

An Exploration of Wireless Sensor Networks with Machine Learning Techniques

M. J. Rhesa¹, S. Revathi^{2,*}

¹Vellore Institute of Technology, India

rhesam.j2019@vitstudent.ac.in

²Vellore Institute of Technology, India

srevathi@vit.ac.in

*Correspondence: srevathi@vit.ac.in

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Abstract: Wireless sensor network (WSNs) sense the changes occurring due to external factor such as climatic changes or internal factors such as those made by computer engineers. Therefore, sensor networks need to alter their design frequently to keep track of such changes occurring in environment. Wireless sensor networks are accessed conventional methods to change the design, but these approaches make networks respond rigidly like more energy consumption due to redundancy and rerouting, delay, data loss, lack of quality, anomaly function and various attacks causes less network lifetime. Hence, wireless sensor networks must adapt quickly to change. Based on the above motivation, this paper presents the state-of-the art of machine learning approaches that addressed the challenges in wireless sensor networks such as localization, energy harvesting, routing, security and quality of service. Based on the review papers, wireless sensor network designers have effectively acknowledged the machine learning techniques react better than conventional approaches. This paper explained various machine learning algorithms under supervised, unsupervised, semi supervised and reinforcement learning. From this study machine learning promotes a myriad of realistic clarifications that make better use of resource exploitation and prolong network presence. The benefits of machine learning when addressing the challenges in wireless sensor networks are less intricacy, high energy efficiency, more potential to find congenial outcomes, and neglects unwanted redesign were identified. This review paper covers the literature study in the year between 2019 and 2022. It provides a comprehensive analysis to help researchers develop the machine learning solutions tailored to their particular application challenges.

Keywords: Energy; Localization; Machine Learning; Routing; Security; Quality of Service

1. Introduction

Different sensors are needed to perceive phenomena such as heat, acoustics, chemicals, pressure, vibrations, weather, and optics in the environment. They collect that data and make it known to the users. Each of those nodes must be small, inexpensive, and operate independently. The managed nodes transmit the data through centralised back-end units called base stations or sinks [1–4]. The Wireless Sensor Network (WSN) is one such multifaceted sensor. Such WSNs are very powerful for creating great applications. Besides selecting efficient methods to develop such optimal applications, it is also a very challenging task to resolve common issues related to event finding, data mustering, localization, energy awareness routing, fault detection, and security in WSN.

The machine learning (ML) technique was introduced [5] to improve applications by surpassing such issues. The tasks used by machine learning techniques are the processes of classification, regression, and

correlation assessment in photo recognition, audio identification, traffic forecasting, medical diagnostics, adaptive websites, bioinformatics, chemistry, computational advertising, gaming, machine perception, optimisation, and metamorphosis, robot locomotion, sample type recognition called pattern identification, irrelevant finding, computer vision, finding out the originality from the fake, and a kind of activity process through advertising networks [6]. Machine learning algorithms' learning models are learned from experience concerning tasks to improve performance [7]. This learning process gives a remedy to get the knowledge and, by implementing the computational process to find and define steadiness and patterns in training the data [8–9] and the issues that arise in wireless sensor networks, enhance the performance for the specific chore by unchanging the program. The main reasons machine learning plays a prominent role in WSN applications are given.

- To function properly in unstable environments without altering their location.
- To get the knowledge from an unable-to-contact and belligerent place [4]
- To design accurate mathematical models when some chores require a complex algorithm to solve.
- To find the correlations between the sensor nodes, even if it is a large data set.
- To enhance the efficiency of the network by discriminating between fake sensor nodes and normal sensor nodes.

Wireless sensor networks have been actively integrated with machine learning techniques for the past decade. But yet, there is a need for a proper explanation of how machine learning works in conjunction with wireless sensor networks. A WSN with ML for data processing survey was presented shortly [10]. A survey of ML with ad-hoc wireless networks was published [11]. A study on the efficacy of neural networks, a decision tree, and reinforcement learning methods was discussed [12]. Then, researchers explored various improved ML techniques in WSNs to compare their vitality and lack thereof. Specifically, it has extensively reviewed the latest learning methods: supervised, unsupervised, semi-supervised, and reinforcement learning.

Based on WSN challenges, machine learning algorithms are discussed in [13] through the existing machine learning solutions in WSN applications. A survey about how machine learning tackles the challenges facing WSN was also presented. Outlier detection uses machine learning concepts [14] and [15]. Data mustering and fusion, routing, scheduling, optimal deployment, localization, and security are all presented using soft computing techniques that fall under machine learning, such as neuro-fuzzy and genetic algorithms [16] [17]. From 2002 to 2013, a brief survey was conducted on how machine learning impacted wireless sensor networks [18]. From 2014 to 2018, a survey based on various machine learning algorithms played a prominent role in wireless sensor networks, with their pros, limitations, and parameters enhancing the network's lifetime [19]. This paper presents recent machine learning algorithms during the pandemic by depicting performance, advantages, drawbacks, and parameters handled with remarks. Instead of addressing them widely, this paper selects only the important challenges in WSN.

The following sections of this remaining paper are framed as follows: Section II betokens the machine learning techniques assorted, followed by challenges in wireless sensor networks such as energy harvesting, localization, routing, security, and quality of service in Section III. Next, in Section IV, challenges are solved by applying ML algorithms to WSNs and tabulated. Section V shows the outcomes of using machine learning techniques. At last, Section VI presents the conclusion.

2. Machine Learning Techniques

In 1950, the technique of artificial intelligence was first introduced. This AI is a system that reflects the cognitive functions of humans. AI can be classified into two types for some reason: strong AI and weak AI. This type of AI speaks and acts like a human, expressing ideas and showing emotions. The other is weak AI. It can handle specific tasks, such as self-driving cars, but has yet to install a robust AI. Machine learning can help make data-based decisions about whether to run this weak AI to perform particular tasks. Machine learning is an algorithm or technique that analyses data, learns from that data, and then makes informed decisions based on what is retained [20].

In general, sensor network designers consider machine learning to be easier to improve application performance and an excellent platform for the following researchers. This machine learning is used for

many WSN applications, and machine learning methods offer tremendous benefits. This section depicts ideas and strategies for applying machine learning to wireless sensor networks.

The model external status framework can delineate the previous survey of machine learning techniques. The general taxonomy of machine learning algorithms is categorized into supervised, unsupervised, semi-supervised, and reinforcement learning. The supervised learning method is furnished with a set of labelled training data (input data) that is pre-encoded in the exact output. The supervised learning methods must create the pattern structure using that training set. The model learns the communication between input and output data once. That model can classify new and missing data sets and predict the outputs [21].

On the other hand, in many scenarios, input data are not encoded in the correct output, meaning that there is no labelled data and also has to find unlabelled patterns from the given dataset. Unsupervised learning is used to solve these types of cases. Unsupervised learning aims to identify the database's basic framework. It can cluster the data based on similarities, and the data set can be delineated in the abbreviated form [22]. The third type is semi-supervised machine learning algorithms, which refer to the intermediate stage between supervised and non-supervised learning methods. It uses a combination of labelled and unlabelled datasets during training. Supervised machine learning requires hand labelling by data scientists, and unsupervised machine learning has a limited spectrum. To overcome these limitations, this kind of hybrid algorithm is needed [23]. Finally, reinforcement machine learning depends on feedback to learn itself; that is, an intelligent agent interacts with environments. Various learning methods are segregated as follows:

2.1. The Supervised Learning Algorithm

This supervised learning algorithm consists of inputs and outputs labelled training sets and test sets to construct a system model. The pre-defined inputs are correlated with the desired results during the training period. Later, this supervised learning algorithm predicts or classifies the outcome based on the model from the training dataset and the methods used in the test dataset. This learning resolves challenges in wireless sensor networks such as energy consumption, localization, routing, security, and quality of service (QoS). Some algorithms use supervised learning to face the above challenges.

2.1.1. K-Nearest Neighbour

This This kind of machine learning algorithm is probably intuitive. This type of learning is used to classify a new data point by storing all the training data points efficiently. It does not build any models by feeding on the training data set. Most machine learning algorithms build a model from the training data set. For example, a linear regression model using intercept and feature coefficient values to create a model by sorting conditions in every node of a decision tree generates a tree. But K-NN does not act like that. The K-NN algorithm compares the new data with the existing data and places it in the same functional category as the current data. The K-NN algorithm stores the available data to classify the new database. It will simply classify the data into a suitable category whenever new data appears. Frequently, it is used for classification problems rather than regression. It's a non-parametric method because it makes no premise about the data. It learns in a lethargic manner because it acts on the dataset at the time of classification from already-stored data only. So, it does not learn promptly from the training set. When new data arrives from the neighbours during the training phase, it reserves the dataset, and then that data can be classified into the same type as the latest data. That neighbour is to predict the new data point. So, K-NN needs to find the nearest neighbour data point by calculating the distance between two data points using features. In the case of the classification process, it selects the polling process. In the case of regression, it is needed to calculate the mean of the K-NN. The probability draw should be neglected. For that, selecting the K value should be an odd number. If the K value is low, it can be unclear and may lead to the effect of an outlier in the model. If the K value is enormous, it seems complex. So, choosing the k value is essential. The selected value for K is mostly five. This algorithm is used to find missing deals and re-sampling datasets in the features and is also used for dimensionality reduction [24–26]. This component combines the relative measurements of nearby nodes to change the k-neighboring neighborhood into a WSN-appropriate distributed learning approach. This algorithm is mainly used for query processing tasks [27].

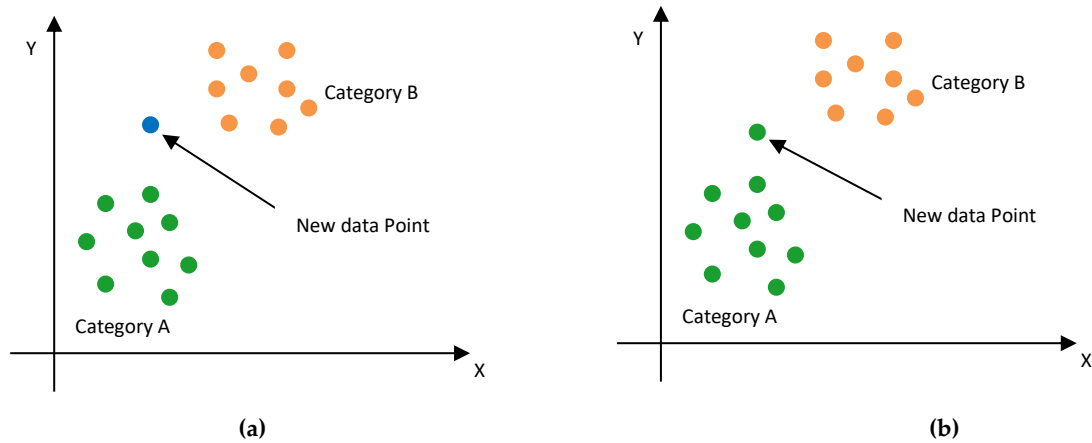


Figure 1. a) Before K-Nearest Neighbor b) After K-Nearest Neighbor

4.1.2. Decision Tree

Because a higher-level representation of the data is iteratively generated from the input, the Decision Tree algorithm is straightforward to understand. In a decision tree, non-linear effects are captured and explained in a simple, straightforward manner that captures sophisticated and forecasted effects [28]. A decision tree asks questions about the data and then calculates the final categorization based on the replies. The tree is built by recursively separating a data set into new groups based on a statistical measure of the data along each dimension. Leaf nodes are the tree's terminal nodes and provide the final predictions [29]. The decision tree can manipulate numerical and categorical data, and there is no need for pre-processing beyond handling missing values. Trees also tend to perform well on large data sets. On the other hand, decision trees are prone to overfitting, where they model the training data too well and do not generalise to unseen data. Decision trees can have difficulty classifying unbalanced classes and can be unstable due to minor changes in the training data. This decision tree works with linearly separable data and is widely used in data mining [30].

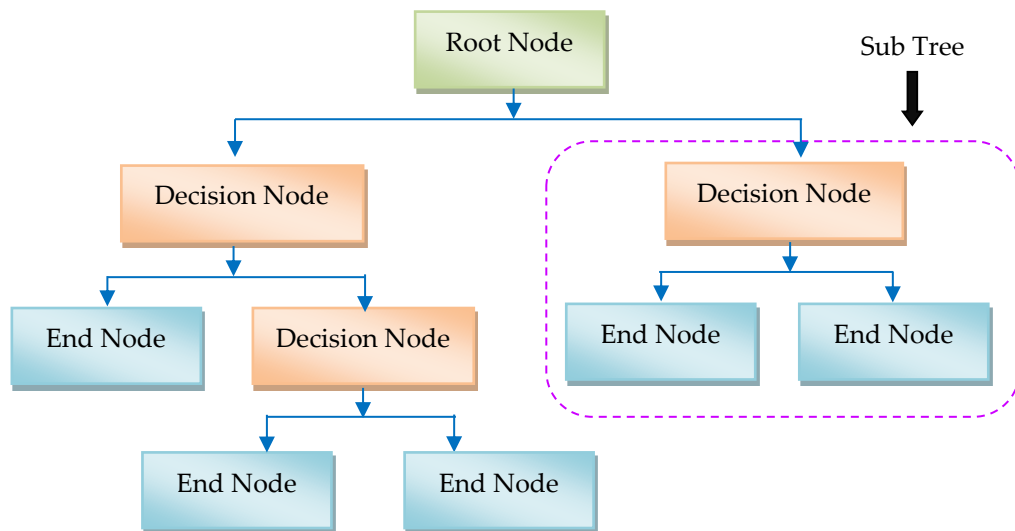


Figure 2. Process of Decision Tree

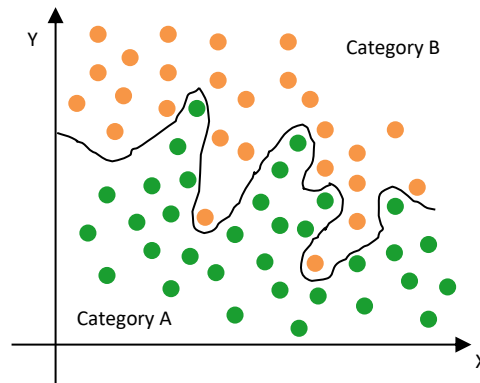


Figure 3. Over-fitting in Decision Tree

2.1.3. Support Vector Machine

One such supervised learning method is the SVM. Classification and regression cases are solved through this algorithm. Usually, these support vector algorithms prefer to solve classification issues [31]. Several dimensional spaces can be classified by determining an ideal line, which is the SVM algorithm's main motto because further data points in the future will be placed in the correct category immediately. Multiple lines or decision bounds isolate the classes in n -dimensional space, but to classify the data points, an ideal or decision spring needs to be manually selected [32]. The support vector machine algorithm has a hyperplane. That hyperplane fixes the optimal precinct. The extreme points and vectors are selected through SVM and help create the hyperplane. Based on the features in the dataset, the hyperplane's dimensions are determined. There are two types of data shown in the figure. 5; one is category A, and the other is category B. In this case, classify the data as a straight line. So here, the hyperplane is a straight line. In case three, the hyperplane is a 2-d plane. There are linear and non-linear SVM classifiers. A linear classifier means it separates the data linearly; it is said to be linearly separable data that classifies the data into two straight lines. A non-linear classifier means a single straight line cannot segregate the dataset and needs more dimensions. Due to the intense instances, this method is said to be a support vector machine [33]. In WSN applications, SVM is used to solve security and localization issues. In [45], SVM theory is explained.

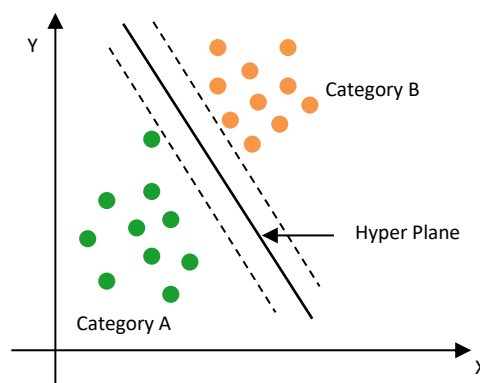


Figure 4. Support Vector Machines

2.1.4. Random Forest

One of the supervised learning algorithms is the Random Forest classification algorithm. Unlike a decision tree algorithm, that too relies on one attribute; instead, it has many attributes because of an ensemble model. Using multiple models to determine a result helps to achieve high accuracy. This algorithm makes its own decision using the results of each node. The model is more accurate by taking the average of the results of the various decision trees.

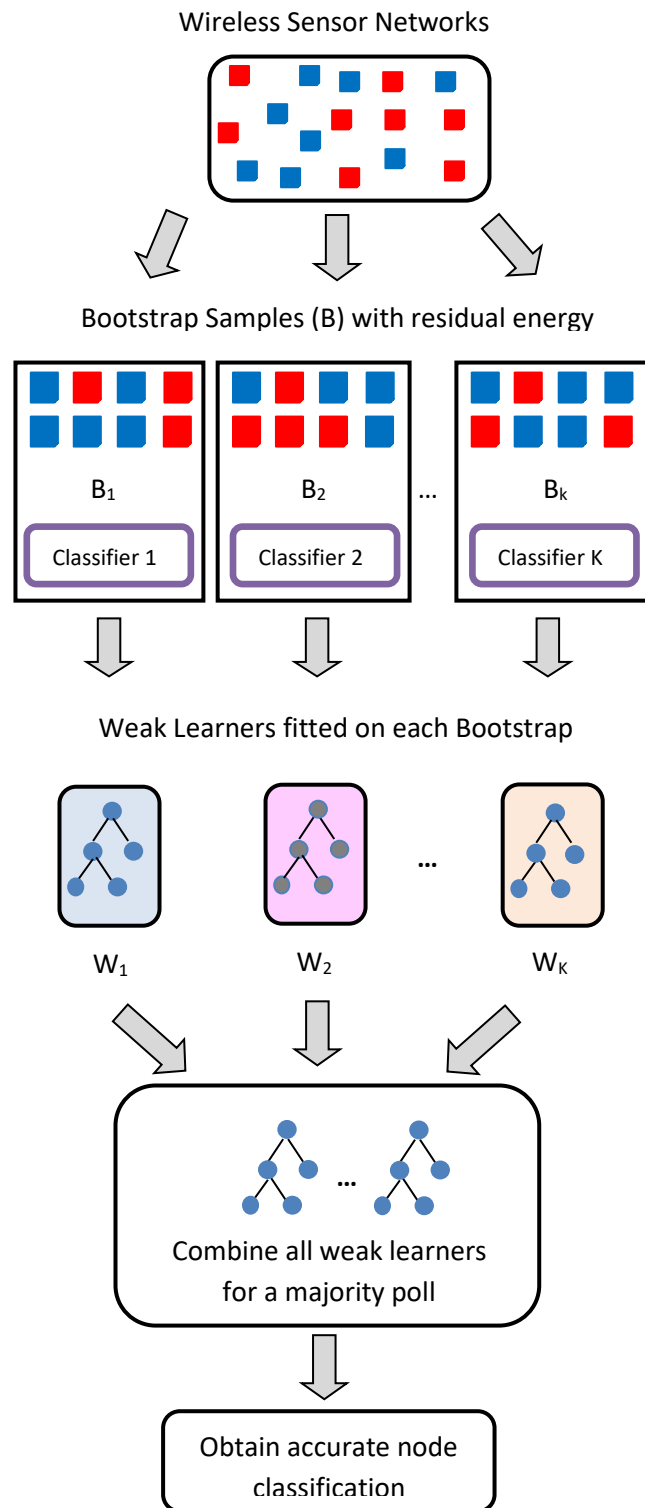


Figure 5. Bagging Process in Random Forest

Random forests work on the bagging principle. The bagging process in the random forest is shown in Figure 5. Bagging, otherwise named Bootstrap Aggregation, is an ensemble method working in a random forest. From the dataset, Bagging selects the sample data randomly. The sequence model is used to create every model to replace the Bootstrap model at the output part. Step-by-step modification of the array model is called "bootstrap." Results will be obtained after each sample is trained individually. Each result is combined, and polling is used to produce the outcome. Based on the poll, the mobilisation process integrates all that is perceived and creates the output. Finally, robust classifiers produce accurate results. This polling or average method eliminates the overfitting problem in the decision tree algorithm [34]. However, if the data has missing or irrelevant data, it functions well. Each decision tree formed is independent of the others,

demonstrating the parallelization property. Because the average answers from a vast number of trees are used, it is pretty stable. It does not take all attributes into account, except in some cases. Therefore, feature space is minimised, but the diversity of the algorithm is preserved. A dimensional curse is not in this algorithm. But it takes more training time due to its complexity. The bootstrap model will miss nearly 30% of the data. Therefore, it neglects to separate the data for training and testing [35].

2.1.5. Bayesian Statistics

Based on the Bayesian theorem, Bayesians develop statistical models. The Bayesian hypothesis prefers training samples to be limited. Unlike other learning algorithms, it is a statistical analysis of a supervised learning algorithm. It determines the correlation between the datasets by learning conditional independence. Bayesian learning permits multiple probability functions for numerous variables in class nodes [36]. The methods of Bayesian machine learning are: 1) MAP: this is the whole Bayesian machine learning method. It's computing the point estimate. The following method is Markov Chain Monte Carlo; this method holds Gibbs and slice sampling are examples of auxiliary approaches. The math underpinning MCMC is challenging but fascinating. In essence, these strategies function by building a known Markov chain that settles into a posterior distribution. Various successor algorithms expand the MCMC methodology by allowing the sampler to travel the parameter space more efficiently, utilising gradient information. In a larger Bayesian model, MCMC and its relatives are frequently used as computational tools. Their disadvantage is that they are frequently inefficient in terms of computing.

The Gaussian process is another Bayesian method; due to the suitability of conjugate functions, the full posterior distribution of Bayesian estimation is analytically computed. For classification, the rear is no longer conjugate to the likelihood; therefore, analytic computations are no longer possible. In this instance, the accuracy is to be achieved at the desired level by approximate solvers such as the Laplace Approximation applied to train the sample appropriately [37].

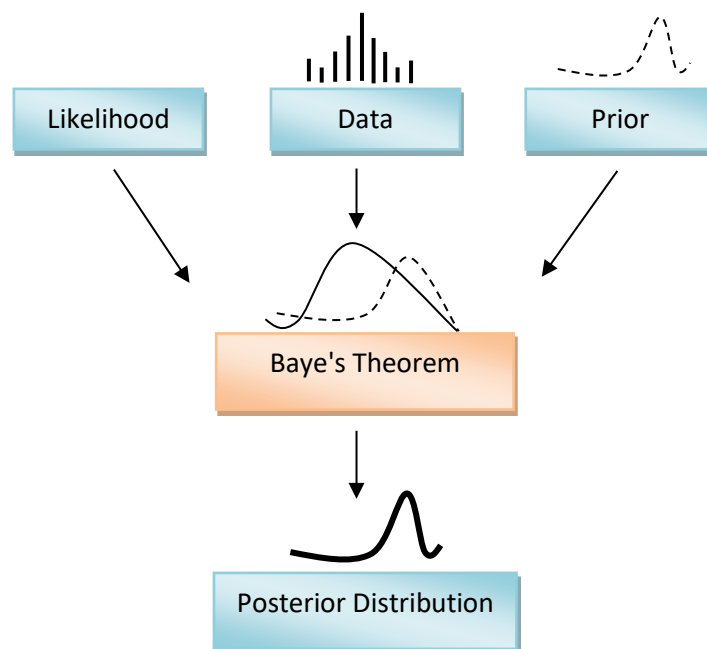


Figure 6. Bayesian Statistics

2.2. Unsupervised Learning

Previously supervised machine learning involves training models with labelled data under the supervision of training data. However, many cases may not have labelled data and must uncover hidden patterns in a dataset. Accordingly, it's imperative to address such problems in machine learning. For that, unsupervised learning techniques are required. Unsupervised learning methods are not like supervised.

Unsupervised learned themselves without any proctor. This model itself finds hidden patterns and valuable insights from the data. This type of learner works on unlabeled and non-categorized data. This learning aims to discover the basic structure of the database, similarities-based data classification, and concise database. This method follows clustering and association types. Clustering is grouping the objects by similarities, and the rest of the things are formed as another group. Therefore grouping the objects by similarities is called a cluster. It recognizes the general characteristics between data objects and classifies them accordingly. Another type is the association type. This type of unsupervised learning method is to identify the relationship between variables in the large dataset. This unsupervised learning identifies cluster formations in the dataset. The effectiveness of marketing strategies improves by the association rule. Due to unlabeled input data, this method produces less accuracy, and also, this algorithm does not know the exact output in advance [38]. This learning algorithm mainly involves data mustering and nodal classification for clustering-related problems. Different clustering algorithms that come under the unsupervised learning are as follows;

2.2.1. K-Means Clustering

A group of the unlabeled data is formed into k different groups by implementing k -means [39]. K is a practical means of dividing an unlabeled database into other clusters so that each database belongs to the same group with similar properties. The k -means helps decrease the distance between cluster and data points through the centroid. This k -means clustering algorithm performs two tasks mainly. 1) Select the k Centre point's values. 2) All the data points are allotted individually to the nearest Centre. Placing data points near a specific k -Centre helps to form a cluster. The following steps can solve the node clustering problem. a) Select the k value to build the number of clusters. b) Select the random centroids of k . c) Assign each data point to its nearest centroid, which will create pre-defined K clusters. d) Calculate the variance and place a new centroid of each cluster. e) Redistributes each data point to the nearest centroid of each cluster. f) If restoration occurs, proceed to Step d; otherwise, complete the process once the conditions are valid [40]. In this scenario, a good grouping is established; however, the approach is less suitable for this dataset due to the unequal equal variation in each dimension.

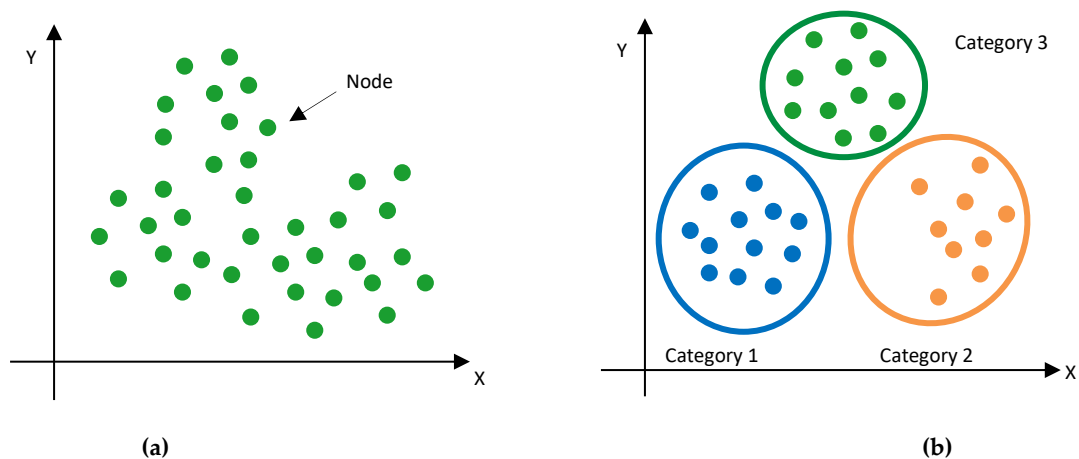


Figure 7. a) Before K-Means b) After K-Means

2.2.2. Affinity Propagation

Affinity Propagation is one of the clustering algorithms. It uses metrics of similarity between paired data points as input. Data points communicate precious information until high-quality prototypes, and related clusters are gradually released [41]. It cannot produce good results in this case.

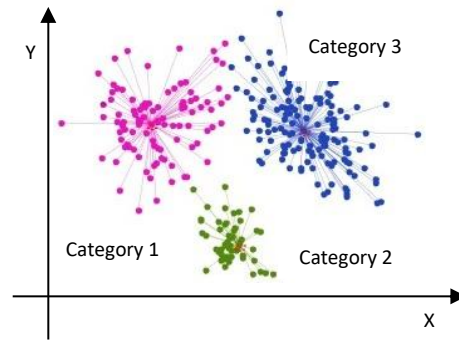


Figure 8. Affinity Propagation

2.2.3. Agglomerative Clustering

Based on similarity, agglomerative clustering is used to put objects in clusters. Agglomerative Nesting (AGNES) is another name for this method. This algorithm considers an object as the first singleton cluster. And then, all the groups together form an extensive collection of all data. Objects are represented in the tree structure at the output. Hence it is said to be dendrogram. Grouping is found reasonably [42].

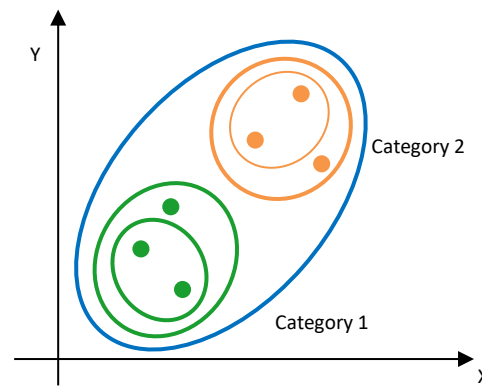


Figure 9. Agglomerative Clustering

2.2.4. Birch

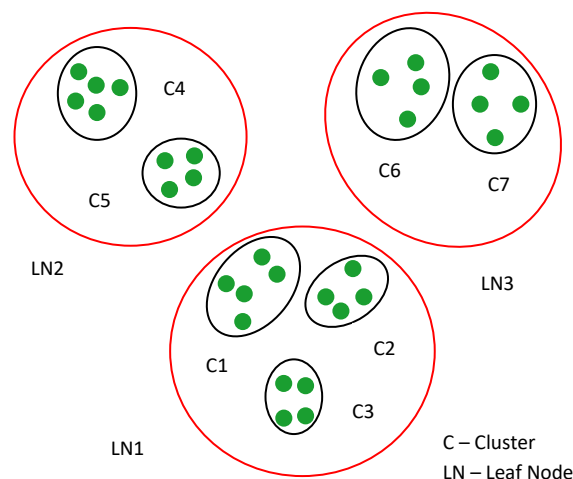


Figure 10. Birch

This approach entails creating a tree model called a Clustering feature tree (CF tree). Cluster centroids are formed from that CF tree. BIRCH clusters create superior quality clustering by increasing and changing incoming multi-dimensional metric data points. This type of clustering algorithm works efficiently for extensive data. BIRCH is a clustering algorithm that first clusters the dataset into short summaries and then

clusters the small outlines. It does not cluster the data in any way. That is why BIRCH is frequently combined with other clustering methods; different clustering algorithms can group the summary after it has been created [43]. Fine grouping is found by this method

2.2.5. DBSCAN

This approach entails identifying the domain with solid areas and forming clusters by elaborating feature space in the solid areas. DBSCAN relies on the density of the sets. Arbitrary pattern clusters are detected in spatial databases with noise. Clusters are detectable in areas with a high density of dots and regions with low-density clusters with noise. Clusters are growing on the basis of solidity link test in DBSCAN algorithm. Clusters are the points connected with the most significant number of densities [44]. According to the aforementioned definitions, the algorithm DBSCAN was created to find clutter and cluster in a dataset efficiently. Two parameters are required by DBSCAN: epsilon, which specifies the distance between the neighbors. Neighbors can be calculated by the distance between two points being less than or equal to epsilon, and a cluster is constructed based on the fewer data points (Minpts). Three points formed the core point, border point and outlier based on the two parameters. This method starts with a random initial point that has never been visited. This DBSCAN method rearranges the perimeter of this point into enough points to make a cluster; otherwise, that point is considered noise [45]. Fine-tuning is needed though it found the reasonable group.

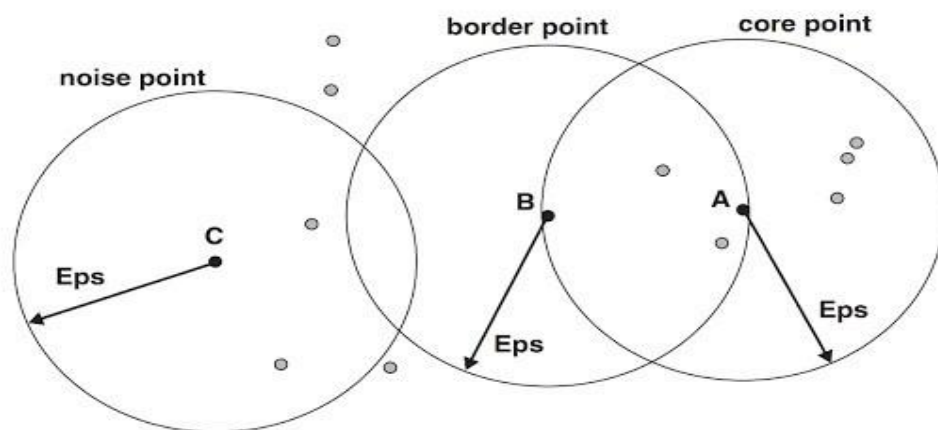


Figure 11. DBSCAN [45]

2.2.6. Mean Shift

This algorithm does not make any assumptions. Hence it is said to be non-parametric. This algorithm entails discovering and taking centroids in the area with the highest density in the feature space. This algorithm has the capability of modelling complex clusters with non-convex shapes. It requires only one parameter, bandwidth, which automatically determines the number of clusters. It is unable to distinguish between significant and insignificant nodes. Here, a set of clusters can be discovered among data reasonably by this shifting algorithm [46]

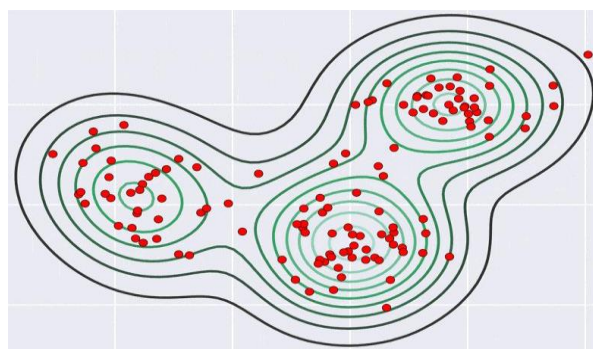


Figure 12. Mean Shift [46]

2.2.7. OPTICS

Ordering points to identify the clustering structure (OPTICS) is an alternate sort of DBSCAN algorithm. This optics approach is used for cluster analysis. It provides an enhanced database continuously that represents its clustering format depending on density rather than creating a clustered data set in a clear and detailed manner. This clustering sorting in a wide span of parameter options has the data related to the clustering, which is based on the density. But the reasonable cluster is not achieved [47].

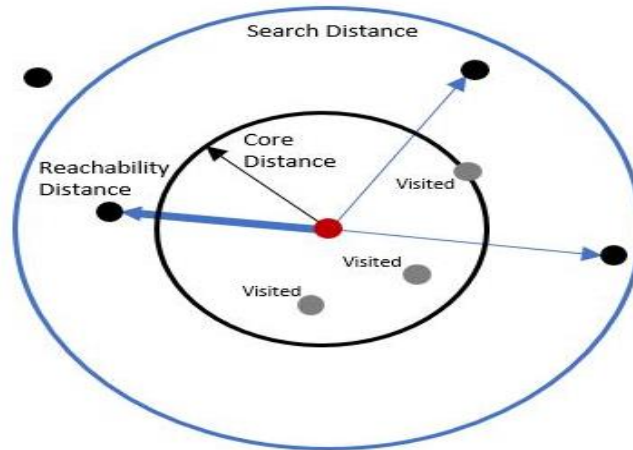


Figure 13. OPTICS [47]

2.2.8. Spectral Clustering

This approach is a broad category of clustering techniques based on linear algebra. Using spectral systems for clustering is a viable option that has lately been developed in several disciplines. The eigenvectors of an upper matrix are formed from the distance between locations and are used. It helps to shape the cluster and can find the centroid of the cluster. In k-means, several iterations are required. But spectral clustering does not follow a stable shape or pattern. Connected points are associated with identical clusters though they are distant. At the same time, it is related to various groups due to being disconnected even if the distance is less, which implies that the approach applies to data of all shapes and sizes. Its working operation is fast for a sparse dataset for several points in thousands. By using this approach, reasonable clusters were found [48].

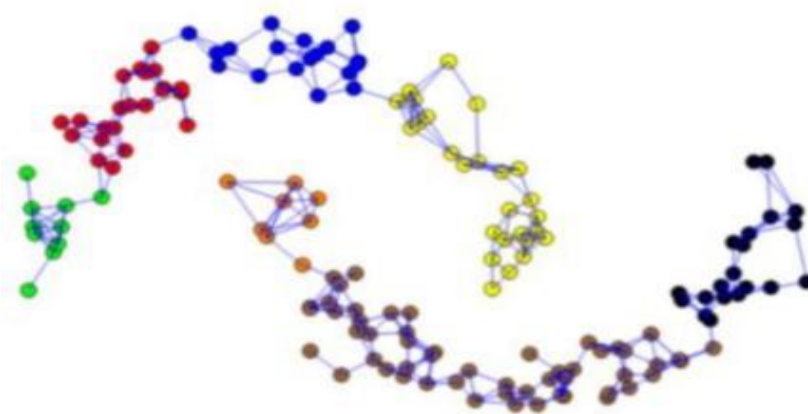


Figure 14. Spectral Clustering [48]

2.2.9. Gaussian Mixture Model

Gaussian Mixture Models are stochastic models that distribute points in various clusters using a soft clustering strategy. The Gaussian compound model brevities the operation of multiple probability densities with a combination of Gaussian probability distributions. Equitably spread all the data sets at all around average values, giving it a bell-shaped curve. In this case, the clusters are identified ideally [49].

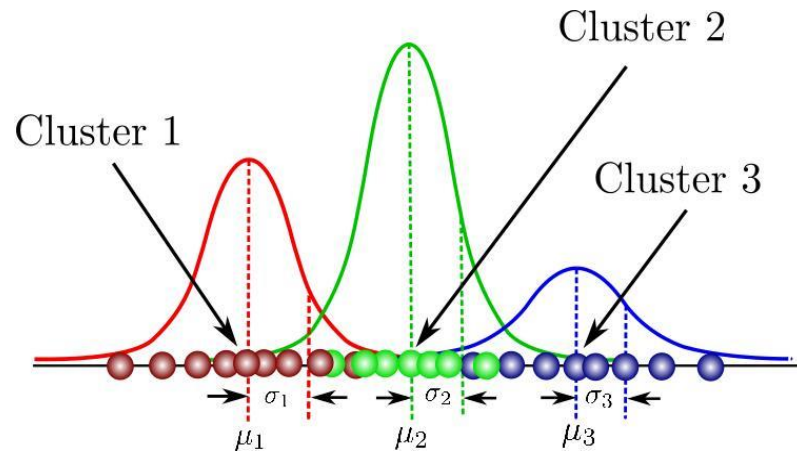


Figure 15. Gaussian Mixture Model [49]

2.2.10. Fuzzy-c-means clustering

Fuzzy C-means (FCM) is used to reduce the similarity of different types while increasing the resemblance of the same kind of materials. When FCM is used to cluster the sensor nodes, members can divide network nodes into several compact clusters to control the transfer distance when sending data to the cluster head, thus reducing the energy consumption while communication at intra-cluster [50]. In 1981 fuzzy-c-mean (FCM) clustering, termed soft clustering, was found by Bezdek to assign findings to many clusters using fuzzy set theory [51]. Clusters are identified through distance, potentiality and relativity of harmony measurement parameters using a fuzzy method. For applications or dataset oriented, this fuzzy algorithm used these types of many harmony measurements. This algorithm works again on top of the clusters for the best cluster centres. FCM works similar to k-means to produce the best grouping formation for imbricate datasets. Because it also needs prior knowledge of the cluster size. The FCM is more time-consuming than other clustering methods as it is often determined by the number of clusters, dimensions, data points and repetitions [52]. Pattern recognition, image segmentation, Bioinformatics, business intelligence, etc., this FCM is applied for that application. This FCM algorithm can solve localisation, connectivity, and mobile sink problems.

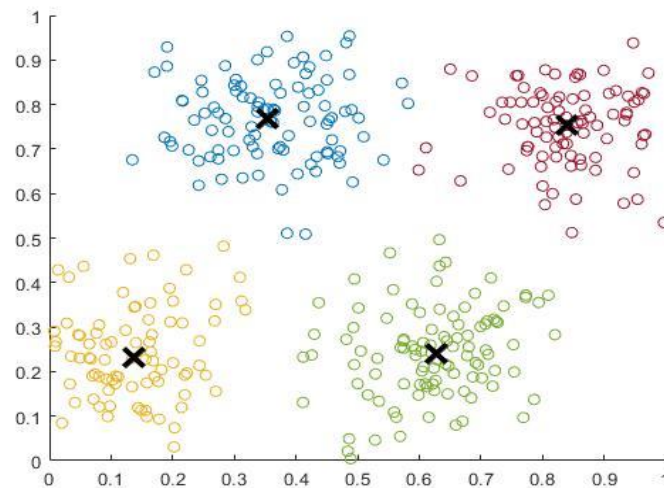


Figure 16. Fuzzy-c-means clustering

2.2.11. Independent Component Analysis

A statistical technique for finding embedded in datasets containing random variables, signals, or measurements is an independent component analysis. It aids in dividing multivariate signals into non-Gaussian subcomponents independent of one another [53]. ICA is an enhanced and advanced method over PCA. Relationships of higher hierarchy can neglect by ICA, but PCA does not. ICA takes data from multi-sources like web data, high pixel images, intelligence quotient, and collaborative and social media

intelligence. ICA observed straight and paralleled data sets in applications. The blind sources separation approach defines these observations [54].

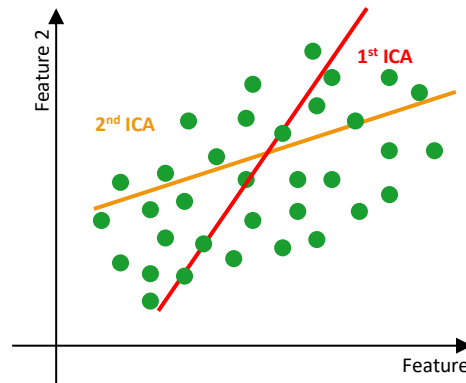


Figure 17. Independent Component Analysis

2.2.12. Principal Component Analysis

It is a statistical approach for dimension reduction. It creates a linearly imbalanced dataset which contains interrelated features by the orthogonal transformation [55]. This algorithm has the latest modified variables principal component. For data analysis and predictive modelling, this approach is used. It is a method of minimizing variations to extract strong patterns from a database. PCA processes high-dimensional data with a shallow dimensional surface area. The PCA considers the variability of each attribute, which minimizes the dimension, revealing a good division between the higher attribute classes. It is an essential feature linear combination. PCA has orthogonal parameters. The mathematical parameters of the PCA algorithm are the Eigenvalue, eigenvector, variance and covariance matrix analysis [56]. In the large set of variables, PCA solves the problem by using fewer conditions that adjust big data into small data representation [57].

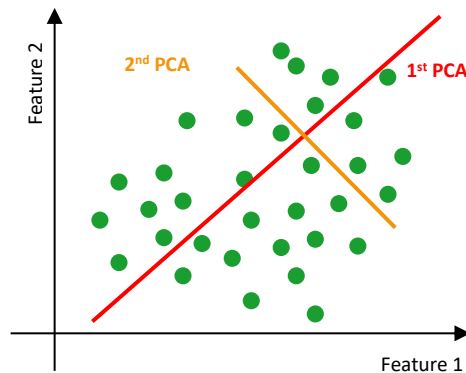


Figure 18. Principal Component Analysis

2.3. Semi-supervised Learning

There are two kinds of data deployed in machine learning techniques: labelled and unlabeled data. Working efficiently with only labelled data is supervised learning algorithms, and working efficiently on unlabeled data is unsupervised learning. But this semi-supervised learning focuses on particular learning tasks using uncovered and covered data. This learning method has semi-supervised classification to classify partially labelled data and clustering with labelled and unlabeled data restrainedly. Unlabeled data processed by regression method in semi-supervised, and for labelled data, spatial minimization is used [58].

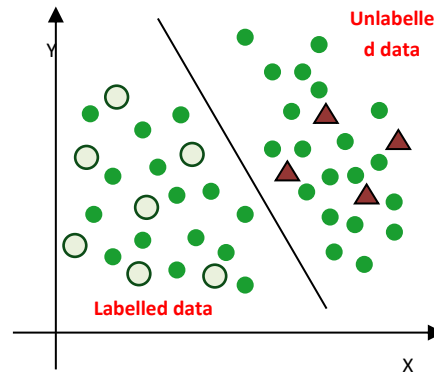


Figure 19. Classification of Semi-supervised Learning

Levels of semi-supervised learning methods are two. In the first level, two procedures are followed: an inductive approach to find a segregation process and a supervised learning method to provide a classification model for forecasting the label of data points not seen before. In given data set consists of defined (labelled) and undefined (unlabelled) data with labels for the defined data [59]. Further, the inductive method involves optimisation over prediction models. From an unlabelled data point, the transductive process is shown interest in getting label forecasting. It is not like an inductive; instead, it directly provides predictions means that for the unlabelled data points, it produces forecasting labels, and it is optimised now over the predictions [60]. Semi-supervised learning, rather than supervised learning, teaches a model with less labelled training data using pseudo-labelling. This learning algorithm is used in the applications such as natural language processing, classification, voice identification, unwanted refining, monitoring the environments through video, orderly classification of protein, etc. [61]. The wireless sensor network's localisation and error identification problems are solved using this kind of semi-supervised learning.

2.4. Reinforcement Learning

A representative is created in this reinforcement learning method. That representative will automatically learn to act as a sensor for interacting with its environment on the basis of hit, trial and experience. This kind of machine learning technique entirely depends on the feedback process. If it gets positive feedback, it is termed a reward and if it gets negative feedback is a penalty [62]. The initial purpose of the representative is to get the maximum number of positive rewards for enhancing performance. Under this RL technique, Q-learning is the most standard learning algorithm in a given state, and actions are taken to update their attained rewards regularly by an agent. The Q-learning method aims to enable each node in the wireless sensor networks to enlarge its continuing returns [63]. It is noteworthy that WSNs used the RL method widely and efficiently.



Figure 20. Reinforcement Learning

3. Machine Learning Techniques in the Challenges of Wireless Sensor Networks

Challenges include sensor power and memory control, network switching, connectivity failures, general administration in localization, energy awareness, routing, query processing, and security. By considering all this, wireless sensor networks adopt machine learning to overcome such challenges efficiently.

3.1. Localization

Localisation is challenging in WSNs to identify the sensor node's location topographically. Finding out the position of the sensor is a challenging task. But wireless sensor network applications do not have enough infrastructures to detect the sensor nodes after they have been placed and deployed in a field without knowing their status. Therefore, the sensor node's location can be found manually or using a geographical position system (GPS), but installing GPS at each node is realistically rugged because of its cost. On the other side, the reference of location is not possible to manually set at every sensor node in a dense network. All put together will direct into an automated localization approach that is enhanced without using GPS and configured manually. The automated localisation approach consists of anchor nodes or beacon nodes that know the current location. As this anchor node or beacon node shares its location with other nodes, the other nodes localize.

An example is shown in Figure 23. In localization, there are two types of location-based systems; one is location-based localization, such as GPS, and the other is an anchor. Localisation based on proximity, range, angle and distance is unknown location-based localization [64].

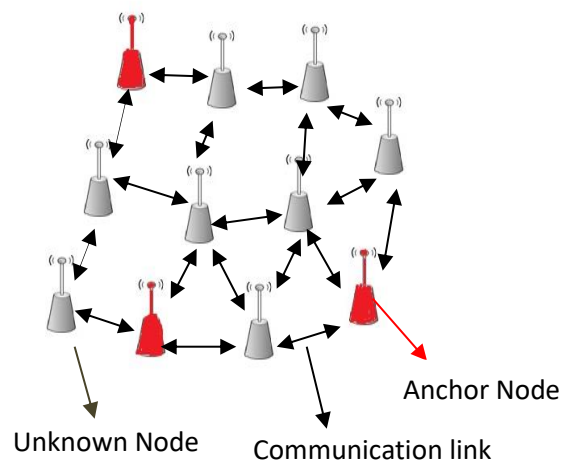


Figure 21. Localization in WSN

External and internal factors change the sensor node's location in the environment. The network needs to be redesigned or restructured to deal with situations where such changes occur. Using machine learning improves the accuracy of the sensor node's location in such conditions [65]. Using machine learning algorithms helps classify beacon nodes and strange nodes. It is used to form clusters. Every cluster has been trained individually to find the coordinates of sensor nodes swiftly. Accurate localization detection is faster and more satisfactory when mobile sensor nodes change their position dynamically according to an environment with machine learning approaches. Localization with machine learning-based algorithms in WSNs is shown in Table 1.

S-SVR, Z-SVR, and R-SVR support vector regression models are proposed in [67]. This kind of supervised learning algorithm works on the basis of feature standardisation. This principle is used to quickly and accurately predict the Localisation localization error (ALE). The parameters used for this accurate prediction are the ratio of beacons, transmission range, node density, and iterations of the features. The structure of clusters fails to estimate location, thus directing to an unreliable process due to low accuracy localization and weak dependability. Lingjun Zhao et al. [68] proposed a Block-Sparse coding method for localization without a reliable device in the IoT environment to overcome such challenges.

Specify the structure of the data using a reliable block-spare method. In the actual signals, severe Gaussian noise is included to protect network-related privacy and improve the model's dependability. Li Wang et al. [69] proposed the Hop count quantization method to determine a strange node's location. Here, to train the proposed method, this approach works on the basis of training inputs as the actual number of hop counts between beacon nodes and strange nodes and training targets as the locations of the anchors.

Trained KELM determines the strange node's location. The test samples of the proposed method are the same as the training inputs. Strange node localization accuracy is to be improved, for that actual number of hop count is needed. It has an integer hop count. Hence, KELM must be converted an integer hop into an actual number of hop counts. This converting process can be done by dividing the one-hop neighbourhood of a node into three subgroups and determining the node's distance. The cross-sectional area is to be calculated to find the node's space. Hongbing Liu et al. suggested [70] blindfolded nodes as a multi-class problem for determining the location by multi-class SVM; this system consists of two parts: offline training and online localization processes. Multi-class support vector machines should have class information; for that, they considers the unique value of the location information as class information while processing offline training, and also multi-class support vector machines are also trained for structuring the decision-making processes. During the online localization process, the location of blindfolded nodes is to be determined; therefore, the decision-making process is used. Later, there are two kinds of approaches: one is the learning lag approach, and the other is the filter method approach. Hence, the author, Hanen Ahmadi et al., proposed an innovative target tracking algorithm that combines both methods using the received signal strength indicator metric. The status of the sensor nodes can be evaluated by an algorithm of regression trees with a received signal strength indicator. This method is combined with Bayesian filtration approaches, which give highly distilled results [71].

The estimation precision of localization is affected by the nodes' density, lack of coverage area, and heterogeneity of topology. The range-free localization method (centroid) is used to improve such limitations. This range-free method is applied with a low node density. The fuzzy system with high node density is used for short coverage, and a soft computing hybrid model is approached for extended coverage to determine vital location. Hence, the author Songyut Phoemphon et al. proposed in [72] to strengthen both approaches. Consequences of irregular sorting are formed. The PSO algorithm is used to decrease such consequences. Later, unstable, anomalous conditions are proposed in [73]. The RSS metric is used to achieving accuracy. To find the network anomaly, this proposed method used a random forest algorithm compared with other machine learning algorithms to prove the accuracy rate.

3.2. Energy Harvesting

A sensor node consists of four components. There are: i) sensing; ii) processing; iii) communication; and iv) power components. The power component is the primary source to run the sensor nodes in today's WSN, and the network's life depends on the power swallowed by the sensor nodes. WSN applications need to prolong the lifetime of the network. To prolong the life of the WSN, adopt energy-saving approaches for each sensor node.

Regarding energy efficiency, multiple protocols for routing in-network, wake-up concepts, portable sinks, portable chargers, and more were introduced by the author. However, the power requirements were not met due to high compute resources, inaccessible monitoring sensors, and further maintenance times. Energy awareness has free maintenance, longevity, and self-activation in the WSN. Energy awareness provides continuous power to sensor nodes from the ambient environment, such as energy sensing, RF, wind, solar, heat, and engine and vibration energy [74]. This energy can be classified into energy repositories and without energy repositories. Several machine learning-based models have been developed for an efficient energy approach for WSNs. Table 2 summarises the machine-learning-based energy efficiency methods. The benefits of machine learning-based energy awareness are that WSNs' ability to predict the amount of energy to be harvested over a period of time is enhanced using the machine learning algorithm [75]. Balancing energy consumption using machine learning methods reduces the computational difficulty in calculating the amount of energy harvested and maintaining it effectively.

The data fusion process of mobile multilevel wireless sensor networks is primarily explored, and the wireless sensor network nodes are viewed as neurons in the neural networks (NN). An intensive learning

machine in NN collects sensory input from a mobile, versatile wireless sensor network, combines it with clustering, and drastically reduces the amount of network data sent to the sink node. [76]. Jianying Zhu et al. proposed an approach in [77] to minimise energy consumption and equally distribute energy to all the sensor nodes deployed in WSN. On the basis of leftover energy, ECRKQ picked the cluster head in the selection of the cluster head step and the distance between the node and the cluster centroid. It also uses dynamic coded collaboration (DCC) transmission to optimise bandwidth usage and underwater communications reliability. Jongmo Kim et al. [78] proposed an energy-efficient method for bi-phase energy storage at sensor terminals. Initially, it uses a hybrid filter-wrapper feature selection to detect minimal sensor nodes and optimal feature subgroups. The simulated annealing optimization method can then be achieved by manipulating the sample ratio and the transfer spacing of the sensor nodes while maintaining QoS by storing N2 energy. In [79], Yongjian Fan et al. proposed that EH-CRN having consists of monitoring, forecasting, and determination methods to reduce the energy consumption and the scarcity of spectrum resources. This approach improves the sensing accuracy and network throughput of two-dimensional energy spectrums. In this technique, to maximise the energy for transmission by secondary users (SUs), a 2D transmission decision module based on deep neural networks (DNNs) is used. Secondary users define energy-spectrum interactions and send data with optimal transmission power using this proposed innovative 2D cognitive programme.

In [80], Santhanakrishnan Chinnaswamy et al. proposed the TAAPML method. The internet access points compute the overall integrity scores for each device on the basis of actions and data integrity scores. Access points ignore that node during the authentication step if the integrity score is under a primary target rate; otherwise, perhaps the token of access is incorrect. The integrity target value is determined recursively using a SVM over the attained congestion on data of the SVM through the network throughput, time Lag, leftover energy, and overhead in data processing, and the performance of the TAAPML approach is determined. Denghui Wang et al. proposed an energy-efficient approach for energy conservation limitations and quality of service [81]. The reinforcement learning-based technique is applied mainly for performing QoS and energy-balanced routing based on dependability and delay information. For ensuring the quality of service, this approach used the RL technique to enable candidate relay nodes to learn about dependability and total delay from the changing environment and also offers that changeable relay node allows the sensor nodes to check the energy level of the sensors based on the leftover energy, in order to retain or not retain the routing tables. A modified clustering methodology is proposed in [82] to extend the WSN's lifetime.

Due to successive and recurring re-clustering, messages are exchanged, thus causing energy loss, which results in burned sensor nodes. This approach can adequately organise the clustering task because of this method's lower clustering and data exchange expenses. Depending on the amount of energy that is leftover in the sensor nodes, clusters is formed in the network. On the basis of energy level, adjacent nodes are linked with the cluster head, and other nodes are determined. The duties of the cluster's head nodes are swapped around according to the nodes' states. Improve energy efficiency used by grouping the nodes; the upgrade loop is generated through fuzzy inference. In [83], S. Radhika and P. Rangarajan proposed the CLONALGM approach to increase energy efficiency by fuzzy rule. This paper approaches the CLONALGM algorithm to clarify the fundamental concepts of the innate immune system. This approach establishes the rough sorting of output-based membership functions that improve the efficiency of fuzzy rule clustering algorithms. In [84], the DA Data Fusion method is proposed to save energy consumption by keeping sensor nodes are only active for a short period and then turn off. This approach is optimised for an ideal balance between energy use and latency when dealing with data integration. During an active state, this approach initially used a fundamental statistical approach to do data fusion at each sensor node to avoid duplication and inconsistent data. After that, the device, which operates intermittently in wireless sensor networks, determines an appropriate transmitting node for every sensor node for connections of data accompanied by the least amount of time and energy; the sink employs RL. Once the data is retrieved from its child nodes, each sharing node makes a one-time data integration.

3.3. Routing

One of the basic issues with WSNs is routing. Saving energy is among the most significant design objectives for WSNs. So, routing protocols are a suitable solution to keep the energy. Networks have a large scale, a vast volume of information to be transported, that transmitted data is to be processed, and finally, that processed data to be get. Due to a lack of sensing and a narrow bandwidth, it is not possible to transfer all of the information to the sink node. The prime function of the routing protocol is route selection and data forwarding. The optimum path between two nodes is chosen during route selection. The data is transmitted by selecting the next node or hop to transfer it to. The transmission of all the information from sensor nodes to the sink node using the multi-hop method is used. The sink node has relay nodes very close. So it consumes more energy generally. The sensor node's energy usage should be decreased. Therefore, an optimal routing protocol should be designed. Thus, it also increases the network lifetime [85]. Recently, many routing approaches have been developed to solve energy issues [87–93].

However, using machine learning techniques in wireless sensor networks to approach routing protocols can manage the rapid accumulation of a lot of data while maintaining accuracy. Machine learning-based routing protocols offer benefits such as changes in the environment; machine learning does not require reprogramming. It decreases communication costs and delays. It also aids in selecting the appropriate number of cluster heads by using simple computational methods and classifiers to minimize routing complexity and meet QoS criteria [86]. Machine learning-based routing protocols are summarised in Table 3. A novel compressed sensing approach is proposed in [87]. When tiny data packets need to be collected, sensitive data on the single can be retrieved with excellent reliability, leading to a significant reduction in network transmissions and thus prolonging the network lifetime.

Compared to other current compression sensitivity-based techniques, the suggested methodology, coupled with the changeable WSN routing architecture, is economical and straightforward to execute in resource-restricted modes since it does not save any component of the k -dimensional vector. Further, this paper proposes a machine learning strategy that is methodically based on WSN sorting and the appropriate representation of the data field, which would be less inconsistent with the k -dimensional vector in terms of the concise sensitivity for gathering the information. This proposed method reduced data recovery errors and also lowered wireless communication costs.

A predictive model strategy is proposed in [88] to determine the network's lifetime and choose a cluster head. The IP power of the Intelligent Grid and Performance Analyser captured the WSNs dynamic characteristics. The survey combines clustering with the optimum routing algorithm using machine learning. Hopping intensity, marketing, motes quantity, core, routes, monitoring period, account in order, frame size from central to end, output voltages, and stable itinerary are among the output responses that the predictors compute in order to design the models to evaluate the power and network performance. In [89], Qingmin Meng et al. proposed software-defined networking, including transmission elements and a customizable framework. Joint route prediction and forwarding are demonstrated using a component-based mesh topology.

In contrast to the traditional transport protocols, an aspect can employ the access control of the SDN flow approach, which comprises an enhanced sending strategy that is used to improve the performance of shorter reactions. Later, offline training is used in prediction to assess the influence of itinerary projection on the efficiency of the transport network. The primary difficulty in this situation is that a decent prototype must have been created out of limited training data. On the basis of recent and previous information, the forwarding rules must be dynamically updated. An intelligent route layout is done by using a parallel neural network classifier. This approach decreases the transport network's signalling overhead and maintains network throughput.

In [90], Nelofar Aslam et al. approached the SARSA routing protocol in regenerated wireless sensor networks to jointly optimise multiple aims for WPCD recharging trace with data routing algorithms that learn themselves. This approach hypothesised that operations could improve both reasonable energy usage and WPCD routing efficiency. The problem's fundamental issue is using the Nodal. An algorithm is to incorporate the innovative approach for WPCD. This approach to training sensor nodes for conceptual transmission data combines grouping nodes and SARSA with clustering SARSA. The entire process

surpasses wireless sensor networks' challenges, such as energy usage and firmness. Additionally, it extends the lifetime of WSN.

In [91], K. Thangaramya et al. proposed a protocol for cluster formation by handling factors such as the cluster head's mobility, range from the sink, area switching across cluster nodes, and current energy level. Using fuzzy rules for weight modification, a CNN learned the network using all these parameters. This method relied on fuzzy reasoning to generate strong clusters and execute routing on the basis of the cluster. In the proposed network, every node within the cluster used four parameters for all the cluster heads by applying the MI system after selecting the cluster head. And for cluster head formation, this fuzzy approach determined energy's highest value. For that, it implements the principles of member join. The proposed method reached the performance of the network well.

In [92], Denghui Wang et al. proposed a routing algorithm based on adaptive co-operative for QoS and energy conservation limitations. The reinforcement learning-based technique is applied mainly for performing QoS and energy-balanced routing based on dependability and delay information. This RL-based approach enables candidate relay nodes to learn about dependability and delay between source to the destination from the dynamic environment, ensuring the desired quality of service is met. It also offers that a changeable relay node allows the sensor nodes to check the energy level of the sensors based on the leftover energy in order to retain or not retain the routing tables. During the transmission of data, routing is affected by overhead. So the network redesign is needed to make the short itinerary to meet the sink node. Hence, parameters like energy, time delay, mean error, size of the packet, and quality of service are handled by the ML technique to transmit data and increase the network's lifetime effectively. The purpose of this approach is to minimise performance delays so that the model learns from its experiences to forecast the right path [93].

3.4. Security

These wireless sensor networks are multi-battery-powered, compact and low-cost sensor terminals commonly used to monitor physical parameters in a specific environment and transmit the data observed to the neighbor node or sink node. Because all sensor nodes are arbitrarily displaced in open areas, they are more likely to be exposed to different types of attacks. There are two major attacks; one is an attack on the sender and receiver, and the other is an attack on transmitted data [94]. This leads to security issues in WSNs. Therefore it is essential to protect all the data of sensor nodes. Accordingly, many intrusions Detection System (IDS) was developed. Attacks can take many different forms to harm the network are follows:

A sinkhole attack in which the coordinate nodes advertise their dummy routing updates to attract network traffic, thus causing harm to the data and the network [95].

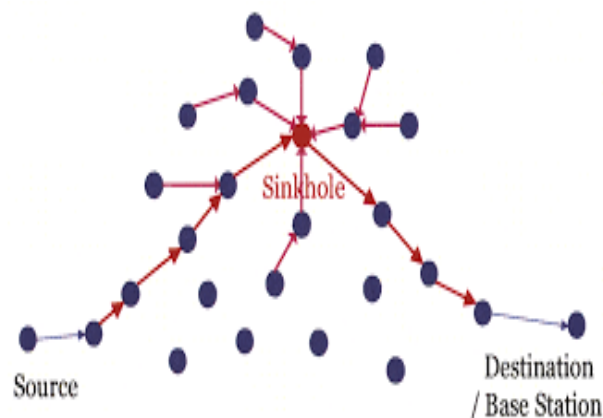


Figure 22. Sinkhole Attack

In a wormhole attack, the malicious node may be within the transfer range of the legitimate nodes, but the proper nodes are not within each other's transmission range. As a result, the malicious terminal will manage traffic between the appropriate nodes and the missing connections that it controls. Finally, the hostile node can drop tunnel pockets or carry out routing protocol attacks [96].

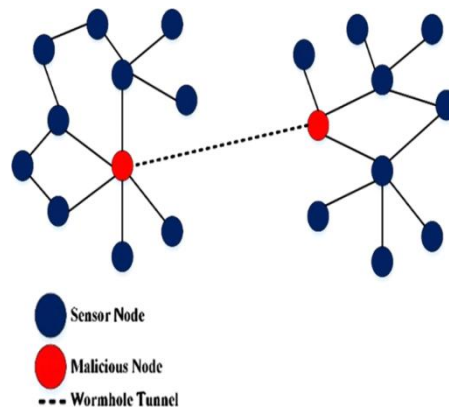


Figure 23. Wormhole Attack

A black hole attack occurs when an intermediary captures a group of nodes and redesigns them to block/leave pockets and generate false messages instead of sending the correct/valid information to the base station [97].

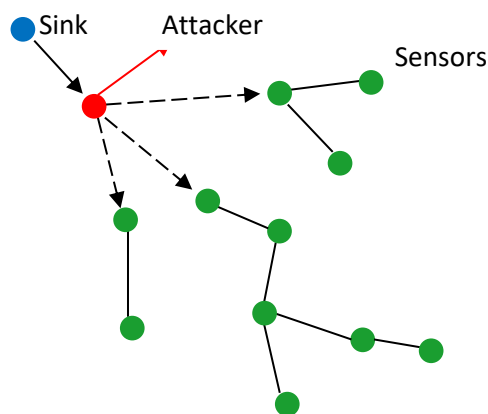


Figure 24. Black hole Attack

A misdirection attack is a type of DoS attack. One of these is malicious tip-pocket misdirection to other nodes. But the purpose is not for the recipient. So that can be reduced. Increase network throughput and final delay from end to end. All kinds of attacks affect the entire network simultaneously as a hybrid attack [98].

ML techniques in WSNs significantly improved the network's security to surpass these issues. The benefits of using machine learning for security greatly extend the lifespan of WSNs by saving terminal power and preventing erroneous data transmission. Users can increase network dependability by getting rid of harmful and erroneous measurements. Avoiding unwanted learning can also be changed into significant and frequently significant acts. Online education and defence against vicious assaults and weaknesses Machine learning techniques for security issues are summarised in Table 4. A Deep Learning (DL) programme implemented in [99] for security authentication was proposed to address security issues when applying BFL and LPL Recognition. In particular, the neural networks in the data collecting portion are examined to identify the characteristics of the data before the cognitive identification structure is formed. A complete identification procedure based on machine learning is deployed to find rogue multimedia devices. A new optimised support vector machine (OSVM)-based navigation detection system has been proposed in [100] WSN. This OSVM is pre-processed by three sub-processes, i.e., pre-processed before converting the input network data into the desired structure. This method includes an efficient selection of optimal kernels. Because WOA modifies the SVM kernel, it is possible to identify intrusions effectively by utilising the OSVM model. A thorough examination of the use of ML and DL in WSN's intrusion detection system is proposed in [101]. To attain this, the Boltzman clustered on the basis of

machine IDS that is RBC-IDS used is a viable deep learning method to monitor essential infrastructure through WSNs. Several agencies established IDS based on the immune strategy proposed in [102]. Every node employs a tracking advisor, and even the end advisor maps the characteristics of the data collected.

The closest lethal advisor is operational and prepared to isolate the abnormal node if an assault on the sensors (SN) is anticipated. The Adaptive Chicken Swarm Optimisation Method, a common clustering approach, was utilized. With this approach, the WSN's enduring value and versatility may be improved, and the required time may be reduced. In addition, a 2-level segregator, ASVM, is used within the programme on the basis of acknowledgement for the alert hostile sink node [103]. Later, the ELM (DBN-ELM) utilised an extended deep trust network with an integrated penetration forecasting system. The model showed the learning pattern by extracting a feature of the DBN and ultimate learning with extreme learning; a majority poll was used to determine their evaluation [104]. For the detection of abnormalities in a wireless sensor network, the OLWP-recognition method is presented [105]. Non-parameter LWP regression methods are used, and present state predictions are derived using only a fraction of the data.

As a result, low computing complexity is one of the requirements of the wireless sensor network. To address inappropriate and undesirable input data, dimensional reduction of LWPR is made online using primary component analysis (PCA). Following the prediction procedure, the dynamic threshold approach uses the formula for calculating the variable cut-off point to discover differences between the predicted and actual perceived values. DoS attacks are attempts by adversaries to disrupt network services. Obstinate server nodes or rogue nodes could be offered upon demand to distract them during an attack of denial-of-service. A CBCA method susceptible to mutual authentication is used within a wireless sensor network. If the source hub starts the cycle by sending a bundle, it will have information to convey. Various types of DoS attacks happened on multiple levels of the standard layer. There are three kinds of MAC Layer DoS attacks: assault from exhaustion, crashes, and caricature. NN, SVM, and MAC protocols are proposed to enhance security by detecting the enemy in response to these attacks [106].

3.5. Quality of Service

With the widespread usage of wireless sensors in various applications, service that provides quality has become a prominent concern in applications of WSNs. Every application has a unique set of quality service requirements. In addition, each application's data might require a distinct service process in terms of quality, alerts, and frequent monitoring messages. Still, because of the unreliability of media and device embedded restrictions, implementing QoS on WSN-based applications remains problematic. Network-oriented and applications-oriented are the concepts in QoS. The parameters used in network orientation are energy and bandwidth. The parameter used in applications-oriented is the network's dimension, deployment, and active sensor node. Strict resource restrictions, unbalanced congestion, data redundancy, a dynamic network, energy balancing, scalability, and one or more sinks are the challenges to sustaining the QoS [107]. Applying ML for quality of service in WSNs is tabulated in 5.

In [108], Chien-Min Wu et al. proposed a MAC protocol based on Q-learning to allow for dynamic modification of the congestion period's duration in response to the current traffic flow. The use of reinforcement learning is to gradually alter the congestion period's length depending on traffic flow, making MAC unique on the basis of QL. The QL-based MAC will solve the algorithms to respond to environmental variables during training without additional inputs. The time-dependent aspects of network behaviors are thoroughly analyzed, and a deep learning technique aggregates the network QoS trusted attributes to create cognitive information for a given IoT device. By evaluating the resemblance of both actual and normal behaviours of networks anticipated by this behavioural model, credibility may also be quantified as continuous numerical values. Trust values are used to determine a device's trustworthiness and are utilised to make decisions. Later, experimentation is used to show that the suggested technique is effective. [109]. For applications of quasiperiodic and monitoring through online mode of each device network performance with documents of quasiperiodic, that is smart metering, surroundings and field monitoring, a traffic model and unsupervised, parametric machine learning algorithms are given. The Lomb-Scargle periodogram, a method devised by astronomers for determining the spectral density of irregularly collected time series, is used in two clustering algorithms. [110].

In [111], Jaewoong Kang et al. proposed using a meta-heuristic method to save energy in two phases on each sensor node. A hybrid filter for wrapper feature selection is applied initially to determine the minimum sensor nodes and the best feature subsets. Later, using the simulated annealing optimisation method, by adjusting the sampling frequency and propagation period of the sensors, N2-energy savings may be made while preserving the quality of service. A hybrid approach to properly configure the network and thus improve the QoS parameters, modelling by SVM and optimising by MSOG, is proposed in [112]. SVR is utilised to determine the association among specifications and network metrics in the suggested quality of service metrics. After discovering the link between these two sets, a goal-programming-based non-linear and non-statistical model was created. Finally, the network's optimal configuration was obtained analytically from the non-linear and non-statistical model with a GA. Because of a solid network setup, all network output metrics are in their best state, and the performance of the whole network will increase. In 6LoWPANs (Internet Protocol version 6 (IPv6) over low-power wireless personal area networks), interference results in meagre quality of service as well as decreased network stability and longevity by arrival packet rates and packet loss rates. For that, the research approached the routing protocol on the basis of deep nets for 6LoWPANs that reduce interference and enhance lifespan and QoS. The 6LoWPAN stack's network layer will incorporate a deep net-based routing sub-layer. At the network layer, a topology is constructed accordingly for IPv6 using the RPL routing protocol and optimises routing paths using a deep network-based layer. The suggested routing on the basis of deep networks minimises network latency from source to destination and increases energy usage dramatically [113].

4. Analysis of Challenges faced in WSN using Machine learning techniques

Table 1. Machine learning in Localization Problem

Ref No.	Technique	Methodology/Approach	Parameters Remarks
[67]	Support Vector Regression (SVR)	Cuckoo Search	Lower RMSE in ALE prediction with lesser time
[68]	Block Sparse Coding with the proximal operator	Block-sparse	Attain strong localisation and performance of signal-recovery
[70]	SVM	Multi-class Support Vector Machines	Localization error is reduced
[72]	PSO	Hybrid Enhanced Centroid and extreme learning machine	Low estimation error
[73]	RF	Asymmetrical, abnormal circumstances	The accuracy rate is increased

Table 2. Machine learning in Energy Consumption Problem

Ref No.	Technique	Methodology/Approach	Parameters Remarks
[77]	K – Means & Q- Learning	Dynamic Coded Cooperation (DCC)	Achieve a more balanced energy consumption
[78]	Fuzzy C Means	hybrid filter-wrapper feature selection and Simulated annealing	Achieved energy savings
[79]	DNN	Energy harvesting cognitive radio network (EH-CRN)	Improved accuracy in sensing, prediction, and network throughput.
[81]	Reinforcement Learning	Energy Efficient Distributed Adaptive Cooperative Routing	Energy consumption is reduced & QoS is improved
[84]	Q-Learning	delay-aware data fusion	Reduced Energy Consumption

Table 3. Machine learning in Routing Problem

Ref No.	Technique	Methodology/Approach	Parameters Remarks
[87]	Deep Learning	CSR	Transmissions reduction & Prolong network lifetime
[88]	Gaussian Process Regression with Bayesian Optimization	Threshold Sensitive Stable Election Protocol	Improved RMSE
[89]	DNN	SDN	Reducing the signalling overhead & inference efficiency
[90]	Reinforcement Learning	SARSA	Energy consumption, stability, and a lifetime of the WSN
[91]	CNN	Fuzzy Rules	Better network performance

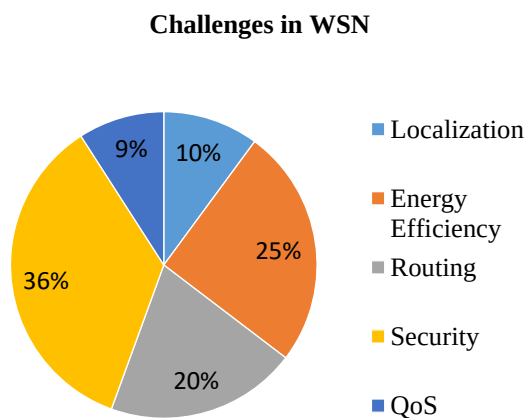
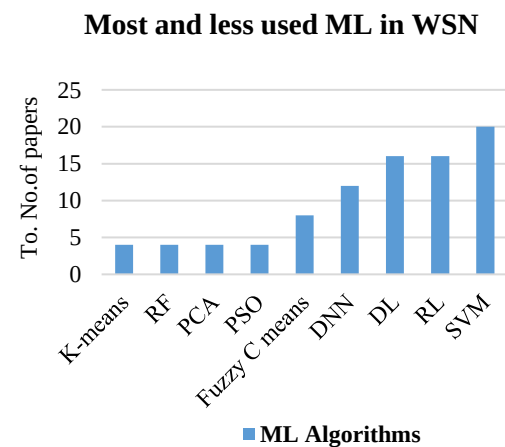
Table 4. Machine learning in Security Problems

Ref No.	Technique	Methodology/Approach	Parameters Remarks
[99]	Deep Learning	Blind Feature Learning & Lightweight Physical Layer Authentication	Improves security
[100]	OSVM	Whale optimization algorithm	Obtaining a superior accuracy
[101]	DL	Restricted Boltzmann machine-based clustered IDS	Achieve the detection and accuracy rates
[103]	SVM	Adaptive Chicken Swarm Optimization	Achieved timeliness and accuracy
[105]	PCA	Online Locally Weighted Projection Regression	Attains Detection Rate & very low error rate

Table 5. Machine learning in Quality of Service

Ref No.	Technique	Methodology/Approach	Parameters Remarks
[108]	Q-Learning	MAC	Attain Max Throughput
[109]	DL	LSTM - long short-term memory	Achieved model accuracy
[111]	Fuzzy C Means	hybrid filter-wrapper & SA	Maintaining the QoS
[112]	SVM	MSOG	Improve the QoS parameters
[113]	DNN	Deepnets	Reduce interference and enhances lifespan and QoS

From this review paper, how many percentages of the researcher shows interest in the selected challenges mentioned above during the epidemic period (2019 to 2022) is shown fig.25. In fig.26, The total number of papers taken for this survey in tabular column from 1 to 5 is 25. Out of 25 papers the most and less used ML algorithms are depicted in the bar chart.

**Figure 25.** Survey of Challenges in WSNs**Figure 26.** Most and less used ML in WSNs

4. Outcome of using Machine learning techniques in WSN

WSN applications are adapted the Machine learning techniques for segregation, reproduction grouping, reduction in dimension, categorical extrication and prediction. The benefits extracted from the ML techniques for WSNs include less complicated computational architecture, high accuracy, extended life of the network, high power efficiency, and so on.

Machine Learning approaches in WSNs provide several advantages but also have several restrictions. This is because WSNs always operate in a constrained space with low battery life, storage, and computational capacity. Self-learning, i.e., necessitates a massive amount of sample sets of data. While forecasting an appropriate assumption and obtaining the aspects of data sets, WSNs spend a lot of energy. As a result, the computational cost of methods and the learned model must be balanced by WSN developers.

6. Conclusion

This survey discussed recently published Machine Learning-based WSN algorithms. This paper presented supervised, unsupervised, semi-supervised, and reinforcement learning techniques. Localization, energy harvesting, routing, security, and quality of service are only some of the concerns addressed by Machine Learning approaches in WSNs, according to this study paper. A group of techniques are used in ML to improve a WSN's ability to adjust to its environment's non-linear response. The table column from 1 to 5 summarizes the research papers from several challenging areas has been used machine learning methods to overcome these challenges. As demonstrated by the discussion, more WSN delineation issues have been solved using existing machine learning methodologies. This survey covering the epidemic years (2019-2022) provided a comprehensive literature assessment of similar investigations. Finally, when using ML techniques in WSNs, reviewing the resources of regional networks and various learning themes and formats is essential. Furthermore, many issues remain unresolved. Further research is needed, including the applications of potable and decentralized messaging approaches, learning through online methods, clustering methods on the basis of hierarchy, and the strategic planning issues of WSNs to machine learning.

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