A Survey of Machine Learning for Information Processing and Networking

[1]**Anna Recchi**
[1]Faculty of Science, University of Amsterdam, Amsterdam, Netherlands.
[1]annarecchi56@hotmail.com

Correspondence should be addressed to Anna Recchi : annarecchi56@hotmail.com

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202202023
Received 04 April 2022; Revised form 06 June 2022; Accepted 10 August 2022.
Available online 05 October 2022.

Abstract – The developments in hardware and wireless networks have brought humans to the brink of a new era in which small, wire-free devices will give them access to data at any time and any location and significantly contribute to the building of smart surroundings. Wireless Sensor Network (WSN) sensors collect data on the parameters they are used to detect. However, the performance of these sensors is constrained due to power and bandwidth limitations. In order to get beyond these limitations, they may use Machine Learning (ML) techniques. WSNs have witnessed a steady rise in the use of advanced ML techniques to distribute and improve network performance over the last decade. ML enthuses a plethora of real-world applications that maximize resource use and extend the network's life span. Furthermore, WSN designers have agreed that ML paradigms may be used for a broad range of meaningful tasks, such as localization and data aggregation as well as defect detection and security. This paper presents a survey of the ML models, as well as application in wireless networking and information processing. In addition, this paper evaluates the open challenges and future research directions of ML for WSNs.

Keywords – Wireless Sensor Networks (WSNs), Machine Learning (ML), Artificial Neural Networks (ANNs), Artificial Intelligence (AI)

I. INTRODUCTION

There has been a rapid increase in the number of Internet users and linked gadgets in the modern age. Therefore, IoT devices should be intelligently controlled in real-life environments by next generation of mobile networks that provide ultra-reliable, low-latency communication. Applications such as real-time traffic data, sensor information from driverless vehicles, or entertainment broadcast recommendation generate enormous volumes of data that must be gathered and analysed in real time. In order to meet these communication needs and core intelligence, Machine Learning (ML) algorithms must be integrated into telecom connections as well as end-user devices. Wireless networking and communications have, over the past few decades, seen a surge in interests in ML algorithms. In order to handle the ever-increasing amount of computation and communication in emerging networking applications, ML-driven techniques and models may be of great use. However, the use of ML methods in wireless communication systems is still up in the air. Research in ML and wireless connectivity has to be bridged further.

An enormous shift is occurring in the world of wireless networking. There has never been a time in history when so many different wireless-enabled gadgets have come together under the realm of the Internet of Things (IoT). New and untested wireless service use cases will emerge in the coming years as a result of this change, which is expected to grow exponentially in the coming decades. IoT clients and the IoT ecosystem are constantly evolving, and the next generation wireless communication networks must be able to keep up with these changes while providing ultra-reliable connection that is both low in latency and sensitive to these changes. Autonomy will be at the heart of the Internet of Things (IoT), thanks to devices like drones and connected cars, for example. Wireless communications must be extremely reliable to manage these autonomous systems in real time and with minimal latency, as a result. Sensors and wearable devices that monitor the physical environment will gather massive amounts of data on a regular and real-time basis in tomorrow's wireless networks. Wireless upstream traffic has typically been less congested than wireless downlink traffic as a result of large-scale short-packet transfers. For cloud-based gameplay, virtual reality applications and HD broadcasting, the same cellular network will be able to support all of these services simultaneously. Cellular networks must thus undergo fundamental transformation in order to handle software innovations and their varying quality of service/reliability requirements.

To keep up with this fast and continual expansion of wireless services, there has been a substantial amount of study into the best cellular network design for the future fifth generation (5G). There must be smart features in the network's edges and core, including micro cells, D2D and millimeter wave (mmWave) communications, in order to construct an IoT wireless network that can manage the issues of IoT. Improved wireless communication management and real-time assurance of QoS requirements for growing cellular and IoT data services need these smart functions to be able to adaptably use wireless transmission resources and generated data. Fundamental machine learning principles like Artificial Neural Networks (ANNs) may be required to implement such core intelligence and mobile edge in end-user and wireless infrastructure devices. When utilized in collaboration to wireless networking, ANN is a typical model for computational non-linear ML, which could be utilized to train under various conditions of supervision or not at all.

To describe ANN-based machine learning, the term "Machine Learning" is employed. Artificial Intelligence (AI) has been used in WSNs to resolve issues such as optimal sensor deployment, energy-aware data exchange, and resource allocation. Data training, machine inferential, and other data processing techniques all use ML methods in some capacity. This article examines the use of ML in WSN from the standpoints of networking and application. The structure of this paper is as follows: Section II presents a background analysis of WSNs and ML. Section III focusses on a critical analysis of ML. Section IV provides a survey of ML for networking, while Section V provides a survey of ML for information processing. Section VI discusses the open challenges and recommendations for future studies, while Section VII draws final remarks about the paper.

II. BACKGROUND ANALYSIS

Wireless Sensor Networks (WSNs)

As electronics and communication have advanced dramatically over the past decade, Wireless Sensor Networks (WSNs) have risen to prominence as the most widely used exploratory tool in the world. It is a collection of small, microscopic sensor nodes that collects and transmits perceived information to end users or decision makers. There are many critical scenarios where sensor nodes can be put to use because of their ability to continuously sense and detect events as well as their ability to deploy quickly and self-organize, which makes them ideal for use in military surveillance as well as in home automation and target tracking systems. Decisions could only be made based on accurate and precise data in these applications. Hundreds of thousands of sensors are placed in a dangerous area to keep an eye on things and gather data for the sink node. Each sensor node collaborates and communicates wirelessly with other sensor nodes through radio connections, which are often installed. Sensor nodes have inadequate computational power, energy resources, and a big challenge is that the environment in which they are placed changes rapidly over time, making it difficult for them to keep up with the changes. Analysis of sensor data in an expeditious way is critical. A sensor node's raw, unprocessed data is inaccurate and incomplete.

The WSN's expertise may be used to a wide variety of applications, from military surveillance to smart building technology. Some of the benefits of WSNs are their cheap cost, low energy consumption, ease of deployment, great sensing range, and ability to organize themselves. However, the benefit that WSNs give is accompanied with a wide variety of difficulties. One of the most key traits of a WSNs is its scalability, as well as its resilience to a variety of failures, including node disintegrates, node interaction failures, sensor node agility, and energy consumption limitations on nodes powered by batteries or other energy sources. Many routing methods have been developed to lower the power consumption of wireless sensor networks, which has historically been a problem. Routing is a term used in WSN to describe the process of processing data from a source to a sink or a sink to a sensor. It is more important to consider issues like as localisation, deployment, scheduling and security when creating a WSN than it is to focus on the flow of dataset. To be sent, administered and received by the WSN, each sensor node contributes a substantial quantity of data. Due to the restricted energy and bandwidth of the sensors, it is unable to process and make choices.

Machine Learning (ML)

Scholars and the research community have achieved significant advancements in "Machine Learning" utilizing neural networks that mimic the functions of real neurons during the last several decades. A machine's capacity to mitigate an issue without human intervention is the most common definition of artificial intelligence. Data is illuminated by AI so it may produce its own answer. Automated learning takes the process to the next level by supplying the machine with the data it needs to learn from and adapt to new information, ultimately producing better outcomes. Learning from past experiences is an important part of the machine-learning paradigm. It is indeed impossible to overstate the importance of ML knowledge, which is employed in a wide range of applications from biology to voice recognition to spam detection to computer perspective or visualization to fraud detection and broadcasting networks, to name just a few. There are a wide range of mathematical, computer, statistical, and neuroscience-based methods and skills used in this application. Automated machines may be trained with the use of Artificial Intelligence (AI). We are unable to get reliable information from the data we have gathered. We use ML in situations like this. In many industries, such as medicine and military, ML is used to extract functional information from data sets. Once a ML algorithm understands what it needs to do with data, it can carry out that work automatically. The ability to use cutting-edge ML technologies in the computerization of WSN operations gives them a competitive edge.

III. REVIEW OF MACHINE LEARNING

Machine Learning (ML) Definition and Application

With the use of possession information and the expansion of system progress, ML expands a computer framework for the training process and provides the best solution to this problem. "The ways of advocate enhancing the effectiveness of the computer in identifying and characterizing unpredictability prototypes in data". For the following reasons, ML is critical in WSN: A wireless sensor network is able to operate in a hostile environment when conventional networks have failed. ML may be used to reduce the complexity and expense of a WSN by arranging assignments in a mathematically replicable manner, such as routing or data aggregation. (1) As a result of the large number of sensors, wireless sensor nodes gather a large quantity of data and transmit it to a base station, which in turn extracts vital information from the data and sends it back. To achieve maximum data coverage with improved sensor deployment, many WSN applications include some level of data coverage, which reduces the power handling by using ML models (2). We put sensor nodes for real-time applications in environments that vary over time, and the results would be affected if the sensor nodes move or change locations. Developing sensor networks that can be strongly controlled in certain contexts is thus gratifying (3). Throughout the last decade, ML techniques have been widely used in wireless sensor networks in order to get better outcomes in the field. WSN applications may benefit greatly from ML's vast array of methods and presuppositions.

It is possible to categorize current ML algorithms into three main groups: those that use supervised learning, those that don't, and those that use reinforcement learning. This is where the initial batch of training data for supervised learning is created and evaluated using the testing data. For classification or taxonomy, an algorithm learns certain approaches from a training data set and then applies them to a testing data set. In unsupervised learning techniques, the sample dataset is segmented into multiple groups centered on their relevant attributes even when no training data is provided. Agents using reinforcement learning algorithms learn from their surroundings in a similar way, therefore the final conclusion is more upbeat.

ML Models

Supervised ML

In Supervised ML, the system model is built using pre-established inputs and output values. Design a learning algorithm for learning the transformation matrix from input to output Y=f using input variables and output variables. The goal of the guesstimate mapping function is therefore to be able to estimate the output variable given the most current participation data. We must remember a few stages while developing supervised ML. (1) The perpetrator should be aware of the nature of the data used as a basis for the abuse. (2) Data used in the training simulates real-world conditions. (3) Algorithms should reflect a single desirable structure for learning. (4) Using the training data, identify the most important features. Finally, after the parameters and structure of the learning algorithm have been selected, it is possible to measure the correctness of the method mapping the outcome variable using a different test set from the training data set. WSNs employ supervised ML models to address a variety of issues, including as object identification and tracking, location query processing, activity recognition, quality of service, penetration testing, and other safety-related concerns. The following is a presentation of the most popular supervised learning algorithms.

K-Nearest Neighbor

Based on similar data samples, K-NN ML can classify a dataset. By flipping over the tag that appears often in the k training instances next to the skepticism point, the skepticism point is recorded. K is a custom parameter that the user may override. Mainly used for the purposes of classifying and regressing When the learner has had a chance to compare the values of the two sets of data, the trainer has introduced the new data to him or her. A smaller amount of k is chosen from a novel set of data as a new class, while the rest is selected from the prime data set. Using K nearest neighbor, computation costs are low, allowing sensor networks to function more effectively. Calculating sensor node sense of absence can be done by looking at neighboring sensor nodes' average distance from the sensor node. A subsystem of the WSN's query processing is built using the k-nearest-neighbor algorithm. By averaging its neighbor nodes' knowledge, the authors in [1] introduced a method for evaluating several lost networks via k- NN. K nearest neighbor's most useful application in WSNs is query processing; however, the K-nearest neighbor (KNN) algorithm has the drawback of requiring large amounts of data from the environment to be stored. K-nearest neighbor boundary tree technique was created by [2]. When an application administrator queries a node outside the boundary location, the node's k-NN region is automatically regulated. 3D-KNN developed by [3] was used in this query processing. K-NN nodes are deployed in 3D space, and these processes limit query processing in this context. The kNN concept was used by the authors in [4] to describe a single target.

Neural Networks

The biological idea of a neuron is the ancestor of the neural network. The receptive neuron received the impulses, analyzed them, and then transferred the messages to another neuron over the same connection. If you are looking for a solution to an issue that falls into one of the seven categories listed above, neural networks may be the best option. The use of neural networks in WSNs is still not widespread because of the high computational demands for training data with reference to sets of networks. The strength of the input signals, transmission angle, and measuring distance are the primary determinants of a sensor node's location in a WSN.

Designed for fire and rescue, the WSN has been rigorously tested. Authors in [5] used neural networks to study forest fire detection in real time. Neural network processing is used to sift through large amounts of data and transmit just the most relevant information to the decision makers. The authors in [6] described a method for determining air quality that relies on neural networks while also removing the reliance on temperature and humidity sensors. The authors in [7] came up with a new way to use neural network algorithms to systematize light inside an elegant construction. Neural networks use Illuminated Matrix to assess the luminance level of a lighted square using the luminance scale. Authors in [8] devised a neural network-based method for predicting sensor node steadfastness. Steadiness is a term used to describe a sensor node's availability, reach, survival, and upkeep. Neuronal networks can also be used to track down energetic activity on additional nodes, as well as the factors contributing to it. By flooding the network with large numbers of error messages, the DoS attack blocks the transmission of useful data. In [9], researchers used a neural network to prevent false flooding signals by evaluating Packet Request Rate (PRR), and the Average Packet Waiting (APW) time. Processing time is used to reduce transmission collisions. Multiple access protocols with time separation have been introduced, resulting in a sporadic instance outline that divides the medium access between divergent nodes. The system’s centralized unit allocates the present timeslot to every sensor node.

Decision Tree

Using a tree-like graph or model of possible outcomes, such as chance events and resource costs and utility, in a decision-support tool known as a decision tree is possible. These diagrams are frequently employed in ML and data mining. There are two types of nodes in a decision tree: those that are simple and those that are complex. There are two types of nodes: those that represent decision rules and those that represent the outcomes of those decisions. In predictive modeling, decision trees are increasingly popular because they can be understood by people who aren't statisticians. When doing a DT assessment, a tree structure is employed to clearly depict the link between the discrete predictor variables and its related independent variables. With both continuous and discrete independent factors, the DT approach has several benefits. This non-parametric modeling method makes no assumptions regarding dataset. Finding out which independent variables best explain a given binary dependent variable's outcome is the goal of the analysis of DT. When it comes to DTs, "if-then" logic can be used to decompose into "yes" or "no." For each split in DT algorithms, there are one or more mutually limited subsections. The target (dependent) variable should be included in all data subsets generated as much as possible.

The CHAID (chi-squared automatic interaction detection) technique was developed as the first tree-based classification approach. Most typically, ordinal variables are derived from continuum predictors. The merging, separating, and eventually terminating phases are the most important elements of the algorithm. The technique of dividing prospective parents is utilized to discover the optimal split; the splitting step specifies which independent variables are used for the node. This method. Stopping rules are checked to see whether the tree-growing process should be interrupted (e.g., attaining the maximum depth of the tree or the minimal child or parent node). Earlier this year, Biggs et al. introduced a revised CHAID method referred to as “Exhaustive” i.e., E-CHAID. E-CHAID alters the CHAID method to make it more computationally expensive, which enhances the integration and screening of predictor variable. Merging occurs until there are only two remaining subcategories in the E-CHAID method. It's probable that E-CHAID won't operate well with huge datasets that include a substantial percentage of continuous predictors because of this. The CHAID algorithm's dividing and halting phases are then carried out by the software. Because the CART process grows as a fully binary tree, it is distinct from CHAID. A parent node is usually divided into two child nodes in CART results, making it easy to interpret Partitioning data using a full binary tree technique yields homogenous groupings of data. To prevent overfitting, we first build the maximum tree, then trim it.

Support Vector Machine (SVM)

The SVM procedure-centric learning approach is critical to the classification of data using ML. The margin calculation divides the data into two categories. Unfasten class patterns are separated from fasten class patterns, resulting in an apparent gap in the SVM representation. As a result of this information, models can predict where these new paradigms will bury themselves. Malicious nodes may be detected in WSN by studying geographical and temporal data correlation. WSN observations are used to divide the space into segments by SVM. A substantial partition gap is used to divide these portions. Innovative analysis will be arranged based on where they sink in the chasm. If you're looking for ways to improve the security and locate the sensors in your wireless sensor network then SVM can help. A WSN requires routing in order to transfer data between sensor nodes and their destinations. Every time information is transmitted, eavesdroppers are on the lookout for ways to steal data from it. Routing Replies (RREP) are sent by malicious nodes when they receive route requests (RREQ). These replies indicate the route to the fraud destinations. We call this tactic "selective forward assault." A black hole and a selective forward attack can be detected using band width, hop count, and routing information. Outliers can also have a negative impact on performance.

The QSSVM method was used by the authors in this one class. As a result of the use of distributed approaches, which reduces communication and complexity between sensors, there is less power and less accuracy from these sensors.When an intrusion occurs, the integrity and confidentiality of the sensor network are put at risk. Imperviousness algorithms for complexity resolution were inspired by biological immunity systems, according to the authors of [10]. Sensor node data is first processed using an immune algorithm, and then SVM is used to detect intrusions. Outlier sensors can be identified using the Ellipsoidal single class SVM's capability to assess temporal and spatial correlations in the obtained results. It is also investigated whether SVM can be used to locate sensor nodes over a large area. Using appropriate training data, the authors in [11] propose a method for achieving localization. For localization, this algorithm employs metrics such as sensor node connectivity information, indicators, and fast activity. It's possible to improve the efficiency of machine learning algorithms by utilizing SVM techniques

Bayesian Network

Additionally, Bayesian network is an illustration of arbitrary variables as well as their conditional dependence. It is mostly used for the purposes of clustering and categorization. The conditional probability is used to plan Bayesian networks, which construct trees depending on their likelihood of occurrence. Although Bayesian networks need a smaller number of training samples than other machine learning algorithms, Bayesian networks use current data knowledge to update sooner to a higher level of confidence than other ML techniques. It is possible to evaluate the stability of an event utilizing partial data sets by using Bayesian networks. In WSN's, Bayesian networks are utilized to identify activity.

Detection of body gesture and movement are proposed by the authors in [12]. It is mostly a hidden Markov model that's applied to each sensor node on the patient's body. Decide on the sensor nodes that will gather the most information about the user's gestures. A Bayesian network structure may be used to generate self-regulating nodes forecasts in order to reach the ultimate gesture option. Bayesian networks may also be used to locate a sensor node based on its radio frequency, received signal angle, etc. To conserve energy, authors in [13] developed a method that employs a Bayesian model network for the times when channels are available. Instead of continuously broadcasting observed mechanisms, we may conserve network and node energy by using the MAC protocol, which is employed in this manner together with sleep intervals for nodes network wide. Using Bayesian belief networks. Outlier detection in Bayesian belief networks was devised by authors of [14]. Relative readings from Sensor nodes are utilized to assess whether there are any potential outliers gathered in the statistics based on conditional probability holding between nodes.

Unsupervised ML

There is no requirement for a training data set for unsupervised learning methods. They take what they've learned from one collection of data and apply it to a new one. Making comparisons between sets of data to classify them. Node clustering and data aggregation are two of the most common uses of unplanned algorithms.

K-Means Algorithm

For unlabeled data, k-means is the algorithm we use. The k-means algorithm is able to separate data into distinct groups. Items that represent the same or similar characteristics are grouped together. As a result of the given characteristic, it emits and allocates k clusters and data sets to each one. There is a nucleus to a cluster that is defined by the average values within it. In WSNs, the k mean algorithm is commonly used due to its simplicity and linear complexity. Randomly select k nodes as cluster centers and map each node to its nearest centroid. The centroids should be computed using a cutoff value equal to the sum of the intervals between nodes. There is a lot of computing and analysis involved when surveillance collects a large amount of data. It is a mobile sensor that employs the K-means technique to divide up the data it detects into distinct clusters. It is utilised to supervise and collect critical data by adding an additional optimization algorithm to the initial tracking method. Outliers are a problem for k-means because it's easy to implement and has low complexity.

Principle Component Analysis

PCA, a data compression and dimension reduction algorithm, can compress and shrink a large data set into a manageable set of variables. Thus, a small number of unrelated variables known as principal components are generated as a result of this. If possible, each subsequent version should have a high degree of scalability to accommodate changes in the data. Reduce the amount of data transmitted by WSN nodes using PCA rather than calculating the uncorrelated components that contain the original readings. PCA reduces the amount of time needed to analyze large sensor data sets in order to solve event detection problems. Using PCA, soaring discrepancy components are extracted from chronological records in a SQL request. Using this query data, sensitive information can be retrieved from the sensor nodes. Extraction of the original attributes is done using Reverse PCA. PCA further reduces the transmitted data by focusing on a small portion of the original readings. Wireless sensor networks and PCA methods are used to gather information from a small number of variables and use that information to solve a problem.

Reinforcement Learning (RL)

In the model of Reinforcement Learning (RL), programmers establish an approach of assigning designated behaviours and potentially punishing the negative ones. This approach allocates positive values to the required actions in order to encourage agents and the negative ones to the undesired actions. In order to find the best solution, the agent is taught to focus on the long-term and overarching reward. These long-term objectives prevent the operative from stalling out on smaller objectives. The agent eventually learns to eliminate the negative and instead focus on the positive aspects of the situation. Unsupervised ML can be guided through the use of rewards and sanctions using this learning method, which has been widely adopted in AI. Whenever a clear reward is available, it is possible for reinforcement learning to take place. Enterprise Resource Management (ERM) can allocate restricted resources among different tasks if RL techniques are used and there is an overarching goal. In this case, the goal is to save be to save money or time.

IV. ML FOR NETWORKING

Optimal Node Deployment and Localization

WSN deployment and localisation of sensor nodes are intertwined concerns that must be addressed together. Algorithms for determining the location of a node can vary greatly depending on the strategy used to deploy the nodes. A walking GPS method, for example, can be used to locate sensor nodes that have been individually distributed. The GPS approach could be of a high cost and time-consuming in case the sensor nodes were widely distributed. For example, data transmission, message delivery time, and relative alignment may be utilized to determine the sensor's position using ML techniques.

Deployment

Fuzzy deployment schemes for WSN surveillance applications were developed by the author of [15]. It is assumed that the ecosystem is homogenous for the majority of node deployments. Assuming this premise, the influence of terrain profiles (such as barriers, elevation, criticality of a given place, and so on) has been overlooked If the region under observation is vital, additional sensors may be needed. However, these profiles may still be significant in the deployment of the node. Choosing an effective node spread pattern to maximize information acquisition is how [16] formulates the deployment issue. As a first step, each of the sub-areas in the study region is given its novel terrain profiles. Secondly, the nodes in each sub-area are calculated using a fuzzy logic technique based on the terrain profile.

Simulations show that the fuzzy distribution strategy may increase the surveillance system's scope and collect more information. [17] proposes a fuzzy optimization approach for adjusting sensor locations following a random deployment. In [18], fuzzy logic is used to establish an ideal dispersion of nodes in the field so that more information may be gleaned. Additionally, the procedure in [19] requires that the nodes have some mobility - one may move them around depending on some local and global communications. Nodes are only re-deployed (or adjusted) once they have been randomly distributed in the field. [20] provide a fuzzy deployment strategy that is only suitable for field observation. Near-optimal sensor deployment models that optimize information acquisition while minimizing communication costs are introduced by the authors of [21] irrespective of the application. This concept may be used for a variety of WSN applications, not only monitoring.

Localization

For both connectivity and application purposes, location data is essential. Detector event grouping and reporting as well as energy-conscious routing need an accurate position estimate. Hardware-centric and plausibility theory estimation-centric WSN localization methods are the most common. Fuzzy logic, rather than strict probabilistic fundamentals, is recommended by the authors of [22] for WSN localization. As a grid-based technique, it leverages a node's degree of confidence that it will stay in a particular position to represent its perspective. Fuzzy logic is used to calculate confidence levels, and sensor data such as signal strength and arrival time change is taken into account. The authors of [23] use an evolutionary approach to improve the precision of extant localization techniques by using a micro technique and its rapid expansion. This is a post-optimizer rather than a detection method. By reconfiguring out existing estimates of node locations or cross-over positions for any extant homologous pairs in subsequent generations, two genetic drivers are used to reduce the main objective value systems that are acquired. Based on simulation results, this post-optimizer boosts numerous localization methodologies by 11–18%.

In underwater communication networks, anchors or exterior beacons tied to the Global Positioning System (GPS) keep the sensor nodes in position. Although location is critical for sensor networks, the ocean currents that they are attached to allow most sensor nodes to be moved. Marine environments present unique challenges to the design of portable sensor nodes. A major problem with underwater sensor networks is their inability to accurately locate themselves due to the poor propagation of GPS signals (electromagnetic). Underwater, only acoustic communication can be used to keep a team in touch. Range-free and range-based approaches, dynamic and static nodes, as well as the single and multiphase schemes are all examples of sensor network localization techniques that can be subdivided. However, while simulations demonstrate that all techniques work, actual experimental studies have not been conducted under the same conditions or presumptions. The current state-of-the-art network functions based on and without specificity were examined in this review article. The most critical concerns in routing are bandwidth limitations, high energy consumption, signal propagation delays, and a lack of memory.

To regulate the location of sensors, current systems use grounded nodes that are placed on a predefined map. AUVs and surface buoys, which receive instructions from a command centre, are frequently used in deep water situations. There is a lot of spending on these systems, yet their performance isn't particularly efficient. The location of each sensor node in terrestrial wireless sensor networks is maintained after deployment. Despite this, sensor nodes do not remain in place after deployment in underwater contexts. They instead follow the ebb and flow of the ocean, the tides, and other natural forces.

Attach the shun nodes to specified anchors using cables in order to keep them from deviating from their deployment location. There is a restriction on movement of nodes below the surface. It's been dubbed AFLA, or "Antenna-Free Localization Algorithm," as a result of these findings. AFLA can be used in sensor networks submerged in the ocean or in the deep sea. An anchor node's information isn't needed by AFLA, which instead relies on the association of nearby nodes to gather its information. Static and dynamic networks can both benefit from AFLA. This approach incorporates a self-localization method for an underwater sensor node that is not dependent on an anchor. To locate all nodes, it doesn't need an anchor. An underwater free-moving node location is still a research area that needs to be explored further, even though this method has proven to be effective in underwater scenarios. If you do nothave precise location information, your data is of no use to anyone.

Resource Allocation and Task Scheduling

In WSN research, the most difficult issues are deciding how much time and resources to devote to each project. While energy-aware communications and optimum deployments and localizations both concentrate on improving nodes' unique target functions, optimization issues under these two scenarios rely on the planning and allocation of sensor network in order to meet system objectives, such as balancing network lifespan with information gain. examines and compares three ML methods for the scheduling of radar sensor networks. Various methods, including genetic algorithms, neural networks, and fuzzy Lyapunov synthesis are used. Nodes in a WSN are assigned a basic responsibility to manage system modes by the authors in [24]. As other nodes' status and feedback evolve, so does each node's functioning. Global results are affected by local interactions despite adaptive procedures being specified locally. Camera networks and acoustic networks have been utilized to test the system in the field. For the selection of WSN cluster heads, a novel fuzzy technique is described in [25]. Hierarchical routing in WSNs involves assigning a cluster leader. assigning a node to the position of cluster head is effectively allocating resources to the node under a WSN resource allocation mechanism. There are three elements that are taken into account in this study's fuzzy system: node energy, node concentration and cluster centrality. This method determines which node will serve as the cluster's "head." For example, the network as a whole will last longer due to the more evenly distributed use of energy.

Energy-aware Communications

In many WSN studies, one of the primary goals is to enhance or optimize the overall network's performance in terms of life span of networks and consumption of consumption. In order to make WSNs more energy-aware, most study is undertaken at the network level to develop an efficient routing mechanism, at the physical layer to pick a low-power modulation technique, or at the data link layer to adopt a power-saving mode of operation. But there is a clear trend of ML approaches being used to investigate energy-aware communications in WSNs. Fast, efficient, and dependable data communication channels are critical to many WSN applications, such as sensor networks. However, the loose coupling of WSNs makes their communication lines inherently unstable. Adaptation based on current conditions is therefore used in communication protocols to find the most energy-efficient and healthy routes. Routing optimization in WSNs can now be accomplished using supervised learning, thanks to the work of [26]. In attempt to optimise communication, the algorithm makes use of ML approaches to enhance situational awareness. To put it another way, it makes use of ML to discover the relationships between various features of the input (such as buffer occupancy rates and network-level performance measures like packet length and node transmission power) and the output (e.g., optimal route and link quality).

In sensor networks, energy conservation is a crucial concern. Another problem in sensor networks is the mobility of sensors. A few of the protocols used in land-centric sensor networks include: Rumor Routing (RR), Gradient (GR), and Directed Diffusion (DD), SPIN (SPIN), and TTDD (TT). These protocols are typically designed for application within the network that is at a complete standstill. As a result, many current ground-based routing methods are not suitable for use in the underwater environment. Proactive and Reactive are the two broad categories of routing systems for Earthly sensor networks. They're just incompatible in a watery atmosphere like this! When the topology is modified, Table Driven or Proactive protocols create massive amounts of signaling overhead to build up the routs. Nodes constantly shift around, and because of the huge acoustic signal delays, proactive methods are ineffective in underwater environments. Submarine networks can't employ protocols of this (Reactive scheme) kind because to the long acoustic delays and asymmetrical connection configurations Efforts are being made by researchers to develop protocols that are more effective in an underwater setting.

Level-Based Adaptive Geo-Routing (LB-AGR) protocols traffic could be broken down into four distinct types, as demonstrated by [27]. All sensor nodes downstream of a specific node are considered upstream, as are all sensor nodes downstream of a specific node regardless of where the node is located. As opposed to current underwater sensor network routing protocols, which broadcast packets to every neighbor node, the packet uplink towards the sink is typically forwarded in a unicast form to the best next hop (VBVA and VBF). In order to find optimal hop amongst various suitable clients, Level-Based Adaptive Geo-Routing considered the factors such as level various between the neighboring nodes, location, density and available energy.

Feature extraction and outputs labeling, sample preparation, offline learning, and online categorization are all processes in the ML model of [28]. An acceptable feature vector is selected by use of a feature selection method that takes into account the nature of the challenge at hand. Fast fading, slow fading, traffic patterns, signal intensity, and other network factors are examples of feature vectors in WSNs. Domain knowledge is used to categorize outputs during the output labeling process. Sample gathering is a procedure of collecting data for educational purposes by way of a collection of samples. An additional function of the backend server is to collect and process data. When it comes to architecture, this is referred to as centralized education. A decentralized/distributed learning architecture, on the other hand, can be more practical in many real-world applications where it is impractical or impossible to use a backend server in WSNs

The real learning takes place offline. DT and the rule-centric learner have been discussed by [29]. The approaches have a longer history, but might not be the ultimate algorithm for WSNs since they follow a systematic approach and do not consider the constraints of the resources. Since offline training is considered in the resource-centric backend servers, it is only taken into account during the online classification phase. Many WSN applications have a significant amount of training overhead, so a distributed, efficient, and scalable learning methodology is needed to minimize this overhead. Reinforcement learning for sensor communications is introduced in [30]. To put it another way, the challenge is to maximize sensor communication throughput while conserving energy. It was possible to develop a reinforcement learning-based transmission strategy that was nearly perfect. This method adapts to an inbound rate of traffic, buffers as well as the channel conditions whereas choosing the optimum transmission power and instrument levels. Resultantly, various channel throughput maximization techniques necessitate the state transmission probabilities to be gotten, and this is typically a challenging task to do. However, a Near Optimum Transfer Protocol in the points-to-points cases might be obtained based on the application of ML.

Sensor communications in WSNs are examined by the authors of [31]. Currently, energy-aware routing protocols rely on precise metrics to make routing decisions. As a result, it is not as flexible as it could be when it comes to adapting to new sensor types or application cases. Nevertheless, this does not permit the enhancement of the isotropic detector (detector might be used for different application domains). A human heuristic based on fuzzy logic can be used to extract useful information from uncertain data. A link between two sensor nodes, according to the author of [32], should cost as little as possible. Remaining energy, queue size, and distance to a gateway are all input variables that can be used to calculate link costs. It is necessary to defuzzify in order to derive a crisp link cost value. If a sensor node's ability to transmit data packets is determined by a fuzzy logic controller, the authors of [33] use this controller to determine the link cost. Remaining node energy, data packet type flags, and other such inputs go into the fuzzy controller. The fuzzy controller's crisp output determines whether or not sensor nodes participate in data communication (bridging, forwarding, etc.).

V. ML FOR INFORMATION PROCESSING

The processing of WSNs data integrates three key phases: Data pre-processing, collection of data, and data extrapolation. Data pre-processing represents the initial phase of data processing. Other basic operations on raw data (smoothing, scaling, etc.), as well as noise filtering, are offered. Sending datasets to the WSN's inference or fusion center is known as aggregation. It is possible to extract hidden information from a huge dataset using machine learning (ML) algorithms. Many research is looking at how machine learning algorithms may be used to infer (the third step in the processing of WSNs data) such as object classification in WSNs and recognizing abnormal occurrences in an environment monitoring WSN based on sensor data. We'll examine a few of them in more detail on the following pages. Machine learning (ML) methods may and should be used in all three processes, it is commonly agreed.

Information Processing

Data collection, preprocessing, neural network building and application are all covered in [34] for how wavelet neural networks may be utilized to manage information in WSNs. There are a variety of multidimensional data series analysis techniques that WSNs use, e.g., the searching for kNN and PCA. For nearly half a century, NN algorithms have been established that were suited to the data processing needs of the WSN, including distributed computation, robust data acquisition and query, as well as classification of data sets. These findings are supported by research. Algorithms like ART (Adaptive Resonance Theory) and FuzzyART (Fuzzy Adaptive Resonance Theory) were proposed. WSN heads must be trained using an unsupervised learning method that only produces sub-global classifications in order to get single globalized results.

Target Monitoring in WSNs

Meng, Wang and Xia [35] define an acoustic surveillance WSN using an unscented Kalman filter and neural network. WSN simulation errors are corrected using a BP (back propagation) neural network, and multidimensional relationships are inferred using a typical Unscented Kalman Filter (UKF). The BP NN (Neural Network) determines the approximate bias between the UKF throughput and the current condition when the input data are modified. Algorithms linked to mobile robots are included in [36]. For the purpose of following a target via wireless sensor networks, it uses an improved form of SLAM Simultaneous Localization and Mapping (SLAM). The Bayesian filter's capacity to automatically average out sensor measurement noise may be a factor in improved tracking and location accuracy in high-traffic regions. The most widely used algorithms for multi-target tracking make advantage of probabilistic information association. As stated in [37], it is difficult to apply the method when the number of targets fluctuates significantly (due to the curse of dimensionality). This study presents the ADMAN (Approach for Detection of Multi-target Acoustic Networks) algorithm that is immune to the dimensionality curse and can handle ever-increasing targets.

Event Categorization and Detection of Target Classes
Various WSN monitoring systems necessitate the tracking and classification of detected targets in the field. Using their sensor data, WSNs monitoring the environment must be able to detect any abnormalities in the environment. Statistical pattern recognition-related ML issues are addressed here. There is a wealth of information available to help with classification. In the spectral domain, wavelet and spectral methods may be used to retrieve the feature representation spanning diverse targets. TESPAR is a technique for extracting time-domain features (Time Encoded Signal Processing and Recognition). Feature vectors of a predefined size are generated from sensor information (acoustic sensor waveform). In order to classify targets, a neural network is used after the matrices have been created. Classifying objects in WSN may be accomplished using the same machine learning methods as were presented by the author of [38]. Every sensor node has an accelerometer that changes its waveform as a result of human movement. SVM and PCA methods are used to cluster and classify this transition in the waveform by the sensor node using PCA.

VI. OPEN CHALLENGES AND RECOMMENDATIONS

Standardized Datasets, Issues, Data Representations and Assessment Metrics

Standard Dataset
An MNIST-based computer vision dataset is essential for comparing different machine learning approaches. In order for ML algorithms to learn properly, they will require a lot of data. To guarantee that the data can be replicated, it is best to have consistent data creation and gathering protocols in place. Some wireless challenges may need a decrease in details of a genuine system due to the fact that [39] reveals that RF signals may be synthesized (e.g., RF gadget fingerprinting). These benchmarks and datasets are still difficult to standardize. There is a lot of work that needs to be done by the wireless scientific community to generate and exchange massive datasets.

Standard Problems
In the future, researchers should define a collection of wireless network challenges that may be used to compare and test supervised and unsupervised learning systems. Standard datasets should be available to help with these issues. For example, the mageNet and MNIST data are often used in computer vision to assess image processing algorithms for picture identification tasks. For example, beamforming, spectrum control and demand forecasting are only some of the common wireless network issues that arise. The design of these difficulties needs special research attention.

Standard Data Representation
DL is rapidly being employed in wireless connections; however, the best data representation remains a mystery. An I/Q samples may be described as either a solitary complex number, tuple of real numbers, or as the magnitude and phase components of their coordinates, for example. Whether or whether there is a single answer for all learning problems is a hot topic of dispute. Additionally, the DL design, the learning aim, and the loss function may all influence how the data is represented.

Standard Evaluation Metrics
A consistent set of measures for assessing and comparing various machine learning models should be developed when standard datasets and challenges have been identified. According to a typical issue, there may be a set of measurements. The following are some examples of key metrics: confusion matrix, accuracy, precision, F-score, recall, mean squared error, etc. (only to name a few). There may also be additional assessment metrics taken into consideration in the evaluation section such as computational complexity, processing overhead, training and prediction time and necessary data size, for example.

Application of ML Models in Real-life Wireless Systems/Platforms
A significant role for Machine Learning (ML) will be played in the growth of wireless systems in the future. However, even if ML is strong, operating it on a single system might be a strain. In addition, the success of DL requires a large volume of data, which puts additional strain on the wireless connection. As a result, improving our knowledge of how to easily and quickly incorporate ML/DL discoveries into restricted computing systems is of critical relevance. What are the network's prerequisites to support the gathering and transmit of massive amounts of data?

Constraint Wireless Devices
Nodes in the Internet of Things (IoT) are often low-cost devices with limited storage, energy, computing power and connection bandwidth. This is not uncommon. Due to the limits of the devices, they are being deployed on, complex ML models encounter a variety of challenges. There is an increased need for hardware and power usage for models of ML that include a high number of neurons, layers and parameters during training as well as in inference.

Reducing Complexity of ML Models
On constrained devices, ML/AI is well on its approach to becoming commonplace. Early achievements in hardware, systems, and learning algorithms are showing promise. Rather of using 32- or 16-bit parameters, binary deep architectures

described in [40] use just 1-bit weights, allowing for simpler models and cheaper calculations. Their capacity to adapt and function effectively in real-world situations is still a concern.

Distributed ML Implementation

Distributing the ML calculation burden over numerous nodes might be another solution to this problem. For example, "Which element of the classification algorithm can be dissected and dispersed?" "How are input data and extract calculated values exchanged among the devices?" "Which device is accountable for the assembling of the final model performance?" and so on are pertinent issues.

Architecture for Data Collection and Transfers

Scalable networking design is needed because the number of network connections and traffic they create is increasing at a fast pace. Large volumes of data must be sent due to the following factors: There are no standards or protocols that can effectively send 100+ Tbps of data per second, making it impossible to analyze the network in real time. Using fog computing/analytics may be a viable solution to this issue. A reduction in or total avoidance of big data transmissions to the cloud via fog computing could result in a substantial network performance increase. Attention must be taken while putting these principles into reality. Cloud computing technology, such as server virtualization, parallelization, and expandable storage, may minimize the cost of analyzing and processing data.

SDN for Network Management

As a new networking paradigm, Software-Defined Networking (SDN) has recently gained a lot of attention. It is difficult to use machine learning to govern and run conventional networks because of the network's dispersed structure. SDN has emerged as a promising enabler for providing intelligence in the network. Breaking vertical integration and introducing the capacity to design a network are the primary goals of SDN, which consists of detaching the control plane from the forwarding plane. In other words, with SDN, feedback control can be logically centralized, and decisions can be made by a network controller with a global network view. There is no limit to how finely granular the controller may get information from various tiers of the network protocol stack, from the physical layer to the data link and network layers, and even to the application layer. A global view of the network, on the other hand, simplifies network management and control.

VII. CONCLUSION

Machine Learning (ML) approaches used in Wireless Sensor Networks (WSNs) are examined from both networking and information processing viewpoints in this paper. ML been used to solve issues such as optimum sensor application, energy-aware communication, task scheduling and resource allocation in WSNs. Data conditioning, machine inference, and other types of information processing are among the many application domains in which ML approaches are often used. When compared to standard machine learning, WSN's ML-based information processing is still in its infancy. Currently, the majority of WSN research is focused on applying ML approaches to a specific issue. ML algorithms may be used in a variety of ways by various academics, with varied assumptions, application circumstances, and preferences. These discrepancies provide a significant obstacle to researchers' ability to build on one another's work in order to amass research findings for the community. As a result, a unified design throughout the WSN ML community is required.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author(s) declare(s) that they have no conflicts of interest

References

[1]. Ö. Ertuğrul and M. Tağluk, "A novel version of k nearest neighbor: Dependent nearest neighbor", Applied Soft Computing, vol. 55, pp. 480-490, 2017. Doi : 10.1016/j.asoc.2017.02.020.

[2]. J. Li and Y. Wang, "A new fast reduction technique based on binary nearest neighbor tree", Neurocomputing, vol. 149, pp. 1647-1657, 2015. Doi : 10.1016/j.neucom.2014.08.028.

[3]. S. Satkin, M. Rashid, J. Lin and M. Hebert, "3DNN: 3D Nearest Neighbor", International Journal of Computer Vision, vol. 111, no. 1, pp. 69-97, 2014. Doi : 10.1007/s11263-014-0734-4.

[4]. P. Gupta and G. Kaur, "A Concept of A-KNN Clustering in Software Engineering", International Journal of Computer Applications, vol. 119, no. 18, pp. 25-28, 2015. Doi : 10.5120/21168-4235.

[5]. K. E and P. Jadhav, "A Study Paper on Forest Fire Detection Using Wireless Sensor Network", International Journal of Psychosocial Rehabilitation, vol. 23, no. 4, pp. 397-407, 2019. Doi : 10.37200/ijpr/v23i4/pr190199.

[6]. G. Corani, "Air quality prediction in Milan: feed-forward neural networks, pruned neural networks and lazy learning", Ecological Modelling, vol. 185, no. 2-4, pp. 513-529, 2005. Doi : 10.1016/j.ecolmodel.2005.01.008.

[7]. S. Maity and S. Hati, "Adaptive Technique for CI/MC-CDMA System using Combined Strategy of Genetic Algorithms and Neural Network", Network Protocols and Algorithms, vol. 4, no. 1, 2012. Doi : 10.5296/npa.v4i1.1330.

[8]. C. Yalkın and E. Korkmaz, "NEURAL NETWORK WORLD: A NEURAL NETWORK BASED SELECTION METHOD FOR GENETIC ALGORITHMS", Neural Network World, vol. 22, no. 6, pp. 495-510, 2012. Doi : 10.14311/nnw.2012.22.030.

[9]. G. Cervera, M. Barbeau, J. Garcia-Alfaro and E. Kranakis, "A multipath routing strategy to prevent flooding disruption attacks in link state routing protocols for MANETs", Journal of Network and Computer Applications, vol. 36, no. 2, pp. 744-755, 2013. Doi : 10.1016/j.jnca.2012.12.013.

[10]. W. Drzewiecki, "Thorough statistical comparison of machine learning regression models and their ensembles for sub-pixel imperviousness and imperviousness change mapping", Geodesy and Cartography, vol. 66, no. 2, pp. 171-210, 2017. Doi : 10.1515/geocart-2017-0012.

[11]. Y. Sun, W. Meng, C. Li and X. Wu, "Panoramic Camera-Based Human Localization Using Automatically Generated Training Data", IEEE Access, vol. 8, pp. 48836-48845, 2020. Doi : 10.1109/access.2020.2979562.

[12]. "Gesture Movement Detection Based on IoT", JOURNAL OF XI'AN UNIVERSITY OF ARCHITECTURE & TECHNOLOGY, vol., no., 2020. Doi : 10.37896/jxat12.03/129.

[13]. T. Chan, H. Ross, S. Hoverman and B. Powell, "Participatory development of a Bayesian network model for catchment-based water resource management", Water Resources Research, vol. 46, no. 7, 2010. Doi : 10.1029/2009wr008848.

[14]. M. Lampis and J. Andrews, "Bayesian belief networks for system fault diagnostics", Quality and Reliability Engineering International, vol. 25, no. 4, pp. 409-426, 2008. Doi : 10.1002/qre.978.

[15]. J. Chen, S. Li and Y. Sun, "Novel Deployment Schemes for Mobile Sensor Networks", Sensors, vol. 7, no. 11, pp. 2907-2919, 2007. Doi : 10.3390/s7112907.

[16]. T. MEI, X. WANG and J. ZHANG, "THE PROCESS AND MODEL OF INFORMATION ACQUISITION", International Journal of Information Acquisition, vol. 01, no. 02, pp. 101-108, 2004. Doi : 10.1142/s0219878904000197.

[17]. G. Walster and V. Kreinovich, "Computational complexity of optimization and crude range testing: a new approach motivated by fuzzy optimization", Fuzzy Sets and Systems, vol. 135, no. 1, pp. 179-208, 2003. Doi : 10.1016/s0165-0114(02)00254-3.

[18]. V. Novák, "Which logic is the real fuzzy logic?", Fuzzy Sets and Systems, vol. 157, no. 5, pp. 635-641, 2006. Doi : 10.1016/j.fss.2005.10.010.

[19]. J. Gustafsson and K. Polynczuk-Alenius, "Media and Communication between the Local and the Global", Media and Communication, vol. 6, no. 2, pp. 145-148, 2018. Doi : 10.17645/mac.v6i2.1637.

[20]. N. Manteghi and A. Zohrabi, "A proposed comprehensive framework for formulating strategy: a Hybrid of balanced scorecard, SWOT analysis, porter‘s generic strategies and Fuzzy quality function deployment", Procedia - Social and Behavioral Sciences, vol. 15, pp. 2068-2073, 2011. Doi : 10.1016/j.sbspro.2011.04.055.

[21]. M. Argany, F. Karimipour, F. Mafi and A. Afghantoloee, "Optimization of Wireless Sensor Networks Deployment Based on Probabilistic Sensing Models in a Complex Environment", Journal of Sensor and Actuator Networks, vol. 7, no. 2, p. 20, 2018. Doi : 10.3390/jsan7020020.

[22]. G. Zhang and H. Li, "An Efficient Configuration for Probabilistic Fuzzy Logic System", IEEE Transactions on Fuzzy Systems, vol. 20, no. 5, pp. 898-909, 2012. Doi : 10.1109/tfuzz.2012.2188897.

[23]. M. Nardini and J. Dunning, "Pulmonary nodules precision localization techniques", Future Oncology, vol. 16, no. 16, pp. 15-19, 2020. Doi : 10.2217/fon-2019-0069.

[24]. S. Babu, A. Raha and M. Naskar, "Trust Evaluation Based on Node’s Characteristics and Neighbouring Nodes’ Recommendations for WSN", Wireless Sensor Network, vol. 06, no. 08, pp. 157-172, 2014. Doi : 10.4236/wsn.2014.68016.

[25]. Sheng-Fu Liang, Shih-Mao Lu, Jyh-Yeong Chang and Chin-Teng Lin, "A Novel Two-Stage Impulse Noise Removal Technique Based on Neural Networks and Fuzzy Decision", IEEE Transactions on Fuzzy Systems, vol. 16, no. 4, pp. 863-873, 2008. Doi : 10.1109/tfuzz.2008.917297.

[26]. M. Gurupriya and A. Sumathi, "HOFT-MP: A Multipath Routing Algorithm Using Hybrid Optimal Fault Tolerant System for WSNs Using Optimization Techniques", Neural Processing Letters, 2022. Doi : 10.1007/s11063-022-10852-3.

[27]. X. DU, K. HUANG, S. LAN, Z. FENG and F. LIU, "LB-AGR: level-based adaptive geo-routing for underwater sensor network", The Journal of China Universities of Posts and Telecommunications, vol. 21, no. 1, pp. 54-59, 2014. Doi : 10.1016/s1005-8885(14)60268-5.

[28]. S. Ren, X. Gu, P. Yuan and H. Xu, "An iterative paradigm of joint feature extraction and labeling for semi-supervised discriminant analysis", Neurocomputing, vol. 273, pp. 466-480, 2018. Doi : 10.1016/j.neucom.2017.08.003.

[29]. "Reawakening the learner: creating learner-centric, standards-driven schools", Choice Reviews Online, vol. 50, no. 05, pp. 50-2799-50-2799, 2013. Doi : 10.5860/choice.50-2799.

[30]. S. Soni and M. Shrivastava, "Novel Learning Algorithms for Efficient Mobile Sink Data Collection Using Reinforcement Learning in Wireless Sensor Network", Wireless Communications and Mobile Computing, vol. 2018, pp. 1-13, 2018. Doi : 10.1155/2018/7560167.

[31]. M. Khanafer, M. Guennoun and H. Mouftah, "Priority-Based CCA Periods for Efficient and Reliable Communications in Wireless Sensor Networks", Wireless Sensor Network, vol. 04, no. 02, pp. 45-51, 2012. Doi : 10.4236/wsn.2012.42007.

[32]. D. Penkin, G. Janssen and A. Yarovoy, "Impact of a half-space interface on the wireless link between tiny sensor nodes", Radio Science, vol. 49, no. 9, pp. 798-811, 2014. Doi : 10.1002/2013rs005365.

[33]. K. K.M.MAKWANA, D. Dr.B.R.PAREKH and S. SHINKHEDE, "Fuzzy Logic Controller Vs Pi Controller for Induction Motor Drive", Indian Journal of Applied Research, vol. 3, no. 7, pp. 315-318, 2011. Doi : 10.15373/2249555x/july2013/97.

[34]. M. Hassan and I. Hassan, "Improving Artificial Neural Network Based Streamflow Forecasting Models through Data Preprocessing", KSCE Journal of Civil Engineering, vol. 25, no. 9, pp. 3583-3595, 2021. Doi : 10.1007/s12205-021-1859-y.

[35]. L. Meng, H. Wang and S. Xia, "TOA Estimation Method in Frequency Domain for Acoustic Ranging of WSN Node", Journal of Electronics & Information Technology, vol. 32, no. 4, pp. 993-997, 2010. Doi : 10.3724/sp.j.1146.2009.00127.

[36]. Y. Kang, B. Xue and R. Zeng, "Self-Adaptive Path Tracking Control for Mobile Robots under Slippage Conditions Based on an RBF Neural Network", Algorithms, vol. 14, no. 7, p. 196, 2021. Doi : 10.3390/a14070196.

[37]. I. Kim, M. Khan, T. Awan and Y. Soh, "Multi-Target Tracking Using Color Information", International Journal of Computer and Communication Engineering, vol. 3, no. 1, pp. 11-15, 2014. Doi : 10.7763/ijcce.2014.v3.283.

[38]. H. BI, H. LIANG and J. WANG, "Resampling Methods and Machine Learning", Chinese Journal of Computers, vol. 32, no. 5, pp. 862-877, 2009. Doi : 10.3724/sp.j.1016.2009.00862.

[39]. M. S.V, "Precision Agriculture Using Wireless Sensor Network System: Opportunities and Challenges", International Journal Of Engineering And Computer Science, 2016. Doi : 10.18535/ijecs/v5i11.70.

[40]. Raghavendra, AVIvizienis and Ercegovac, "Fault Tolerance in Binary Tree Architectures", IEEE Transactions on Computers, vol. -33, no. 6, pp. 568-572, 1984. Doi : 10.1109/tc.1984.1676483.