Incorporation of Machine Learning Methods, Applications, and Algorithms for WSN QoS

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Abstract — This article explores the integration of Wireless Sensor Networks (WSNs) with machine learning algorithms, highlighting their synergistic potential across various real-time applications. WSNs, composed of spatially distributed sensor nodes, are vital in monitoring and collecting environmental or physiological data. However, their resource constraints and dynamic environments necessitate intelligent data processing and adaptive decision-making. Machine learning (ML) addresses these challenges by enabling predictive analytics, anomaly detection, data compression, and energy-efficient routing within WSNs. This paper reviews key ML techniques—such as supervised learning, unsupervised learning, reinforcement learning, and deep learning—and their implementation in WSNs. Applications covered include healthcare monitoring, environmental surveillance, smart agriculture, and industrial IoT. Additionally, the article discusses the limitations and future directions in achieving scalable, secure, and energy-efficient smart sensor networks powered by ML. The integration of WSNs and ML holds significant promise in transforming raw sensor data into actionable insights for intelligent, autonomous systems.

Keywords: Wireless Sensor Network, Machine Learning, IoT, Neural Network

I. Introduction

A wireless sensor network (WSN) often contains many independent, low cost, small, low-power sensing devices that have sensing capabilities. These sensors collect data from their surroundings and work together to send data collected at a central sink or base station for further procedure. Sensor's nodes can adjust a variety of sensors including thermal, acoustic, chemical, pressure, weather, and optical sensors. Due to these differences, WSNs have great possibilities for powerful applications, each with its characteristics and requirements [1]. WSN designers should take care of special visitor problems related to information clustering, information firmness, localization, central clustering, energy-awareness management, event planning and mistake location. Machine Learning (ML) began in the late 1950s in the field of Artificial Intelligence (AI). Its concentration turned over time and focused on calculations that are reliable and computationally viable. The last 10 years have seen a long significant increase in the use of machine learning techniques for various types of works such as: and publishing systems. The strategies and calculations used come from a variety of subjects, including cognition, science, neurology, and computer science. When these concepts are associated with WSNs, it becomes clear that the machine learning can upgrade the system of sensors on the trends without the need for again-programming [2].

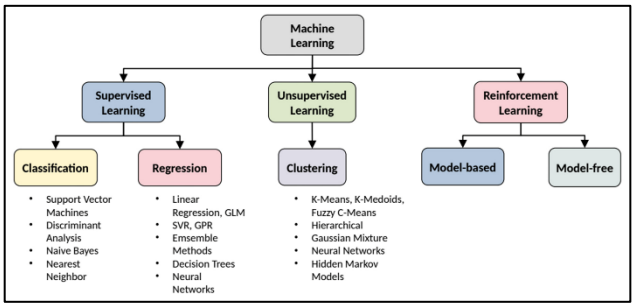

Fig. 1: Machine Learning Algorithms

Machine Learning (ML) is presented as a set of defense methods to define the forecast models by the inventors of the sensor system regularly. Either way, ML experts believe that it can be a rich subject with huge subjects and designs. It is useful for those who need. The machine learning technique provides great adaptation benefits when working with completely different WSN applications. This section presents some hypotheses and strategies to perform ML in terms of WSNs.

K-NEAREST neighbor (K-Nn): This directed learning strategy classifies an information test (called inquiry point) agreed with the identities (ie the yield values) of the imminent information [4]. For illustration, by taking normal estimates of adjacent sensors inside some width boundaries, the lost values of the sensor hub can be estimated [1]. The closest assembling of the hub can be found using some diverse abilities. It is easy to use Euclidian removal between diverse sensors. Since the work is calculated about the nearby focus (ie, the most focus, where K may have a slightly positive number), K nearest neighbor does not require too much handling control.

Decision Tree (DT): This classification method resumes bolting of input data for information name [3]. To reach a particular category, characteristic properties against option criteria are compared. WSNs have a mind-making number within the writing writing using DT calculations to illuminate various plan issues.

In directed teaching, the framework show is designed to employ a nominated preparation set (ie, performance input and known output). The relationship learned between input, yield and framework parameters is shown by this model [3]. To reach a particular category, characteristic properties against option criteria are compared. WSNs have a mind-making number within the writing writing using DT calculations to illuminate various plan issues.

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network are safe. For illustration, by separating some important parameters such as misfortune ratio, debasement ratio, frustration for cruel time, and cruel repetition time, DT gives a direct but successful process to decide the connect unwavering quality of a WSN.

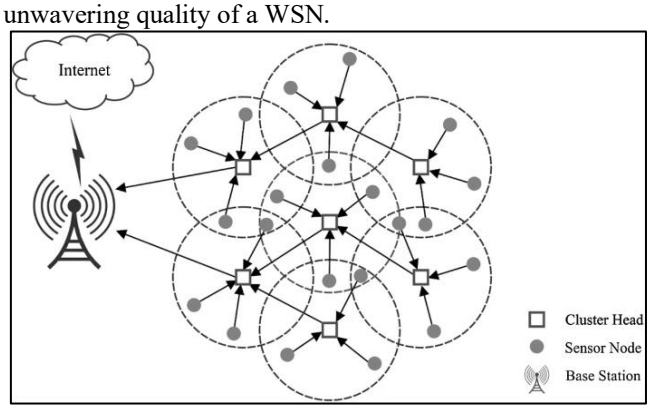


Fig. 2: node localization in WSNs

No marks are given to unheard learners (no result vector). The most objective of the calculation of an unsafe learning is to analyze their similarity and separate a set of tests into specific bunches. Fortification Learning allows an operator (such as the sensor hub) to recall together with its environment. The operator employs his information to discover the ideal course of action to maximize its long -term pick up. Q-learning is the most famous strategy of learning support.

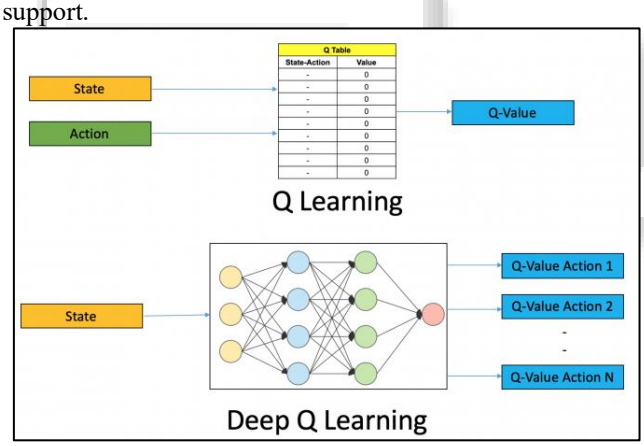


Fig. 3: Visualization of Q-Learning method

Experts often change the awards based on the functions done in a given stage. The condition is used to calculate the entire remuneration (also known as Q-value) in each state.

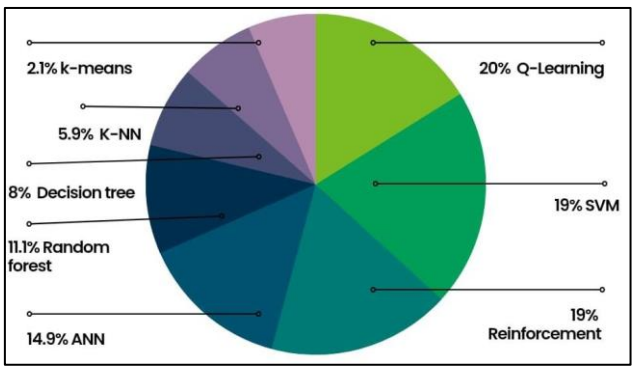


Fig. 4: Survey report of ML algorithms in WSN

Functionality Challenges: The major functionality challenges are discussed as follows:

1) Routing in Wireless Sensor Networks

It includes vitality use, defect resistance, adaptability, and information scope within the steering convention plan of WSN System [6]. The sensor hubs are given to no memory capacity, low transmission capacity and restricted computing control. In the remote sensor system, it is common to portray the direction problem as chart g = (V, E), where V means all hub sets and E means E means a set of channels that interfaces the hubs bidoratively. According to that paradigm, the routing problem is the process of determining the cheapest passage using the available edges of the graph, which begins from the original, and moves towards all destinations. This path is called Spanish Tree T = (V, E). A graph-based details of the sensor network routing problem, routing costs for each path, traditional spreading one routing, and machine learning generated sub-problems required by local communication (ie, only one-hop communication) to achieve the optimal path.

2) Using a self-organizing map (SOM), root data

As it appeared in this inquiry, Spike Anco et al. Som presented "sensor insight steering" (SIR) using som unsupervised learning to discover leading courses. To decide to arrange the spine of the network and decide the most limited courses from the base station to each arrangement, Sir replaced Dijkstra's strategy to some extent [9]. Second layer neurons compete to save long weight within the learning series between learning courses. In the arrangement of better coordinating input designs, the weight of the winner neuron and its nearby neighbours is modified [8]. Clearly, the task of creating nerve systems makes the learning phase a dark complex operation. This should later be an intelligent central to the interior

3) WSN Networks Used in Machine Learning:

The work of IOT WSN Hubs is expressed in clever cities, which is to continuously screen and control physical volumes such as temperature, magni, weight and increasing speed. The most task of these sensor hubs is to gather information and send it to the most WSN-iOT portal node [11]. The information is sent from the door hub to the cloud server. Cloud computing puts within Iot Cloud [9]. The IOT Cloud is directly connected to inaccessible servers, users' phones, computers, cell towers, etc. [12]. IOT and machine learning assignments require huge information and ability requirements. In this way, the IOT cloud server is lined as a long performance, long handling control computer with tremendous capacity. As it may be, the WSN conclusion is not restricted in the Hub computing control, constrained handling, small memory, and no rechargeable battery control. The major issues in the WSN based IOT (WSN-iOT) are completely independent operations, the biggest organized lifetime, vitality proficiency, quality of profit (QOS), cross-layer optimization, long transmission capacity requirement, sensor information examination, cloud computing, communication conference scheme, etc. [11]. Right now, Mechanical IOT (IOT) or Industry 4.0 is the biggest rebellion for loving businesses, curious fabricant segment, car divisions, Keen cities and medical healthcare sections. Different companies like Microsoft, Google and Amazon worldwide are working on the progress of AI and ML-based calculations in progress IOT applications for lover cities [6]. Machine learning can be added to the splitting of the Hub localization, identification, and faulty hub for hub

localization, identification, and network optimization in portable WSN-IT nodes, for the energetic overhaling of the direction tables in WSNS in WSNS and Writability. Through this letter, the creators have tried to respond to taking after investigation: Why is the machine learning strategies used in the WSN-Iot? What are the preferences to use Ml on traditional adaptation strategies in WSN-Iot? Why the clever city for IOT applications [12] is a general use case.

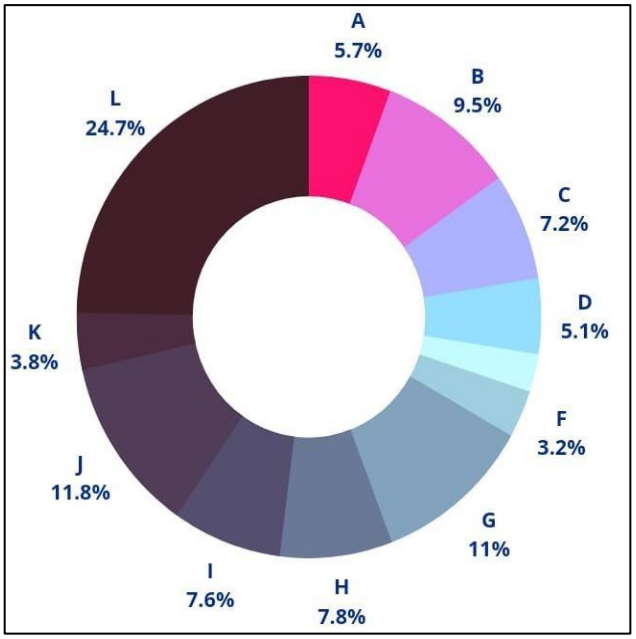


Fig. 5: No of WSN IoT research papers included in this survey

Where,
A = Connectivity, G=Security, B = Routing, H=QoS, C=Switching, I=Event detection, D= Data Aggregation, J=Fault detection, E=Energy harvesting, K=Congestion control, F=Node localisation, L=Anomaly detection.

Routing Protocols	Topology	Machine learning Algorithms(s)	Overhead	Scalability	Delay	Distributed /Centralized	QoS
Distributed regression	Flat/multihop	Kernal linear regression	Low	Limited	High	Distributed	No
SIR	Flat/multihop	SOM	High	Limited	Low	Hybrid	Yes
Q-MAP multicasting	Flat/multihop	Q-Learning	Low	Moderate	High	Distributed	No
RLGR	Hierarchical/ geographic routing	Q-Learning	Low	Good	Low	Distributed	No
Q-Probalistic	Flat/ geographic routing	Q-Learning	Low	Limited	High	Distributed	Yes
FROMS	Flat/multihop	Q-Learning	High	Limited	High	Distributed	No

Table 1: ML techniques for WSN

II. Literature Review

The first wireless network that can be defined as modem WSN is known as the Sound Surveillance System (SOSUS). SOSUS was developed to detect Soviet submarines by the U.S. Military in the 1950s. SOSUS network is designed to have submerged sensors and hydrophones which are scattered in the Atlantic and Pacific Oceans (Cui et al., 2005). For widespread monitoring, wireless sensor networks (WSNs) are the most significant and practical technology because they provide sensor measurements with high temporal and spatial precision (Pathan & Lee, 2006). The deployment of massive sensor networks, made up of tens of thousands of tiny sensor nodes, is something that is conceivable for the future (Khemapech et al., n.d.). Wireless sensors have seen a significant evolution recently, primarily due to advancements in sensor hardware technology (miniaturization of components, increased ROM and RAM capacities, more energy capacity etc (Martínez et al., 2007). The position of sensor nodes need not be engineered or pre-determined. This allows random deployment in inaccessible terrains or disaster relief operations (Portillo et al., 2018). To meet the issues, we confront in daily life, pervasive computing, artificial intelligence research, and wireless sensors and sensor networks have combined to create the interdisciplinary idea of ambient intelligence (Alemdar & Ersoy, 2010). The industrial Internet of Things (IoT) was created at the same time as the deep integration of industrialization and information technology made it possible to gradually connect different parts of industrial production (Alemdar & Ersoy, 2010). As all data can be gathered and processed centrally, WSNs monitoring offers continuous and nearly real-time data acquisition as well as autonomous data acquisition (no supervision is necessary); increased monitoring frequency compared to manual inspection; and better data accessibility, management, and use compared to non-networked systems (Hodge et al., 2015). With a wide range of applications, including environmental, industrial, military, and health applications, WSNs have been a prominent research area for

the past 20 years. The random deployment of WSNs in inhospitable locations where it is frequently impractical to replenish a node's energy source is one of their fundamental characteristics (Kosunalp, 2015). The main responsibility of the sensor nodes in each application is to sense the target area and transmit their collected information to the sink node for further operations (Radi et al., 2012). Many autonomous nodes with limited processing and energy resources, wireless communication interfaces, and sensing capabilities make up wireless sensor networks. WSNs are employed for the distributed and collaborative sensing of interesting physical phenomena and events (Saleem et al., 2011). Typically, a military force or other authority will place sensor nodes in a predetermined area, and these nodes will then automatically form a wireless network (Zhou et al., 2008). WSNs consist of small nodes that sense their environment, process data, and communicate through wireless links. They are expected to support a wide variety of applications, many of which have at least some requirements for security (Amin et al., 2008). As the name implies, preventative measures work to stop attacks or, at the very least, significantly hinder them. This is the area with the most study and uses common cryptographic primitives to ensure confidentiality, integrity, and authentication (Healy et al., 2009). WSNs typically consist of sensor devices that are powered by batteries and have computation, data processing, and communication components. The sensors may be used in an uncontrolled environment or in a regulated setting where monitoring and surveillance are essential. Security for sensor networks becomes crucial in uncontrolled contexts (Kumar et al., 2014). Wireless transceivers are used in wireless sensor networks to facilitate communication in between sensors. Numerous researchers have been drawn to investigate on various problems relating to these kinds of networks by their appealing properties. However, despite the popularity of routing techniques and wireless sensor network design, security concerns have not yet received significant attention (Portillo et al., 2018). Because sensor networks pose unique challenges, traditional security techniques used in traditional networks cannot be applied directly. First, to make sensor networks economically viable, sensor devices are limited in their energy, computation, and communication capabilities (Boyle & Newe, 2008). When developing a security system for a WSN, it is crucial to make sure that all known attacks are guarded against. The stability and resilience of the application against assault will be key factors in determining its success (Das & Thampi, 2015). Thousands of sensor nodes make up a large-scale sensor network, which may be spread out over a huge region. Typical sensor nodes are battery-powered, compact, and have constrained communication and computing capabilities. These tiny sensor nodes are vulnerable to a variety of attacks, 2008. Security goals in sensor networks depend on the need to know what we are going to protect. We determine four security goals in sensor networks which are Confidentiality, Integrity, Authentication and Availability (Pathan & Lee, 2006). A few economic and technological developments, such as Moore's Law, have made sophisticated electronics accessible to the public. These technologies have the potential to enhance our daily lives with true ambient intelligence when combined with WSNs (Baker et al., 2007). The combination of wireless sensors and sensor networks with computing and artificial intelligence research have built a cross-disciplinary concept of ambient intelligence to overcome the challenges we face in everyday life (Darwish & Hassanien, 2011).

III. Proposed Methodology

Wireless sensor network comprises of a huge number of hubs and these hubs are characterized by moo information transmission rates and moo fetched, and at the same time these hubs fulfill the recognition or control of a few physical wonder through communication. Since the hubs in WSN are battery-powered, their vitality is extremely constrained, which limits the node's transmit control appropriately. This causes information sent from the source hub to reach the sink hub through numerous bounces, devouring a part of hub control. Messages cannot be conveyed in a convenient way due to time delays amid information transmission. This record investigates ways to decrease the control utilization of remote sensor communications, altogether make strides arrange execution, amplify arrange lifecycle, and make strides arrange control utilization balance. Various aspects are optimized in this paper to keep the energy consumption as low as possible. We optimize various aspects of this work to minimize energy consumption as much as possible. First, analysing from the physical layer, the power consumption of the WSN physical layer is as follows.

$$EPHY = \left(\frac{Psend}{\quad} + Pamp + PSC + PAC\right) * Talln \quad (1)$$

Psend is the transmission control and is decided by the S/N proportion κ and the blunder rate ρsend on the accepting side. The control unearthly thickness of added substance white Gaussian clamor, the relationship between signal-to-noise proportion and outline mistake rate, depends on the coding conspire. This article employments the BPSK encoding component for inquire about. Hence, the relationship between outline mistake rate and signal-to-noise proportion is given by ρsend=Q((2κ)1/2). where η alludes to the enhancement proficiency of the flag intensifier on the transmitting side, Pamp. Pamp=ΩPsend is the control utilization of the control speaker, PSC is the control utilization of the transmitting side circuit, and PAC is the control utilization of the getting side circuit amid information transmission. On the getting side when sending information, Tall alludes to the time required to total the information exchange, and the completion of information exchange compares to the time required to send each date. Assuming a fixed frame error rate ρsend for each transmitting node, the transmit power of a WSN can be expressed as

$$Psend = f(\rho send) * \lambda * PN * \mu \quad (2)$$

Where, f(ρsend) could be a work of ρsend, ρsend = exp-

Psend, λ is the weakening figure of the information transmission channel, PN is the commotion control at the collector, and μ is the get clamor figure. The higher the transmit control, the lower the outline mistake rate ρsend. Subsequently, transmission control can be brought down as it were by progressing the outline mistake rate, and transmission control misfortune can be reduced.

Transmit control can be characterized concurring to the definition of signal-to-noise proportion:

$$Psend = 2B * N0 * G * \kappa \quad (3)$$

On the other hand, the control pick up figure G = G1dkMl, where G1 is the recieving wire pick up, k is the way constriction figure, and M1 is the information connect confirmation pitch equipment variety, commotion, and impedances. Subsequently, the control utilization Pc of the acquired circuits of the transmitter and collector can be communicated as

$$Pc = PSC + PAC = 2(Pmixer+Psyn) + Pfilter + PDAC + PLNA + PDAC + Pdec \quad (4)$$

Pmixer is the blender control utilization, Psyn is the recurrence synthesizer control utilization, Pfilter is the channel control utilization, and PDAC is the digital-toanalog converter (DAC) control utilization. PLNA is the commotion intensifier control utilization, PADC is the A/D converter ADC control utilization, and Pdec is the decoder control utilization. In rundown, the whole vitality utilization E for transmitting one information parcel of L bits is:

$$E = \left\lfloor \frac{(1+\Omega n)2B\times N0\times G\times k\times Tall}{n} \right\rfloor + PC + Tall \quad (5)$$

Data Information is sent outline by outline amid the genuine information transmission. Hence, the outline mistake rate definitely influences the control utilization of the organize. The higher the wrong positive rate, the higher the likelihood of retransmitting transmitted information bundles in blunder control mode holding up for ARQ retransmissions, which can result in numerous transmissions of information parcels and misfortune of organize vitality. Be that as it may, in the event that the outline blunder rate is moo, the retransmission time can be diminished. It requires expansive flag transmission control additionally increments control utilization. Hence, the outline blunder rate should be adequate to play down the control utilization of flag transmission. It is expected to be in resend halt control mode. Outline blunder rate of ρsend, 0<ρsend<1, on the off chance that n outlines of information are sent each time, (n*ρsend) outlines must be loathe in case n outlines of information are sent each time. Add up to number of outlines sent for time information transmission. In case the vitality per bit at the input of the demodulator is E, at that point l signifies the length of each information outline and the overall vitality utilization Eall when transmitting n information outlines is given by

$$Eall = N*1*E = \_\_\_\_\_^{(n*1*E)} \quad (6)$$

Concurring to the entire vitality utilization and the transmit control transmitted by the remote sensor organize, the target optimization work z is

$$Z=\max(\alpha Psend,\beta \_\_^{1}) \quad (7)$$

While, α and β are weighting components, separately, by understanding the objective-optimized work in trusts of getting the foremost adjusted vitality utilization by understanding the objective-optimized function.

A. Proposed Algorithm:

BEE-C could be a steering calculation that can decrease vitality utilization in WSN. A routing technology called BEE-C can reduce the amount of energy used by WSNs. In this study, Da Silva Rego et al. offered BEE-C aggregates the network using a biologically influenced mechanism based on behavior during reproduction [5]. It is used to connect sensor nodes to reduce energy consumption. Experimental results show that BEE-C performs better than other traditional algorithms such as LEACH and LEACH-C[6]. The life span of the arrange, the little number of parcels conveyed by the base station and the entire scope of the organize are the result of the productive utilize of vitality within the arrange. BEES are considered the core architecture technology of a state-of-the-art WSN. The purpose of this technique is to produce bees that resemble regular hexagons around the pharyngeal knot. The main advantage of BEES is that it helps to reduce many difficulties faced by WSNs, including localization and clustering difficulties [8]. It can also simplify many administrative tasks, including data collection, driver selection, task management, and routing [5].

In quintessence, the Q-MAP multicast steering strategy is created to guarantee exact asset conveyance. There may be heterogeneous hubs in a versatile advertisement hoc organize, each of which has interesting capabilities [6]. Too, it isn't down to earth to keep abreast of the complete organize structure all-inclusive and persistently. In two stages, the multicast courses are chosen [8]. The primary arranges, called "Connect Inquiry Forward," finds the leading way whereas too overhauling the Q-values, which are forecasts of future rewards made by the Q-learning calculation. The "Connect Answer In reverse" moment stage sets up the most excellent way for multicast transmissions. In portable advertisement hoc systems, course looking overhead can be diminished by utilizing Qlearning for multicast routing. Neural network-based large-scale arrange clustering: This approach centers on the clustering issue in enormous systems with constrained transmission radii where centralized methods might not perform well. However, in terms of adequacy and level of benefit, this calculation performs almost as well as centralized strategies for expansive transmission radii. Using choice trees to select a cluster head: By repeating the input vector through the choice tree, this strategy makes advantage of various vital parameters, counting vicinity to the cluster centroids, battery life, degree of versatility, and defenselessness indicators. The reenactment appears that, in comparison to the "Moo Vitality Versatile Clustering Pecking order" (Filter) strategy, this arrange makes strides the generally execution of cluster head determination. a strategy for the transformation of high-dimensional spaces to low-dimensional spaces. "Cluster-based self-Organizing Information Conglomeration" is the title of the progressive organize design Lee et al. proposed (CODA). Employing a self-organizing calculation, the hubs in this architecture are able the collected data [13].

By utilizing CODA for information conglomeration, information quality will be made strides, organize vitality will be moderated, and organize activity will be decreased.

B. Processing of queries and event detection

Any large-scale sensor organize is thought to have useful prerequisites for occasion location and inquiry processing. This highlights the necessity for solid occasion planning and discovery with small human involvement [14][15]. Basically, machine learning gives ways to constrain the scope of inquiries and assess the veracity of occasions for compelling strategies for inquiry preparing and occasion detection.

– Using a negligible number of stays focuses to convert the relative areas of hubs to outright ones [16]. This will make it pointless to use range estimation gear to urge separate estimates.

– Machine learning can be utilized in reconnaissance and protest focusing on frameworks to gather the observed destinations into different clusters, where each cluster speaks to a particular area indicator [17].

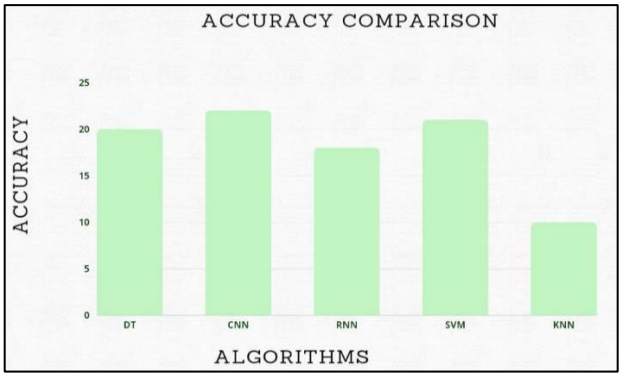
A hub that's incapable to pinpoint its exact position is said to be unknown.

Every hub that can decide its area utilizing situating gadgets or by manual situation is alluded to as a beacon hub (or stay node).

First sensor data environment. The collected data was then pre-processed to remove noise and outliers, and features were extracted

IV. Result and Discussion

The collected data was then pre-processed to remove noise and outliers, and features were extracted We investigated the use of Machine Learning (ML) to reduce the dimensionality of the data set. We selected techniques in Wireless Sensor Networks (WSN) to an appropriate ML algorithm based on the specific improve performance, power efficiency, and scalability. The methodology involved the random placement of processed data and selected features. The trained model's sensor nodes within the network area, assigning unique were evaluated against another set of test data. The results identifiers to each node, and collecting data from the efficiency, and scalability. The use of ML algorithms has improved the accuracy, latency, and throughput of the network by predicting the state of the environment and making decisions based on the predicted state. Additionally, the use of ML technology has optimized the power consumption of sensor nodes by reducing the number of transmissions and optimizing routing, leading to improved energy efficiency. Furthermore, ML techniques have been utilized to dynamically allocate resources to sensor nodes based on current conditions and network load, thus enhancing scalability. The results obtained from our experiments indicate that the use of ML techniques on WSN is highly effective in achieving significant improvements in performance, power efficiency, and scalability. The performance gains achieved using ML techniques are depicted in the accompanying graph, demonstrating the potential of these techniques to transform the field of WSN. Overall, the results of this study provide compelling evidence for the effectiveness of ML techniques in WSN and open up new avenues for future research. Fig.6 graph showing the performance gains achieved by using ML techniques on WSN. The proposed technique have been utilized to dynamically allocate resources to sensor nodes based on current conditions and network load, thus enhancing scalability. The results obtained from our experiments indicate that the use of ML techniques on WSN is highly effective in achieving significant improvements in performance, power efficiency, and scalability. The performance gains achieved through the use of ML techniques are depicted.



Performance-enhancing graph

This graph shows a comparison of the accuracy of different machine learning algorithms. CNN and SVM ML algorithms outperform traditional ML algorithms in terms of accuracy.

V. Conclusion

Wireless sensor networks are Diverse from Conventional Different viewpoints of the organize that require conventions devices that address one of a kind challenges and restrictions. As a result, remote sensor systems require development Energy-conscious real-time directing, security, planning, localization, hub clustering, information conglomeration, Blunder location and information astuteness. Machine learning provides a set of techniques to improve the ability of remote sensing systems to adapt to their native energy behavior. The discourse so distant has uncovered that numerous plan challenges for remote sensor systems have been unraveled.

References

[1] S. Laha, N. Chowdhury, and R. Karmakar, "How Can Machine Learning Impact on Wireless Network and IoT? - A Survey," *2020 11th International* Conference on Computing, Communication and Networking Technologies, ICCCNT 2020, 2020, doi: 10.1109/ICCCNT49239.2020.9225652.

[2] H. Farag and C. Stefanovic, "Congestion-Aware Routing in Dynamic IoT Networks: A Reinforcement Learning Approach," 2021 IEEE Global Communications Conference (GLOBECOM). IEEE, Dec. 2021. doi: 10.1109/globecom46510.2021.9685191.

[3] C. L. D. Santos, A. M. Mezher, J. P. A. León, J. C. Barrera, E. C. Guerra, and J. Meng, "ML-RPL: Machine Learning-Based Routing Protocol for Wireless Smart Grid Networks," IEEE Access, vol. 11. Institute of Electrical and Electronics Engineers (IEEE), pp. 57401–57414, 2023. doi: 10.1109/access.2023.3283208.

[4] P. Chithaluru et al., "An enhanced opportunistic rank-based parent node selection for sustainable & smart IoT networks," Sustainable Energy Technologies and Assessments, vol. 56. Elsevier BV, p. 103079, Mar. 2023. doi: 10.1016/j.seta.2023.103079.

[5] A. Seyfollahi and A. Ghaffari, "A Review of Intrusion Detection Systems in RPL Routing Protocol Based on Machine Learning for Internet of Things Applications," Wireless Communications and Mobile Computing, vol.

2021. Hindawi Limited, pp. 1–32, Aug. 04, 2021. doi: 10.1155/2021/8414503.

[6] M. Pushpalatha, T. Anusha, T. Rama Rao, and R. Venkataraman, "L-RPL: RPL powered by laplacian energy for stable path selection during link failures in an Internet of Things network," Computer Networks, vol. 184. Elsevier BV, p. 107697, Jan. 2021. doi: 10.1016/j.comnet.2020.107697.

[7] M. Pundir and J. K. Sandhu, "A Systematic Review of Quality of Service in Wireless Sensor Networks using Machine Learning: Recent Trend and Future Vision," Journal of Network and Computer Applications, vol. 188. Elsevier BV, p. 103084, Aug. 2021. doi: 10.1016/j.jnca.2021.103084.

[8] F. F. Jurado-Lasso, L. Marchegiani, J. F. Jurado, A. M. Abu-Mahfouz, and X. Fafoutis, "A Survey on Machine Learning Software-Defined Wireless Sensor Networks (ML-SDWSNs): Current Status and Major Challenges," IEEE Access, vol. 10. Institute of Electrical and Electronics Engineers (IEEE), pp. 23560–23592, 2022. doi: 10.1109/access.2022.3153521.

[9] X. Tan, H. Zhao, G. Han, W. Zhang, and T. Zhu, "QSDN-WISE: A New QoS-Based Routing Protocol for Software-Defined Wireless Sensor Networks," IEEE Access, vol. 7. Institute of Electrical and Electronics Engineers (IEEE), pp. 61070–61082, 2019. doi: 10.1109/access.2019.2915957.

[10] G. Han, H. Wang, J. Jiang, W. Zhang and S. Chan, "CASLP: A confused arc-based source location privacy protection scheme in WSNs for IoT", IEEE Commun. Mag., vol. 56, no. 9, pp. 42-47, Sep. 2018.

[11] I. Al-Anbagi, M. Erol-Kantarci and H. T. Mouftah, "Priority- and delay-aware medium access for wireless sensor networks in the smart grid", IEEE Syst. J., vol. 8, no. 2, pp. 608-618, Jun. 2014.

[12] H. Teng et al., "A novel code data dissemination scheme for Internet of Things through mobile vehicle of smart cities", Future Gener. Comput. Syst., vol. 94, pp. 351-367, May 2019.

[13] M. Faiz and A. K. Daniel, "FCSM: Fuzzy Cloud Selection Model using QoS Parameters," 2021 First International Conference on Advances in Computing and Future Communication Technologies (ICACFCT), Meerut, India, 2021, pp. 42-47, doi: 10.1109/ICACFCT53978.2021.9837347.

[14] Narayan, V., Awasthi, S., Fatima, N., Faiz, M., & Srivastava, S. (2023, January). Deep Learning Approaches for Human Gait Recognition: A Review. In 2023 International Conference on Artificial Intelligence and Smart Communication (AISC) (pp. 763-768). IEEE.

[15] Earshia V., D. ., & M., S. . (2023). Interpolation of Low-Resolution Images for Improved Accuracy Using an ANN Quadratic Interpolator. International Journal on Recent and Innovation Trends in Computing and Communication, 11(4s), 135–140. https://doi.org/10.17762/ijritcc.v11i4s.6319

