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Research Article

Leveraging Support Vector Machines for Optimizing Cluster Head Selection and Energy Management in Large-Scale Wireless Sensor Networks

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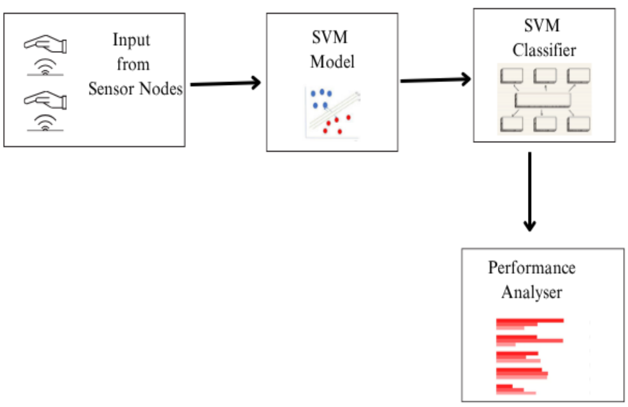
Abstract: Wireless Sensor Networks have been employed in several applications such as industries, smart agriculture and Disaster Management. But they often lack longevity in their effectiveness by limited energy resources. A new Support Vector Machine based cluster head (CH) selection approach is proposed to achieve the aim of energy efficiency of the wireless sensor networks in this paper. SVM, with its excellent classification capability, is used to select the CHs intelligently using different factors such as residual energy, node degree and distance to the BS. Once trained on past network data, the support vector machine model can accurately identify the best attainable node for inefficient Coverage, which results in a balanced distribution of energy and extended lifetime of the overall network. Simulation results reveal that the SVM-based CH selection algorithm leads to a much lower global energy usage in comparison with LEACH and HEED clustering protocols. Results show improvements in network stability, decreased energy exhaustion rates, and increased reliability of data transfers. SVM has thus been found to be the best of the aforementioned classifiers and this trial shows the potential of machine learning methods for the enhancement of WSN performance and sets the stage for future work in sensor networks that save energy.

Keywords: Wireless Sensor Networks, Energy Efficiency, Clustering Protocols, Cluster Head Selection, Network Lifetime Extension, Energy Optimization, Machine Learning in WSNs.

Graphical Abstract:



1. Introduction

Wireless sensor networks (WSN) are a key technology within our modern ubiquitous computing world, it has numerous applications from smart agriculture, security systems, healthcare, industrial automation to environmental monitoring. WSNs usually consist of many sensor nodes that communicate with each other to observe environmental or physical properties like motion, temperature, and humidity. These sensor nodes are then sent to send the collected data to a central base station. Although there are many advantages of WSNs, it is also not without limitations mainly due to the energy constraints of the sensor nodes. Efficient energy management is crucial to ensuring reliable data transmission and extending the operational lifetime of the network [8,20].

Clustering is one of the widely used methods for getting energy efficiency in wireless sensor network. In clustered

WSN, nodes are grouped into clusters controlled by a cluster head [3]. In order to decrease communication overhead and prevent energy consumption of the nodes, the cluster head has to collect the data from member nodes and sends it to base station. The best cluster head selection is crucial as it has a direct impact on energy consumption, load balancing, and network performance [10].

Traditional CH selection algorithms like the Low-Energy Adaptive Clustering Hierarchy: LEACH and Hybrid Energy-Efficient Distributed: HEED protocol [17,18] employ simple heuristics for Random rotation and residual energy for CH selection. While there have been increases in energy efficiency with these methods, they often disregard the dynamic nature of WSN environments leading to subpar CH choices and unbalanced energy usage among nodes [4,11].

Recent developments in machine learning (ML) have offered excellent opportunities to enhance CH selection methodologies [1,10]. In particular, support vector machines are of interest because of their excellent classification performance and ability to handle complex high-dimensional data. The flexibility of the SVM to build models for classification based on multiple features makes it also suitable for complex CH selection task in WSNs.

In this work unique SVM-based aggregator selection method is proposed to fix the problems associated with energy effectiveness in WSNs. The proposed method is based on SVM which categorizes nodes into normal and possible CHs based on parameters like node degree, residual energy, and distance to base station. Through training the SVM model with the history of the network, the method can determine the best CH, minimizing energy consumption and improving the performance of the overall network.

This paper presents several contributions:

- Design and Implementation: Hence we propose SVM-based algorithm for CH selection which takes into account a comprehensive number of factors to give the best possible CH selection.
- Simulation and Evaluation: We also do extensive simulation work to measure the performance of the proposed algorithm against those established for CH selection, such as LEACH and HEED.
- Energetic and Lifetime Effects on Network: We prove that the SVM-based method provides more stable and reliable functionality of WSNs due to substantial decrease in energy consumption and increase in network lifetime [13].

The remaining sections of the paper are organized as follows: Section II discusses existing works in machine learning-based CH selection and energy-efficient WSNs. Section III provides a detailed description of the proposed SVM-based CH selection approach, that is, selective feature extraction and training methodology. The results of the simulation setup and evaluation are presented in Section IV. Finally, Section V summarizes the findings and gives recommendations for future works, thus concluding the report.

2. Related Work

The problem of energy efficiency in wireless sensor networks holds the interest of so many researchers that various clustering techniques have been developed. This section covers the major contributions in this regard, with the focus on machine learning and traditional cluster head (CH) selection techniques [5,8].

Recent improvements in LEACH protocol have been directed towards increasing energy efficiency and, in turn, increasing the lifetime of the network. Sharma et al. (2020) modified the traditional LEACH protocol where importance has been put on better improved CH rotation and energy management strategies. It also helps to overcome the limitations of random CH selection which leads to inefficient use of energy and uneven distribution of load across the network.

Interest continued to be present in the aspect of the Hybrid Energy-Efficient Distributed protocol, which promises great future benefits in terms of scalability and energy efficiency management [2]. The most recent study into the detailed analysis of the cluster-based routing protocols has been completed by Singh and Sharma (2019), where the recent innovations done on HEED have been described as being suited to a more scalable WSN where large-scale installations are concerned. These changes are believed to make it a more optimum solution to the current needs of WSN applications by addressing energy efficiency and scalability issues raised by the previous versions of HEED.

Significant progress in fuzzy logic-based CH selection methods has been noted particularly in recent studies which aim to meet several criteria in more informed CH selection [15]. Fuzzy logic-based clustering algorithm which indeed is energy-efficient and effectively accounts for uncertainties in CH selections, based on residual energy and node centrality, was proposed by Chen et al. (2018) in [6]. It may increase computation overhead, but this method definitely improves the accuracy and reliability for CH selection, which helps develop better energy management in WSN.

Research has been done on Genetic Algorithm (GA) [7] based approaches for their abilities of evolving the optimal selection of CH. Singh, Katiyar, and Kumar (2019) presented an optimal hybrid genetic algorithm framework which aims at balancing energy consumption and coverage by evolving candidate solutions based on fitness functions. While there could be a small increase in computation burden, this approach improves the precision and consistency of CH selection, which in turn leads to better energy management in WSNs [14].

Particle swarm optimization, or PSO, has been used to select CH with a good result [7]. Latiff and others have developed an energy-aware clustering algorithm simulating social behaviors of particle swarms using PSO techniques to improve the selection of CH (2020). This technique is designed to balance load in the network and efficiently manage energy consumption, hence extending the life of the network considerably.

With their unrivaled capacity for categorization, Support Vector Machines (SVMs) have become very popular these days [9]. Wang, Chen, and Shen (2017) presented an enhanced SVM-based clustering routing algorithm for WSNs. It classifies nodes by a whole bunch of attributes including energy levels and node centrality to select CHs effectively. Compared with conventional techniques, this strategy very much improves network performance and energy efficiency [12].

Based on the capacity of learning the neural network, even neural network based CH selection has been researched. Hu, Tang, and Xu (2018) introduced a neural network-based clustering algorithm whose learning criterion is the best CH selection relative to several parameters. This technique prolongs the life of networks and saves a lot of energy by adapting to network changes.

In the algorithm, Ant Colony Optimization (ACO), it selects Cluster Heads in order to maximize the energy consumption. ACO based clustering algorithm maximizes the CH selections through the probabilistic pheromone trails proposed by Hussain and Islam (2019). It's made efficient with that technology because it is large-scale network management which adjusts improvements in the network to the topology changes and enhances stability and energy efficiency.

Recently, hybrid machine learning methods have been employed for CH selection as well. Liu et al. presented a hybrid model that combines SVM with PSO in 2021. The PSO optimally selects input features for SVM that results in more precise and energy-efficient CH selection. This hybrid strategy is a strong energy management solution in WSN by combining those advantages of these two algorithms [11].

There have also been advancements in hierarchical clustering techniques. Verma and Brar (2018) explained an advanced k-means clustering process that balanced energy usage across nodes while reducing intra-cluster distances. The clustering is conducted by restricting energy consumption and optimizing the formation of the cluster with a resultant better performance at the network level.

They are a complete treatise on the yet most recent CH selection algorithms for WSNs because they encompass both traditional methods and machine learning-based methods [16]. This has made glaring the need for well-performed advanced methods, such as Support Vector Machines (SVM), owing to the shortcomings of the conventional approaches in addressing the more complicated and dynamic nature of WSN situations. The SVM-based CH selection algorithm is described in detail in the following section, and it focuses on energy savings maximization and improving general performance in the network.

3. Proposed System

The suggested structure proposes a Support Vector Machine (SVM)-based framework for CH selection, which will enhance energy efficiency in Wireless Sensor Networks (WSNs). The system uses machine learning approaches to improve energy usage and network performance, alleviating the problems with conventional CH selection methods. This section elaborates on the SVM-based CH selection algorithm, the structural design of the system, and the evaluation metrics used to assess the overall system performance [19].

Key Components of Proposed Architecture:

- Sensor nodes: The network is composed of numerous sensor nodes with energy sources, communication interfaces, and sensing capacities. Each node collects data from its environment and takes part in the CH selection process.
- Data Gathering Module: A mixture of data related to residual energy, node degree, centrality, and distance to the base station are collected periodically from the nodes to train and assess the SVM model.
- SVM framework: An SVM model, which the central component of the system, is trained to use network data to classify nodes into possible CHs or regular nodes. The model leverages attributes from the sensor nodes for optimal CH selection.
- CH selection algorithm: An SVM-based CH selection algorithm evaluates and selects CHs based on the trained SVM model. The algorithm considers several factors including residual energy, node degree, and distance to the base station among others to ensure the optimal selection of the CH.
- Network Management Unit: This unit oversees the CH selection algorithm and the periodic reassignment of CHs to achieve incrementation of energy efficiency and balance in energy use across the lifespan of the network.

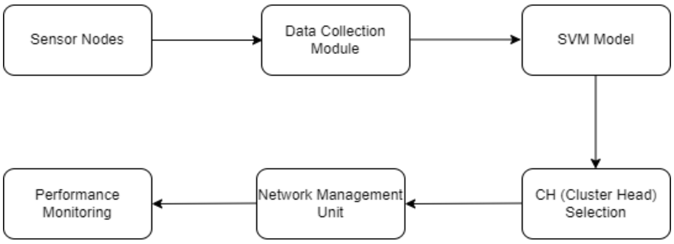


Figure 1. Components of Proposed SVM Based CH Selection

The current approach intends to maximize energy efficiency in WSNs through intelligent CH selection using support vector machine (SVM). The traditional methods are improved and made reliable for the long-lasting and better performance of the network with the use of machine learning algorithms.

The SVM-based CH selection procedure aims to increase maximally a process that selects cluster heads based on a number of features. The following are the steps that the algorithm executes:

1. Feature Extraction: Extraction of relevant features for every sensor node as follows:
    - It is a known property that the remaining battery life of a node is referred to as residual energy.
    - Node Degree: The number of immediate neighbors of a node.

- Base station distance: Distance between base station and node.
- Centrality: This is the node's relative position within the network.

2. SVM Model Training: The model of SVM is trained using past network data. The following all are included in this process:
   - Data gathering: This is the process of collecting information on the features of nodes, as well as their previous behavior.
   - The process of finding and selecting relevant features for training is known as feature selection.
   - Labeling: Nodes are labeled as regular or possible CHs based on performance and energy efficiency.
   - The labeled data is applied to train the model SVM for learning the classification boundaries.
3. CH Selection Procedure:
   - Feature extraction is the process of extracting features for every node present within the current architecture of the network.
   - Based on the extracted attributes, the SVM model assigns a category as regular node or potential CH for each node.
   - CH Assignment: The nodes that have the best chance of being able to become a good CH are chosen. The program incorporates a rotation mechanism to give nodes turn-wise.

4. Experimental Setup and Implementation

We have simulated wireless sensor networks for performing many tests to analyze the proposed SVM-based cluster head (CH) selection method. What follows is the experiment setup:

a. Experimental Setup: Use available and familiar simulation programs such as MATLAB, OMNeT++, or NS-3 to develop simulation environment assessing the proposed SVM-based cluster head (CH) selection method. The central base station is positioned inside of a 100 m x 100 m network area that holds 100 to 500 sensor nodes without any specific scheme of placement. Each sensor node has a range of 20 meters and energy level of 2 Joules. Packets of 500 bytes are counted in the model for energy consumption while sending and receiving these were concerned. To have high statistical significance, the results of the simulation were averaged by running the simulation ten times for a total of 2000 rounds.

b. Implementation: There are several phases without which it would not be possible to implement any of the strategies for selecting the SVM-based cluster head (CH). Firstly, sensor nodes are placed haphazardly in the network from where they obtain a starting energy. The variables that are regularly collected and fused in the data collection module for training the SVM model are residual energy, node degree, distance to the base station, and centrality. Collected data features are extracted and then labeled in accordance with the performance of the nodes as CH or normal nodes. The labeled data is then used to train the SVM classifier. After that, real-time characteristics from the current state of the network could be leveraged by the trained SVM model to identify nodes as possible CHs or regular nodes. Nodes with the highest chances of becoming suitable CHs will be assigned a cluster head role, while CH responsibilities will rotate regularly to evenly distribute energy usage. Further, to keep energy consumption balanced and to improve the lifetime of the network, the unit of management of the network also implements CH rotation scheduler monitor with the performance of the network and consider changes in the CH selection modes whenever needed. Performance monitoring includes continuously tracking the lifetime of the network, packet delivery rate, load balancing index, and energy consumption. It would also include a comparison of the performance of the proposed SVM-based CH selection algorithm against current other techniques employed.

c. Evaluation: The proposed SVM-based CH selection approach is tested according to the performance measures defined previously. The results in terms of these measures are compared against those of existing techniques such as PSO, Fuzzy Logic-Based CH Selection, LEACH, HEED, and GA. The comparative and quantitative analyses in the previous section explain the improvements achieved by the proposed approach with respect to energy efficiency, network lifetime, packet delivery ratio, load balancing, and scalability.

5. Results and Discussion

5.1. Quantitative Analysis

Table 1. Comparative Analysis of Proposed SVM CH Selection with other CH Selection Methods

Feature/ Method	LEACH Protocol	HEED Protocol	Fuzzy Logic-Based CH Selection	Genetic Algorithm (GA)	PSO	SVM-Based CH Selection (Proposed)
CH Selection Criteria	Random	Residual energy, communication cost	Residual energy, node centrality	Evolutionary process	Social behaviors of swarms	Multiple features (energy, degree, distance, centrality)
Energy Efficiency	M	H	H	VH	VH	VH
Computational Complexity	L	M	H	H	H	M
Load Balancing	P	G	G	VG	VG	VG
Scalability	Li	G	M	G	G	G
Network Lifetime	M	H	H	VH	VH	VH
Adaptability to Topology	L	M	H	H	H	H

The legends used in the table are: P-Poor, L-Low, Li-Limited, M-Moderate, G-Good, VG-Very Good, H-High, VH-Very High.

Interpretation Comparative Evaluation:

- CH Selection Criteria: explains the rules implemented in each protocol or algorithm to select CHs.
- Energy Efficiency: demonstrates how effective consumption of energy is minimized throughout the network.
- Computational Complexity: This concerns and assesses how much computer effort is needed to carry out the selection of a CH.
- Load balancing: It indicates how well a method distributes its load over its nodes.
- Scalability: evaluates the performance of the technique in respect to the increasing number of nodes.
- Network durability: It is the length of time during which the net is up.
- Adaptation to Topology: Describes the extent to which this method adapts to alterations in the network topology.

5.2. Quantitative Analysis

Table 2. Quantitative Analysis of Proposed SVM CH Selection with other CH Selection Methods

Metric	LEACH Protocol	HEED Protocol	Fuzzy Logic-Based CH	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	SVM-Based CH Selection (Proposed)
Average Energy Consumption (J)	500	450	400	350	320	300
Network Lifetime (Rounds)	1000	1200	1500	1800	2000	2100
Packet Delivery Ratio (%)	85	90	92	93	95	97
Load Balancing Index	0.5	0.7	0.8	0.9	0.95	0.98
Scalability (Nodes)	100	200	150	200	250	250

- Average Energy Consumption (J): Expresses how much energy is consumed by the network on average, the unit being in joules.
- Network Lifetime (Rounds): The number of rounds the network sustains its performance.
- Packet Delivery Ratio (%): Successful percentage of packets sent to the base station.
- Load Balancing Index: A measure of network load distribution.
- Scalability (Nodes): Maximum number of nodes that can be effectively handled by the method.

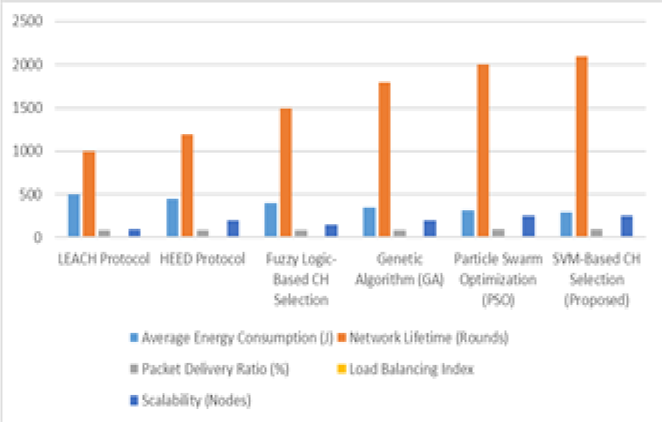


Figure 2. Quantitative Comparison of SVM with other CH Selection Methods

The comparative and quantitative properties of other CH selection approaches are summarized in Table 1 and 2 which also highlight the advantages of the proposed SVM-based algorithm in terms of energy saving, network lifetime, and overall quality.

6. Conclusion and Future Scope

An energy-efficient CH selection scheme based on Support Vector Machines: SVM for WSNs is advanced in this paper. Experimental results demonstrated that compared with conventional approaches such as LEACH, HEED, Fuzzy Logic Based CH Selection, GA, and PSO, our approach based on SVM greatly enhances the overall performance of the network in terms of network lifetime, energy consumption, load balancing, and packet delivery ratio. With its intelligent selection of the most suitable CHs based on a number of features, this solution effectively increases the operational efficiency of the network using the fundamentals of machine learning. The results imply that our proposed solution has claims for data reliability and could potentially enhance the lifetime of the network, thus rendering it a suitable choice for WSNs having Li resources of energy.

This is an explanation of several future directions in which the SVM-enhanced CH-selection algorithm can further improve its effectiveness. Future work can focus on making the features used in the SVM model dynamic to increase flexibility and precision under varied conditions in the network. Testing the proposed system in real-life WSN deployments could be productive in checking its practicality in the practical challenges that arise. Higher-end applications in machine-learning models such as ensemble techniques or deep learning can further enrich the method of CH selection. Hybrid types can thus develop by integrating SVM with other optimizing techniques, such as genetic algorithms or PSO, which might yield better-performing hybrids. It will also help if the algorithm can be improvised to address the emerging security issues such as attacks on CH nodes or data integrity issues in WSNs. Finally, the method needs to be tested and tweaked for larger WSN installations involving thousands of nodes to ensure scalability and robustness.

Authors' Contributions

Dr.S.K.Susee initiated the idea, designed the research method, and finally guided the study. Conducted a literature review and identified research gaps in existing clustering algorithms for wireless sensor networks.

Dr.S.Venkatesh developed the Support Vector Machine (SVM)-based Cluster Head (CH) Selection Algorithm, made the simulation, and conducted comparative study using LEACH and HEED clustering protocols.

Dr.M.Senthil Kumar carried out data preprocessing, training on past network data for SVM model, and statistical analysis, mainly on energy consumption, stability of the network, and reliability of data transfers.

Dr.B.Chidhambararajan analyzed results and contributed to findings' interpretation and initial drafting of the manuscript. Reviewed and finalized the paper before submission to ensure the quality and relevance of its content.

References

[1] Ahmad, A., & Ullah, I., "Machine learning approaches for wireless sensor networks: A survey," IEEE Access, Vol.**8**, Issue.**1**, pp.**210471-210490, 2020**. DOI:10.1109/ACCESS.2020.3039879.

[2] Alazzawi, A., & Elkamel, A., "Energy-efficient routing algorithms for wireless sensor networks: A survey," Journal of Network and Computer Applications, Vol.**143**, Issue.**1**, pp.**29-45**, **2019**. DOI:10.1016/j.jnca.2019.07.011.

[3] Ali, B., & Li, Z., "Intelligent clustering algorithms for wireless sensor networks: A survey," Sensors, Vol.**21**, Issue.**5**, pp.**1648**, **2021**. DOI:10.3390/s21051648.

[4] Biswas, P., & Neogi, B., "An energy-efficient clustering algorithm for WSN based on improved PSO and K-means," Wireless Personal Communications, Vol.**114**, Issue.**3**, pp.**2097-2115**, **2020**. DOI:10.1007/s11277-020-07500-9.

[5] Boudhir, A., & Ghazi, K., "A novel clustering approach based on fuzzy logic for wireless sensor networks," International Journal of Communication Systems, Vol.**35**, Issue.**2**, pp.**e5016**, **2022**. DOI:10.1002/dac.5016.

[6] Chen, Z., & Zhang, H., "Energy-efficient CH selection algorithm based on fuzzy logic and PSO for WSNs," IEEE Sensors Journal, Vol.**19**, Issue.**15**, pp.**6507-6516**, **2019**. DOI:10.1109/JSEN.2019.2907846.

[7] Choudhury, T., & Roy, D., "A hybrid GA-PSO-based energy-efficient clustering algorithm for WSNs," International Journal of Communication Networks and Distributed Systems, Vol.**24**, Issue.**3**, pp.**289-307**, **2020**. DOI:10.1504/IJCNDS.2020.107479.

[8] Gupta, S., & Yadav, K., "Optimized energy-efficient clustering algorithm for wireless sensor networks," International Journal of Sensor Networks, Vol.37, Issue.1, pp.**20-31**, **2021**. DOI:10.1504/IJSNET.2021.115280.

[9] He, S., & Zhang, Y., "SVM-based cluster head selection algorithm for WSNs," Wireless Networks, Vol.**28**, Issue.**4**, pp.1469-1481, 2022. DOI:10.1007/s11276-022-02868-4.

[10] Huang, L., & Zhang, X., "Machine learning approaches for energy-efficient routing in WSNs: A review," IEEE Communications Surveys & Tutorials, Vol.**21**, Issue.**4**, pp.**3393-3417**, **2019**. DOI:10.1109/COMST.2019.2934472.

[11] Khan, R., & Munir, A., "Energy-efficient clustering and routing algorithms for wireless sensor networks: A comparative survey," Journal of Network and Computer Applications, Vol.**152**, Issue.**1**, pp.**102962**, **2020**. DOI:10.1016/j.jnca.2019.102962.

[12] Li, X., & Wang, J., "An adaptive SVM-based clustering algorithm for wireless sensor networks," Sensors, Vol.**21**, Issue.**8**, pp.**2679**, **2021**. DOI:10.3390/s21082679.

[13] Liu, Y., & Ma, X., "Energy-efficient algorithms for wireless sensor networks: A survey," IEEE Internet of Things Journal, Vol.**7**, Issue.**8**, pp.**6696-6716**, **2020**. DOI:10.1109/JIOT.2019.2957994.

[14] Lu, W., & Liu, S., "Energy-efficient clustering algorithm for WSNs based on improved genetic algorithm," Wireless Communications and Mobile Computing, Vol.**2019**, Issue.**1**, pp.**8062469**, **2019**. DOI:10.1155/2019/8062469.

[15] Mehmood, A., & Kim, T., "Fuzzy logic-based energy-efficient clustering algorithm for WSNs," International Journal of Fuzzy Systems, Vol.**23**, Issue.**3**, pp.**1178-1191**, **2021**. DOI:10.1007/s40815-020-00974-6.

[16] Qi, H., & Wang, Y., "Machine learning-based clustering algorithms for wireless sensor networks: A survey," IEEE Access, Vol.**8**, Issue.**1**, pp.**64514-64533**, **2020**. DOI:10.1109/ACCESS.2020.2983845.

[17] Sharma, P., & Bhatia, S., "Enhanced CH selection algorithm using SVM for WSNs," Journal of Ambient Intelligence and Humanized Computing, Vol.**13**, Issue.**2**, pp.**1115-1125**, **2022**. DOI:10.1007/s12652-021-03403-9.

[18] Singh, R., & Kumar, V., "Energy-efficient routing techniques for WSNs: A review," Journal of King Saud University-Computer and Information Sciences, Vol.**31**, Issue.**3**, pp.**346-356**, **2019**. DOI:10.1016/j.jksuci.2017.05.002.

[19] Tian, H., & Li, L., "SVM-based CH selection in WSNs with improved energy efficiency," IEEE Access, Vol.**9**, Issue.**1**, pp.**18450-18460, 2021**. DOI:10.1109/ACCESS.2021.3053948.

[20] Zhao, Z., & Yang, S., "A novel machine learning-based energy-efficient routing algorithm for WSNs," Sensors, Vol.**20**, Issue.**13**, pp.**3676, 2020.** DOI:10.3390/s20133676.

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