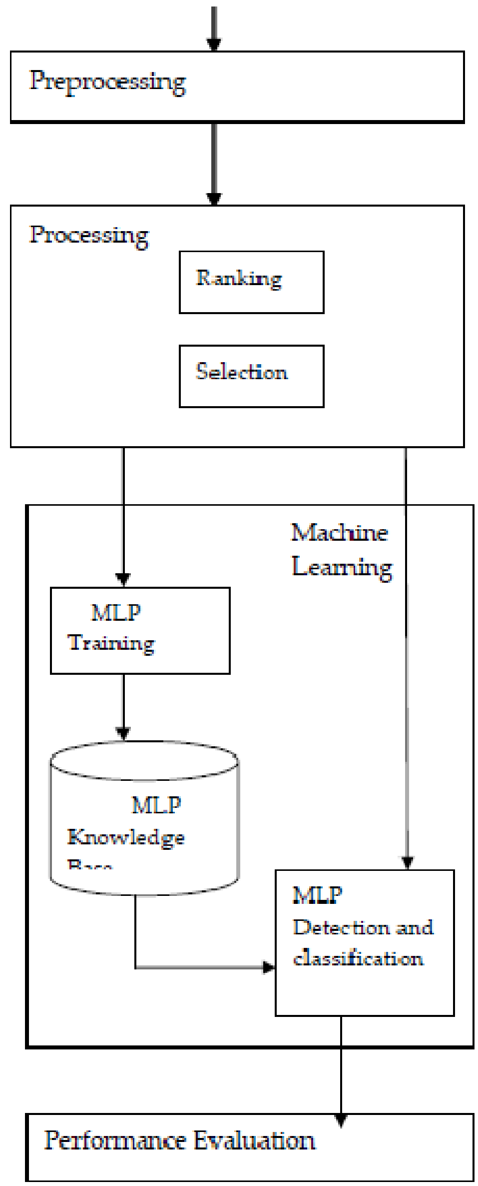

Figure1:Block diagram of the proposed system

Figure1 shows the block diagram of the proposed system. The pre-processing stage is needed to clean the input dataset and put it in the proper format. In the processing block, two functions are performed on the selected dataset.

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The first is the Rank function that ranks the features/sensors from the most significant to the least significant according to their significance of use in the dataset which corresponds to wireless sensor networks.

This function includes two sequential processes, namely, the significance level calculation process and the sorting process.

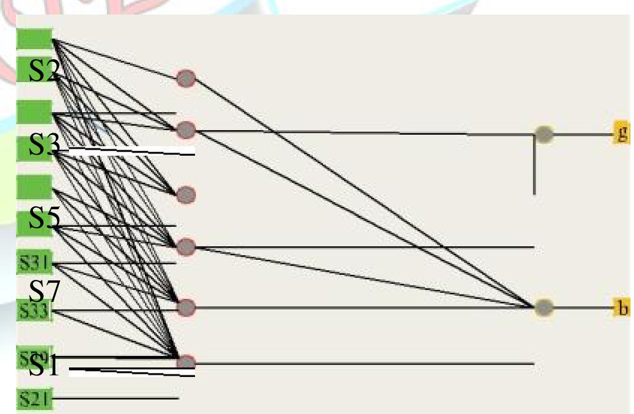
Parameters	Value
% of Training	40%
% of Testing	60%
Learning rate for MLP	0.4
Number of epochs for MLP	400
Number of hidden layers for MLP	1
Number of hidden neurons for MLP	6

Table 1: Experimental parameters

5.Experimental Work

This experiment was conducted on Ionosphere dataset, which is a radar dataset collected from 34 different real sensor nodes. MATLAB was used to perform the selection algorithm. This selection algorithm ranked the sensors on the significance of their use, from the most to the least significant.

Table 2 shows the results of this sensor ranking on the Ionosphere dataset. The first row of the table shows the number of the 10 most significant sensors. We also selected this case in order to provide it with a NN structure (as in Figure 2), since it is small in size. The numbers in the first row of Table 2 are exactly the same as those in the NN structure in Figure 2. Therefore, the inputs into the NN structure for the selection of 10 in Figure 2 are S2, S3, S5, S7, S1, S9, S31, S33, S29, and S21, which are exactly the same numbers as the first row in Table 2. It is important to point out here that there is one hidden layer in Figure 2 with six hidden units. This is because if we apply the formula in Table 1, given by (# selected sensors + # classes)/2, the number of selected sensors is 10. It is also clear from the specification of the Ionosphere dataset that the number of classes/outputs is 2. Therefore, there are (10 + 2)/2 = 6 hidden units.If we consider the first and the second rows together, it is clear which 20 sensors were the most significant. Consider the best 20, for example. If we look at Table 2, it is clear that the feature/sensor that had number 2 was the most significant, while that which had number 6 was the least significant. Similarly, the best selection of 30 features/sensors was calculated by considering the first, second, and third rows, with the feature/sensor that has number 2 being the most significant and that with number 32 being the least significant.



S9

Figure 2: MLP structure for the selection of 10 sensor nodes

1	2	3	4	5	6	7	8	9	1

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1	2	3	5	7	1	9	31	33	29	2
2	15	23	8	13	25	14	11	12	16	6
3	19	10	18	22	27	4	17	34	28	3

Table 2: Selection and ranking on Ionosphere dataset.

6. Conclusions and Future Work

This paper presents an intelligent model for efficient energy management in WSNs using MLP. The proposed system aims to reduce the number of sensor nodes based on ranking and thereby increasing the lifetime of network. As future work, the performance of MLP can be evaluated with other benchmarking datasets. Moreover, a comparative study can be done with different classifiers such as KNN, Bayesian approach, Self-Organizing Map, Naive Bayes and Support vector machine.

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