Machine Learning Applications in Wireless Sensor Networks: A Review

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Abstract: The Wireless sensor networks (WSN) is a network of independently operating, spatially scattered sensors that monitor the physical environment and cooperatively exchange data for further processing. Information from nodes can be transmitted to the central node using WSNs. The application of machine learning, a cutting edge technology, can improve performance and handle information in wireless sensor networks. This paper discusses a variety of machine learning(ML) methods and their uses to improve the network, particularly in the fields of data security and error detection. Finally, we analyze several machine learning techniques applied in WSN applications.

Keywords: Wireless Sensor Networks, Machine Learning

I. INTRODUCTION

WSNs technology has a promising future in many application domains. They have been used as battlefield surveillance instruments in military applications, building structural monitoring in construction industry, disaster management, patient bio-signal monitoring in health-care industry etc. With the rapid progress in MEMS technology, it is possible to deploy large-scale sensors in the field soon [1,2]. However, large-scale sensor network also unavoidably introduces large amount of data in WSNs to be processed, transmitted, and received. Transmitting all data back to a base station for processing and making inferences is merely impossible due to the sensor's limited energy and bandwidth constraints. Thus, there is a need for applying machine learning methods in WSN. This strategy could significantly reduce the amount of data communications and truly utilize the distributive characteristic of WSNs. This paper will survey the machine learning methods and applications used in WSNs. different machine learning algorithms applied in WSNs to improve network performance [3]. Also, machine learning methods have been used for information processing in WSNs [4].

The rest of paper is organized as follows. Section II presents different machine learning algorithms applied in WSNs to solve some specific network associated problems, such as energy-aware communication, node localization, resource allocation etc. Section III surveys application of machine learning in WSNs information processing, including object detection or event tracking, pattern recognition etc. Section IV discuss summary of the survey analysis and future trends of machine learning in WSNs. Section V summarizes the survey result and concludes the work.

II. MACHINE LEARNING

This section gives a general overview of the machine learning algorithms that were applied in WSN. When used in WSNs, these algorithms, which are divided into several groups, include supervised learning, unsupervised learning, and reinforcement learning.

I. Supervised Learning

The target/outcome variable in this method must be predicted using a provided set of predictors. We create a function that maps inputs to the desired outputs using this set of variables. The training procedure is carried out repeatedly until the model's accuracy on the training data reaches the target level[5]. Regression, decision trees, random forests, KNN, and logistic regression are a few examples of supervised learning.

II. Unsupervised Learning

There is no target or outcome variable to forecast or estimate in this method. It is frequently used to divide customers into several groups for targeted actions and group populations into various groupings [6].

III. Reinforcement Learning

The machine is educated to make decisions using this algorithm. The machine is exposed to an environment where it continuously trains itself through trial and error [7].

III. MACHINE LEARNING FOR WSN

Certain WSNs interact with security-sensitive data inadvertently under malicious conditions. In these circumstances, it is essential to apply WSN security measures. The security methods can help with data freshness, confidentiality, authentication, and integrity. solutions for conventional network security, like user [8]. Due to the WSNs' limited resources and processing power, authorization, are not appropriate for these applications [9]. To evaluate IoT malware network behaviors, for instance, the authors of [10] created an access gateway employing ML classification algorithms including Random Forest, k-NN, and Naive Bayes. According to the results of performance evaluation using various kinds of methodologies, the k-Nearest Neighbor (k-NN) method demonstrated the highest accuracy.

A privacy-preserving Support Vector Machine (SVM) training approach for IoT data was also provided by the authors in [11], requiring only two transactions in a single iteration and omitting the need for a trustworthy third party. This method significantly reduced computational complexity when compared to traditional SVM harmful behavior, tracking, and defense against DoS, as well as during packet analysis [12]. Therefore, ML technology offers a suitable framework for lowering the cost of several security-related domains. For instance, anomaly detection produced outstanding outcomes against all forms of malicious behavior, as well as during packet analysis, tracking, and DoS defense [13]. The ML technique is also used to improve network availability, error detection, and traffic congestion. It may be a good option in addition to the physical layer's authentication procedures. The use of ML approaches in WSNs thus tries to address many of these issues and offers enormous benefits in terms of flexibility and accuracy.

Techniques for Machine Learning.

An overview of the different machine learning algorithms that were applied to WSN security is given in this section. Several categories, including supervised, unsupervised, reinforcement learning, and deep learning, are used to categorize these algorithms. Therefore, in this section, we examine the categories of machine learning algorithms that were applied in the research that were evaluated in Section 5. This is because many surveys have a thorough and operational specialization in machine learning. Figure 6 presents a classification of the ML algorithms in use.

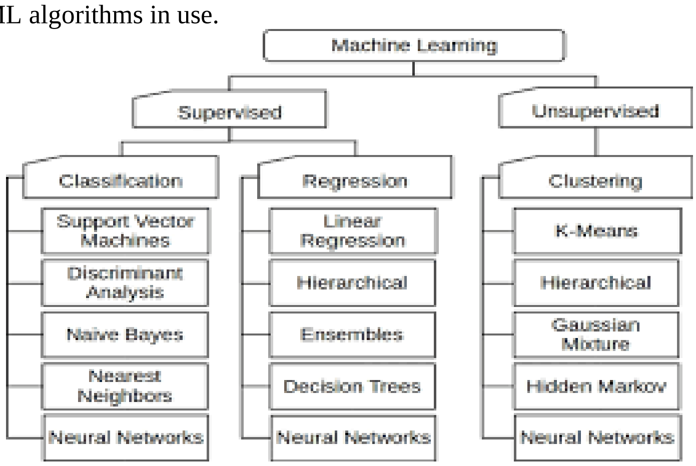

Fig-6: Classification of Machine Learning Algorithms

Here, ML algorithms are briefly explained; nevertheless, several research publications in this area have studied ML algorithms in detail.

1. ML for Energy-aware Communications

A near-optimal reinforcement learning framework for energy-aware sensor communications is presented by the authors of [14]. The formulation of the issue is average throughput maximization for overall energy consumption in sensor communications. Based on a reinforcement learning framework, a transmission approach that is close to being optimal was obtained. This approach selects the best modulation level and transmission power while adjusting to the channel, buffer, and incoming traffic rate conditions. Utilizing machine learning is motivated by the fact that many channel throughput maximization solutions call for state transition probabilities, which can be challenging to obtain. In a point-to-point case, however, machine learning might produce a close to optimal transmission policy without relying on a complicated communication model.

The authors of [15] and [16] investigate sensor communications in WSN using fuzzy logic. Crisp metrics are used by current energy-aware routing systems to decide where to route traffic. Because measurements vary depending on sensor type and application scenario, it has the drawback of being difficult to adjust to changes in sensor kinds. This contradicts the idea behind isotropic sensor design (sensor can be deployed for multiple purposes). On the other hand, fuzzy logic allows for imperfect data and uses heuristic human thinking to produce results. To maximize the network lifetime, the author of [16] defines a fuzzy method to compute the desired value of cost of a link between two sensor nodes.

As input variables, link cost is chosen, along with transmission energy, residual energy, energy consumption rate, queue size, and distance from gateway. To determine a crisp value of the link cost, defuzzification is used. The authors of [15] use a fuzzy logic controller at each sensor node to assess its capacity to transfer data packets in the WSN rather than utilizing fuzzy logic to determine a routing decision (finding the link cost). The fuzzy controller's inputs include node residual energy, a data packet's type flag, and others. Based on the precise output of the fuzzy controller, sensor nodes will either participate or not in data connections (forwarding, bridging, etc.).

2. ML for Optimal Node Deployment

If sensor nodes have to be distributed randomly on a big scale, the GPS method would be too expensive and time-consuming. In this situation, machine learning approaches can be used to estimate the sensor location by taking into account factors like signal intensities, message delivery rates, and relative orientation.

A fuzzy deployment strategy was created by the author of [17] for a WSN surveillance application. The environment is assumed to be homogeneous for most of the node deployment. Under this premise, the impact of the terrain profile (including obstacles, altitude, the criticality of particular areas, etc.) has been disregarded. The deployment of a node may still be impacted by these characteristics; in this instance, a more crucial area under observation may require more sensors. In [17], the deployment problem is described as choosing the best node distribution pattern to maximize information gain. The area of interest is then split up into smaller sections, each with a unique terrain profile. Second, a fuzzy logic approach is utilized to determine the number of obstacles depending on the terrain profile.

Simulation tests demonstrate that a higher coverage ratio and information gain in the surveillance system might be attained using the fuzzy deployment technique.

After a first random deployment of sensors, the author of [18] offers a fuzzy optimization approach to effectively modify sensor locations. The fundamental strategy in [18] is similar to that in [17]; both use fuzzy logic to determine the ideal distribution of nodes in the field to maximize information gain. The approach in [18] assumes that nodes have some mobility in addition to fuzzy systems; a node may change its position in response to local or global interactions. Only after the nodes have been randomly distributed in the field is a fuzzy re-deployment (or adjusting) technique implemented.

There are very few uses for the fuzzy deployment technique described in [17] and [18], such as field surveillance. The authors of [19] introduce a generic near-optimal sensor placement model that maximizes information gain while minimizing transmission cost. This paradigm can be used for additional WSN applications in addition to surveillance WSNs.

3. ML for Localization

Location data is a crucial component in the WSN's networking and application domains. For energy-aware routing and the localization and reporting of sensor event, accurate position estimate is a fundamental requirement. Hardware-based and probabilistic estimation-based techniques are typically used to address the localization issue in WSNs. In order to replace rigorous probabilistic rules with heuristic fuzzy rules for localization in WSN, the authors of [20] suggest employing fuzzy logic. A node's position is expressed by its confidence level that it is located at a specific place in the grid by the algorithm, which employs a grid-based method.

The fuzzy logic system is used to calculate the confidence level, and the input variables are sensor readings like signal strength, arrival time difference, and others. The authors of [21] use an evolutionary strategy, specifically a micro genetic algorithm and its extension, to increase the accuracy of current localization techniques. This is a post-optimizer for any other localization techniques, not a localization algorithm itself. It employs two genetic operators—mutation and crossover—with the goal of opportunistically decreasing the objective values obtained to mutate out the present node location estimation or crossover points for any existing pairs of chromosomes throughout successive generations for localization.

According to simulation data, this post-optimizer increases the accuracy of several localization algorithms by an average of 11.0% to 18.6%.

4. ML for Resource Allocation and Task Scheduling

In terms of system-wise interaction, the two main research issues in the field of WSNs are resource allocation and job scheduling. The optimization problems formulated under these two scenarios are from a more global perspective, i.e., how a group of sensor nodes could be managed and scheduled to achieve some system objectives, such as a tradeoff between network lifetime and information gain. This is in contrast to energy-aware communication or optimal deployment and localization, which optimizes a specific objective function of a node.

For task scheduling in radar sensor networks, the authors of [22] investigate three machine learning techniques and contrast the outcomes of simulations. Fuzzy Lyapunov synthesis, neural networks, and genetic algorithms are the algorithms employed. According to the simulation results, GA outperforms the competition. Although this study was initially conducted to solve the radar scheduling issue, the findings may easily be applied to WSN due to similar system architecture settings (WSNs and radar sensor network).

A relatively straightforward local action must be taken by each node in a WSN to manage the system modes, according to the adaptive distributed resource allocation strategy proposed by the authors of [23] and [24]. With time, each node modifies its operation in response to the feedback and status of the nodes next to it. Although the adaptive operation is defined locally, these local interactions lead to the best possible global behavior. Two distinct application scenarios, acoustic WSN for field surveillance and camera network for traffic monitoring, have been used to study the method. According to simulation results, it offers a favorable trade-off between performance goals such target tracking precision, coverage area, and network lifetime.

TABLE I
TABLE OF ANALYSIS OF ML ALGORITHMS

Sl. No.	ML Applications	Algorithms Used	Efficiency	Benefits
1	Energy-aware Communications	Bayesian, Neural Network	89.92.%	suitable for large networks
2	Optimal Node Deployment	K- Means, Decision Tree	86.37%	consider the load management between nodes
3	Localization	Reinforcement Learning	91.09%	Enhanced detection accuracy
4	Resource allocation and task scheduling	SVM, K- Nearest neighbor	96.22%	Improved detection accuracy

IV. CONCLUSION

WSN’s require various innovative solutions for anomaly recognition, scheduling, clustering, routing techniques, data security and network management. Machine learning maintains a compilation of methods to increase the ability of WSN’s. Many design challenges in WSN resolve with various ML techniques. In this paper, we have covered operational and non-operational challenges in applications of WSN with the help of machine learning strategies.

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