A Survey on Machine Learning-Based Performance Improvement of Wireless-Networks: PHY, MAC and Network layer

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Abstract— **This article gives a systematic, complete overview of the latest research results of implementation improvements for remote systems based on machine learning (ML). First, discuss related work and written commitments, and then provide non-machine learning experts with information-driven methods and basic knowledge of machine learning for non-machine learning experts to view all the checked procedures. Until then, a profound investigation was conducted on the use of ML-based methods to handle advanced remote communication parameter settings to complete the improved system management properties (QoS) and experience properties (QoE). We initially devolved these works into radio inspections, MAC surveys, and system forecasts, and tracked after each subcategory. Finally, it discusses the difficulties of openness and broader perspectives.**

***Keywords**: Machine learning , PHY, MAC,* **QoS, QoE).**

I. INTRODUCTION

The expansion of the information age is available in every logical sequence [1], for example, PC vision, discourse confirmation, finance (opportunity check), advertising and transactions (such as customer shock check), drug stores (such as drug disclosure), Customized social insurance (eg, biomarker differentiation evidence in malignant exploration), precision agriculture (eg, agricultural product testing, weed testing), government affairs (eg political and national crusades). Until recent years, this model has rarely been described in the field of remote system management, mainly because of the lack of large amounts of information and "huge" communication restrictions [2]. However, with the advent of the fifth-generation (5G) cell framework and the Internet of Things era, the huge information storm in the field of remote system management has been on track. For example, the use of inevitable sensors in eager urban areas [3] generates a lot of information (for example, screening the availability of parking spaces in urban areas [4], or screening street traffic conditions to monitor and control traffic flow), a clever framework (For example, for checking the status of railways or scaffolding), the accuracy of farming [5] (for example, for checking yield status, soil temperature and humidity), natural observation [6] (for example, pollution, temperature, precipitation detection), The intelligent lattice system of the Internet of Things [7] (for example, screening the propagation network or tracking energy consumption for request prediction) and so on. By 2022, there will normally be 28.5 billion gadgets connected to the Internet [8].

Then, arrangements with profitable communication schedules are also growing. They follow the equivalent restricted radio range assets, and there is an urgent need to upgrade their concurrency and use more and more rare range of assets. In addition, in the field of portable frameworks, the use of general information is greatly expanding. Air conditioners related to Ericsson's latest portability report. There are 5.9 billion universal broadband members worldwide, and each longer telematics traffic generates more than 25 EB of traffic [9], which increased by nearly 88% between the fourth quarter of 2017 and the fourth quarter of 2018!

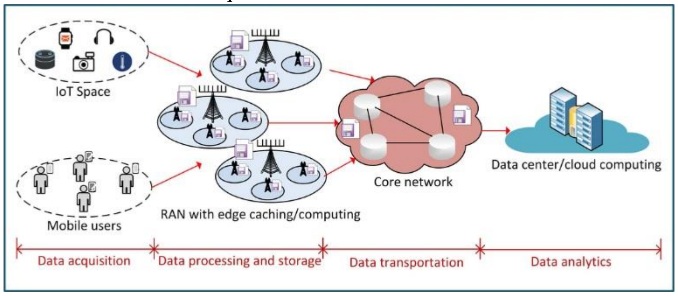

Fig. 1. Architecture for wireless big data analysis

For example, study Figure 1, which demonstrates an architecture with advanced heterogeneous remote access, suitable for collecting a large amount of sensory information from wireless gadgets, processing, and ML estimation, so that the structure can help choose through better Options to update the working boundary and improve the system's QoS thought and experience nature (QoE)

II. DATA SCIENCE FUNDAMENTALS

2.1 Data Science

One meaning of the term information science, gave by Dhār [23],is:

Definition 3.1. *Information science is the investigation of the generalizable extraction of information from information.*

Information science uses data mining, machine learning, artificial intelligence programs, and other different methods, such as heuristic computing, operations research, insight, and causal derivation.

2.2 Data Mining

A very simple definition is:

Definition 3.2. *Information mining alludes to the utilization of calculations for separating designs from the information.*
Contrary to ML [24], information mining usually focuses on solving practical problems, that is, solving the actual problems encountered by misusing the calculations created by the ML staff group. Therefore, first convert the information-driven problem into an appropriate information mining strategy [25], which will be discussed in detail in Section 5.

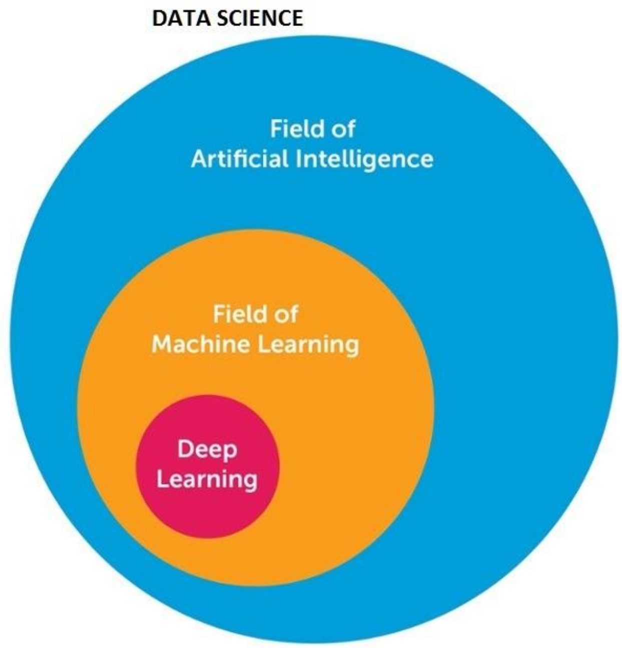

Fig 2: Data science vs. data mining vs. AI vs. ML vs. deep learning

2.3 Artificail Intillegence

As coined by [25], AIis:

Definition 3.3. *The science and planning of making in-Telligent technologies, especially PC structures by duplicating human information through getting the hang of, thinking and self-amendment/adaption.*

Artificial intelligence uses clever experts who will see their condition and carry out activities to increase their risk of effectively achieving their goals

2.4 Machine Learning

As coined by [26]:

Definition3.4.*A PC program is said to gain from experience E as for some class of undertakings T and execution measure P, if its presentation at errands in T, as estimated by P, improves with experience E.*

The foundation of ML experts is to display the newly calculated numerical attributes. Unlike the data mining master, the latter is dedicated to understanding the precise attributes of the existing graphs to which it applies. In the broader prospects of data science, machine learning is taking action to obtain cleaned/changed data and anticipate future results. There is no doubt that ML is no longer a way in another field. With the continuous growth of existing information and progress in identifying and improving equipment, ML has been one of the evaluation hotspots in academia and industry for many years. [27]

2.5 *Deep Learning*

A meaning providing by [28], is:

Definition 3.5. . *Profound learning licenses computational models that are made out of various getting ready layers to learn depictions of data with different degrees of reflection.*

A key ideal situation for in-depth study of standard ML methods is that it can therefore remove enhanced functions from complex data. The learning system should not be arranged by humans, which will greatly simplify the hand-made of existing elements [28].

III. MACHINE LEARNING FUNDAMENTALS

Due to their extraordinary nature, remote frameworks are an interesting application area of data science because they are affected by ordinary wonders and human factors. The basic elements are set in this area for you to study carefully to master the ideas of AI.

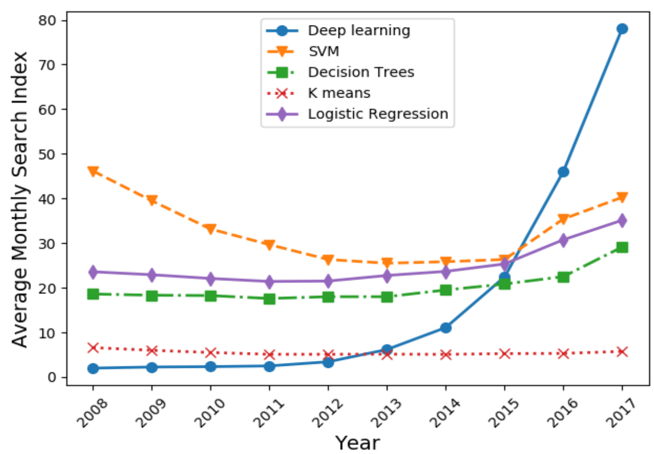

Fig 3: Google search trend showing increased attention in deep learning over the recent years

3.1 The Machine Learning Pipeline

Before applying AI graphics to the problem of remote frame organization, the problem of remote frame organization should be converted into a data science problem. Believe it or not, the entire method from release to game planning can be seen as an AI pipeline with two stages. Figure 5 illustrates these methods, which will be explained immediately below:

Problem definition. In this movement, problems are perceived and transformed into data science problems. Practice by arranging problems as data mining tasks. Section 5 further explains well-known data mining procedures, such as request and back slides, and presents relevant survey data collection on various remote framework organization issues.

The information is ready. After posting the questions point by point and collecting the data, the rough data will be pre-processed to be cleaned and changed to another space, where separately data configuration is addressed by the vector x Rn. This is called a component vector, and its n segments are called features. Through this feature extraction system, each model can be converted into isolated points in n-dimensional space (called component space or data space). By convention, starting with some valuable functions P, and finally selecting the n most useful functions in the component assurance process.

Model preparation. Since the component space where the data is located is depicted, an AI count needs to be set to obtain the model. The system starts by limiting plan data or preparing settings. Allow to merge vectors and consider new production considerations.

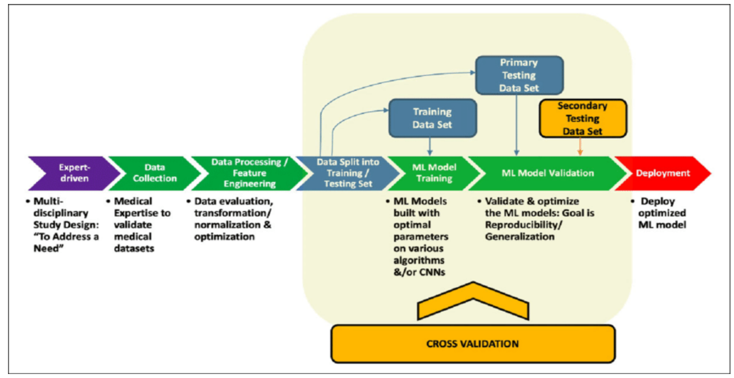

Fig 4: Steps in a machine learning pipeline

3.2 Learning thefeatures

The prediction accuracy of machine learning models depends to a large extent on the decision of the highlights used for information characterization or training. Therefore, when constructing the ML model, a lot of work is devoted to the organization of preprocessing and information change chains. These chains bring about the description of the information that can support successful ML expectations. By the way, this is called the highlight building. Highlight design is the process of displaying, connecting, and controlling highlights by using human creativity and earlier main information to display in more and more representatives. The component extractor φ changes the information vector d Rd to another structure x Rn, n <= d, which is more and more suitable for prediction [29], namely

$$\varphi(\mathbf{d}) : \mathbf{d} \rightarrow \mathbf{x}. \qquad (1)$$

3.3 Types of learningparadigms

This area pondered different sorts of learning models in ML

Directional learning. Trusted learning utilizes predefined inputs, and recognized aspects can build structural models. The role of the data source and the rate of return affect the named "ready" data set, which is used to tell the learning count to best predict the future rate of return of a new data source that does not belong to the arrangement set. The directional learning method is applicable to the remote frame problem where there is existing earth data and can be stamped. Directional learning has been further widely used in various remote framework applications, for example, human development confirmation [29], [30], event recognition [31], power load monitoring [32] security [61], etc. Some of these works will be broken down in more detail later [36].

Learn solo. Independent learning computing strives to find hidden structures in unlabeled data. This unsatisfactory research can be done skillfully only with a promise of no known benefit, and the knowledge can be mastered by performing these studies by finding comparable qualities in the data. Within this scope, these calculations are applicable to remote frame problems, in which there is no previous data on the results, or it is difficult to identify the data (named) in the end. For example, you can use solo learning to group remote sensor centers according to their currently recognized data aspects and land intimacy. (No need to know the social affairs of each center in advance). Regarding remote frameworks, independent learning methods are commonly used: data classification [35], WSN central batch processing [37], [38], data collection [39], [40], event recognition [41] and several abstractions Radio applications [42], dimensionality reduction [44], etc.

Semi-supervised learning. There is some mixing between the two learning methods and it has developed into semi-supervised learning [45]. Semi-coordinated learning is used when there is a limited number of named data and a large amount of unchecked data [43]. It has unprecedented practical considerations because it can reduce the cost of making a fully named plan set, especially if all events cannot be marked. For example, in the human development confirmation system, the changes in activities are shocking. The purpose is to keep some activities unlabeled or customers unwilling to be interested in the protagonist of data collection. Hosted learning may be the best competitor confirmation model [46], [48]. Other potential use cases in the wireless framework may be the restriction structure, which can reduce the tedious social event preparation data (scheduling) system in fingerprint-based game planning [49] or semi-coordinated traffic collection [50]. .

3.4 Offline vs. Online vs. ActiveLearning

Learning can be arranged as discontinuous learning or web-based learning depending on the way information is provided to students [47]. In discontinuous learning, students will immediately prepare the entire preparation information, while in web-based learning, preparation information will be opened in continuous requests and used to refresh the student's representation in each focus.

Learn offline. When the displayed frame cannot effectively change its attributes, discontinuous learning can be used. Disconnected educated models are difficult to implement because the models do not need to continue to learn and can be effectively retrained and redeployed. For example, in [51], a learning-based connection quality estimator is implemented by transferring the disconnected prepared model to the system stack of the Tmote Sky remote hub. The model is prepared based on the measured values of the current state of the remote channel obtained from the extensive survey arrangement conducted from the remote test bench.

e-learning. Web-based learning is very useful for the problem of displaying each model in turn or being unable to perform calculations on the entire data set due to limited resources. For example, in [52].

Active learning. In situations where the cost of obtaining tests from all high-level factors is high, dynamic learning has proven to be valuable. In ML, dynamic learning has always been an important topic, and a comprehensive writing review is beyond the scope of this article. We will mention other subtleties of dynamic learning calculations [53].

VI. MACHINE LEARNING FOR PERFORMANCE IMPROVEMENT IN WIRELESS NETWORK

The execution enhancement of the remote framework depends on the execution pointer and general insights obtained from the device as information (for example, information about the radio medium). These programs abuse ML to generate models or make estimates. These models are used to adjust the working boundaries of the PHY, MAC, and framework layers [54].

Perform data processing on the data transmitted by remote obscene things at the application layer. The order covers a variety of applications, such as IoT natural inspection applications, development confirmation, constraints, precision agricultural integrated enterprises, etc.

4.1 Machine Learning Research for Performance improvement

Observe the information generated during the remote system management infrastructure (such as throughput, start-to-end delay, jitter, bundling failure, etc.) and the information generated by remote sensor gadgets (such as range observation), and may be destroyed by the ml program remote system settings , Along these lines, is comedy in the end customer environment. Different programs have applied ml programs to gain experience to help improve system performance. Depending on the type of information used in the ml algorithm, we initially divided the search order into three types.

- Radio spectrumanalysis
- Medium access control (MAC)analysis
- Network prediction

4.2 Radio spectrumanalysis

The radio range check implies studying the remote information detected by the remote gadget to infer the use of the radio range. Usually, the goal is to distinguish unused scoping
In order to distribute it to other existing customers in the network without generating too much impedance to each other. In particular, as remote gadgets become more and more inescapable throughout society, the accessible radio range

(which is a rare asset) will see more helpless signals than before. Therefore, collecting data about internal signs of conspiracy and scheming becomes increasingly important and complex. This drove the use of ML to dissect signals occupying the radio range. Explained in ML, perhaps the most important task determined by radio range inspection is procedural rule confirmation (AMR). Other relevant radio distance survey tasks that use ML strategies include innovation confirmation (TR) and sign differentiation certification (SI) technologies. Usually, the goal is to detect the vicinity of the signal that may cause an obstacle to stabilize it on the impedance adjustment system. In this way, we present those objects that are getting closer and closer as a remote obstacle recognition (WII) task.
Plan balance confirmation. AMR expects to play a key role in a variety of non-military labor and military applications. It is possible to safely transmit and obtain physical signs, but the opposite signs must be discovered, identified and pasted. Simply put, the purpose of this work is to see a graph of how manufacturers use unrefined instances that rely on unrecognized instances by the authorizing party to manage their transmissions. Programs under development can provide information about manufacturers that exist under such corresponding systems and radio conditions.
Standard AMR estimates are organized into a likelihood-based (LB) method [55] and incorporated into a (FB)-based method [56]. The LB method relies on recognition theory (for example, speculative testing) [57]. Their containers provide extraordinary execution and are regarded as perfect classifiers. In any case, they persist through high computational versatility. Therefore, since the hazard classifier is suitable for convenient use, the FB method is adopted. Conventional FB methods rely heavily on ace data, which may perform well in a definite course of action. In any case, they are poor and dull in clearing pronunciation. Specifically, in arranging the preprocessing time of the AMR estimate, the standard FB method removes the complex hand-planned features (such as certain symbol boundaries) from the rough symbols, and uses a count to select the parity school after a while Inspection plan [58].

Starting very late, remote communication arrangements have made progress by mastering an in-depth learning system for remote areas. In [42], the deep convolutional neural system (CNN) is clearly applied to complex spatio-temporal signal data to collect varying structures. The manufacturer's insidiousness began when CNN defeated the functions in the ace plan and merged with conventional ML classifiers, such as SVM, k nearest neighbor (k-NN), decision tree (DT), neural network (NN), and Naive Bay Yes (note). The elective strategy is to be familiar with the changing process of the signals obtained by various depictions of unrefined symbols. In our [59] work, CNN is used to adapt the criteria for various signs
The crude oil's in-phase and orthogonal (IQ) information descriptions are used to obtain symbols. The other two information descriptions do not affect the directness of the information. We point out that the sufficiency/stage description goes beyond the other two [60], and so on.

Wireless interference recognition. WII basically implies to distinguish the types of remote producers (signals or technologies) that exist in the neighborhood radio conditions. This can be extremely supportive data that can be successful between iron ore escape and concurrency. For example, for progress to work in the ISM group in order to effectively coexist, it is essential to recognize which different producers are available on the planet (eg Wi-Fi, ZigBee, Bluetooth, etc.). Like AMR, FB and ML are also close (for example, using time

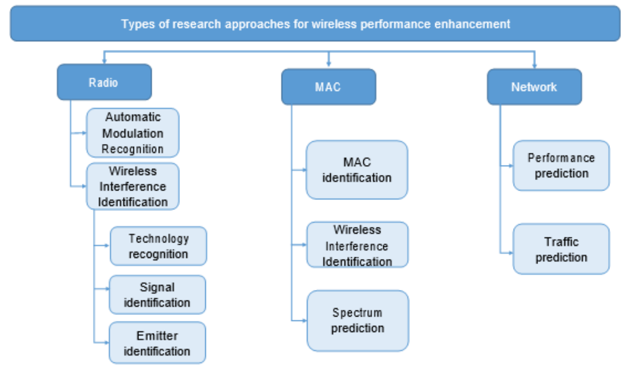

Fig 5: Types of research approaches for performance improvement of wireless networks

(Or the highlighted part that appears repeatedly) can be used for innovative identification, and the identification ID is getting closer. Thanks to the creative menu of the deep learning application for remote sign classification, significant achievements have been made in using it additionally for the WII method.

In [46], the creator uses the signal's time-domain orthogonal (for example, intelligence level) characterization and sufficient/stage vectors to help the CNN classifier improve its understanding of intervention innovations within the ISM. The results of the evil existence indicate that the proposed conspiracy is suitable for distinguishing between Wi-Fi, ZigBee and Bluetooth signals. In [47], we are familiar with the philosophy of end-to-end learning from various signal descriptions, and also explored the recursive region (FFT) description of ISM signals and evil states, that is, the CNN classifier uses FFT information as the external information structure. The CNN model used by the creator in [61]. Similarly, the creator of [62] established a CNN model to encourage the detection and identification of duplicate spatial markers for consistent progress against the 802.x standard. In contrast to the creators in [63], the range check is used in the entire ISM area (80 MHz) as a contribution to the CNN model. In [64], the creator used the CNN model to perform the identification of LTE and Wi-Fi transmissions, depending on the two remote symbol descriptions, especially the IQ and repetitive principle descriptions. The inspiration for driving this methodology was to obtain accurate data on progress in the vicinity of distant conditions to select a suitable mate-U design that would allow reasonable consent to Wi-Fi within an unauthorized range. Different models include [65], and so on.

4.3 Medium access control (MAC)analysis

Sharing mandatory operating resources is the main pressure of remote frameworks [66]. One of the key functions of the MAC layer in the remote framework is to coordinate the channels to the remote media and share mandatory resources in an ad hoc manner. The central point of the wireless self-organizing network (WANET) is denied as a unified structure in which components such as base stations control and disperse resources and need to dominate resources.

Therefore, some MAC displays have been introduced in the portfolio. The ordinary MAC program planned for WANET combines time division multiple access (TDMA) carrier sense multiple access/collision avoidance (CSMA/CA) code division multiple access (CDMA) [67] and cream philosophy [68]. In any case, considering the ever-changing framework and conditional conditions, arranging a MAC display suitable for each understandable condition and diverse application requirements is a test, especially when these conditions are not available or previously unknown. This section will study the progress related to the MAC layer to solve the problem of successful range given to AI. We recognize two arrangements for MAC inspection: I) obvious evidence of MAC, and ii) interference confirmation. Record the MAC assessment allocation for the survey.

Macintosh unique proof. These philosophies are often used in abstract radio (CR) applications to develop correspondence and simultaneity between specific programs. The CRS relies on the information collected during the powerful identification process to explain the state of the earth, the proximity and range holes developed. Scope holes are duplicate bundles that have been distributed to approved frame customers, but are not used at a specific time and can be used by CR customers. As an accomplice, the distinction can be made by choosing the degree of repetition of the ranging holes, while the layout information reaching the boundary in a similar way is darker.

The differentiated proof method of the Macintosh convention can help CR customers determine the planning data of the range gap, while the air conditioner can adjust its bundle transmission period accordingly, which provides potential advantages for arranging implementation improvements. Therefore, some MAC layer attributes may be misused.

Interference recognition. Like the method of identifying obstacles based on the radio range check, the goal here is to identify the type of radio impedance that cancels the performance of the review system. It is possible that, compared to the recently proposed work, the MAC investigation-level work focuses on distinguishing specific highlights between the transmitting channel and the package to identify and measure impedance, thereby identifying the usefulness of the interfering channel and the pioneer transmission in the channel. Choose the right technology and existing obstacles. It is recognized that this depends on the data accessible on handy ready-made gadgets, for example,

Spectrum prediction. In order to share the accessible spectrum in a progressively effective manner, there are various attempts to predict remote media accessibility to limit transmission impact and thus increase the overall execution of the system.

The creator of [69] considered the problem of sharing time opening among many time-open systems in order to maximize the overall throughput of a considerable number of systems. The creator uses ResNet and executes it in comparison with ordinary DNN. Documented Macintosh inspection method.

4.4 Networkprediction

System prediction refers to tasks that are determined by speculating on the remote system execution or system flow based on given historical estimates or related information. Table 7 summarizes the machine learning transactions used for organizational-level expectations tasks, such as I) network execution prediction and ii) network traffic expectations.

The system performs expectations. Machine learning methods are widely used to create conjecture models for certain remote network applications. Generally, the goal is to measure the display or perfect device boundaries/settings and use this data to change the corresponding boundaries to adapt to changing conditions and the necessity of applying QoS, thereby upgrading the overall framework execution.

For example, in [70], manufacturers want to choose the ideal MAC boundary settings in the 6LoWPAN framework to reduce the most serious accidents, packaging disasters and delays. First, the MAC layer boundary is used as a commitment to the NN to predict throughput and laziness, and then the time interval calculation is performed to achieve high throughput with minimum delay. The creator of NN can predict the QoE of the customer in the cell frame, taking into account the throughput of ordinary customers, the number of dynamic customers in the unit, the typical amount of data for each customer, and the channel quality indicators, thereby indicating higher measurement accuracy .

System traffic forecast. Carefully speculate on customer traffic in the unit framework to evaluate and improve system execution. For example, a pragmatic base station rest framework can be balanced by using data on future traffic requirements, which is expected to depend on the NN model. These data have reduced the general electricity consumption, and with the development of the battery business, this has become a noteworthy aspect.

In addition, in [71], manufacturers use CNN and LSTM for common flow measurement and use deep learning. By effectively isolating the common features of the codes, their recommendations are more accurate than conventional systems such as ARIMA.

Highly accurate determination of the amount of data traffic that adaptive customers will consume is becoming increasingly important for carefully handling framework resource tasks on demand. More and more model philosophy can be found in [72].

V. OPEN CHALLENGES & FUTURE DIRECTION

5.1 StandardDatasets.

In order to be able to evaluate between different ML actions, the most basic is to have a common benchmark and standard data set, similar to the open data set MNIST commonly used in PC vision. In order to learn effectively, machine learning computing will require large amounts of data. In addition, there should be undeniable standardized data age/grouping procedures to allow data to be recreated. It is possible to explore in this way to consolidate the design time of RF signals. In any case, some wireless problems may need to subvert the point of interest of a veritable system in the data (such as RF device fingerprints).

Table 1 introduces many conventions to improve vitality, time efficiency, and system strength to expand throughput and limit the delay in sending information to the receiver hub. Guidance conventions are additionally quoted in Table 1. These methods based on bunching have been characterized. We have referred to the various concerns and shortcomings of these guidelines, which have recently been used for information transmission in UWSN. Some practices that have only recently appeared have reduced the utilization of vitality and upgraded the reliability of submerged systems, but exploration is still continuing with high vitality utilization and higher throughput rates. Reduced the misfortune of transmission, prepared for overhead and repeated information transmission.

5.2 StandardProblems

Future research activities should distinguish many common problems in remote systems to encourage scientists to benchmark and compare their regulated/helpless learning calculations. These issues should be supported through standard data sets. For example, in PC vision, which uses PC vision calculation as a reference for image recognition, MNIST and ImageNet data sets are often used. Examples of standard issues in remote systems may be: remote identification of identification, beamforming, range management, remote system traffic request expectations, etc.

5.3 Standard Datarepresentation

DL has been gradually used in remote systems, however, the ideal information description is still vague. In terms of location, the I/Q test can be said to be a single complex number, a real tuple or by the sufficiency of its polar direction and stage estimation. No one in the discussion will provide a portrayal of information suitable for all situations for each learning problem [73]. The ideal characterization of information may depend on different factors such as DL design, learning goals and unfortunate work decisions.

5.4 Standard evaluationmetrics

After distinguishing between standard data sets and problems, future research activities should recognize many of the standard metrics used to evaluate and compare different ML models. For example, each standardized problem may solve many standard metrics. Examples of standardized measurements can be: disordered lattice, F score, accuracy, review, accuracy, mean square error.

5.5 Implementation of Machine Learning models in practical wirelessplatforms/systems

There is no doubt that ML will assume clear responsibilities in the development of future remote systems. In any case, despite the fact that ML is a breakthrough, it may be a burden if you follow the bad habits of loneliness. Moreover, DL, which has proven extraordinary achievements, requires notable measurement of information to make it function properly, which brings more difficulties to remote systems. It is essential in this way to drive us to understand how to coordinate ML/DL results fairly and effectively within the necessary processing stages. The second query that needs special consideration is what prerequisites need to be met by the system to help the classification and transfer of massive information?

5.6 Constraint wirelessdevices

For example, remote hubs found in IoT (such as phones, watches, and implanted sensors) are usually cheap gadgets with rare assets: capacity-limited assets, vitality, computing power, and corresponding bandwidth. These gadget requirements pose some difficulties in executing and running complex ML models.

5.7 Infrastructure for data collection andtransfer

The number of remote gadgets and their traffic requirements has skyrocketed, and a common system management design is needed to help large-scale remote transmission. For concomitant reasons, transmitting large amounts of information is a difficult task: I) There is no principle/convention that can effectively transmit more than 100T of information bits per second; ii) It is very difficult to continuously filter the system because of the huge traffic flow in a short time range The change

A promising headline intended for this test is the concept of fog volume calculation/research [19].

VI. CONLUSION

With the development of device and graphics capabilities and the ability to collect, store, and process large amounts of information, machine learning (ML) has discovered ways to enter various fields of logic, including remote systems. We see that part of the current work focuses on clear wireless system management tasks (for example, remote symbol verification), some work using explicit ML strategies (for example, deep learning methods), and some work on specific remote Conditions (such as IoT, WSN, CRN, etc.) have attracted attention in a wide range of application scenarios (such as restrictions, security, environmental checks, etc.). In order to fill this gap, the father introduced me to I) a non-machine learning expert's all-round organized start-up phase, providing the basic knowledge of ML in an accessible way, and ii) systematically and thoroughly detailing ML In order to enhance the execution capability of the remote system, look at the different views of the system agreement stack. Therefore, we studied the future direction from two levels: I) execute ML on demand remote gadgets (by reducing the versatility of ML models adjust the basis of huge information classification and movement (Through edge inspection and distributed computing).

REFERENCES

[1] A. Abbasi, S. Sarker, R. H. Chiang, Big data research in information sys- tems: Toward an inclusive research agenda, Journal of the Association for Information Systems 17 (2) (2016) I.

[2] L. Qian, J. Zhu, S. Zhang, Survey of wireless big data, Journal of Com- munications and Information Networks 2 (1) (2017) 1–18.

[3] M. M. Rathore, A. Ahmad, A. Paul, Iot-based smart city development using big data analytical approach, in: 2016 IEEE international confer- ence on automatica (ICA-ACCA), IEEE, 2016, pp. 1–8.

[4] H. N. Nguyen, P. Krishnakumari, H. L. Vu, H. van Lint, Tra ffic con- gestion pattern classification using multi-class svm, in: 2016 IEEE 19th International Conference on Intelligent Transportation Systems(ITSC), IEEE, 2016, pp.1059–1064.

[5] P. Lottes, R. Khanna, J. Pfeifer, R. Siegwart, C. Stachniss, Uav-based crop and weed classification for smart farming, in: 2017 IEEE Interna- tionalConferenceonRoboticsandAutomation(ICRA),IEEE,2017,pp . 3024–3031.

[6] I.Sa,Z.Chen,M.Popović,R.Khanna,F.Liebisch,J.Nieto,R.Sieg- wart, weednet: Dense semantic weed classification using multispectral imagesandmavforsmartfarming,IEEERoboticsandAutomationLet- ters 3 (1) (2018)588–595.

[7] M. Strohbach, H. Ziekow, V. Gazis, N. Akiva, Towards a big data analyt- ics framework for iot and smart city applications, in: Modeling and pro- cessing for next-generation big-data technologies, Springer, 2015, pp. 257–282.

[8] Cisco, Cisco visual networking index: Forecast and trends(2019). URL https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-741490.html

[9] Cisco systems white paper, https://www.cisco.com/c/en/us/solutions/collateral/service-provider/

[10] M. Bkassiny, Y. Li, S. K. Jayaweera, A survey on machine-learning tech- niques in cognitive radios, IEEE Communications Surveys & Tutorials 15 (3) (2012) 1136–1159.

[11] M. A. Alsheikh, S. Lin, D. Niyato, H.-P. Tan, Machine learning in wire- less sensor networks: Algorithms, strategies, and applications, IEEE Communications Surveys & Tutorials 16 (4) (2014) 1996–2018.

[12] X. Wang, X. Li, V. C. Leung, Artificial intelligence-based techniques for emerging heterogeneous network: State of the arts, opportunities, and challenges, IEEE Access 3 (2015)1379–1391.

[13] P. V. Klaine, M. A. Imran, O. Onireti, R. D. Souza, A survey of machine learning techniques applied to self-organizing cellular networks, IEEE Communications Surveys & Tutorials 19 (4) (2017) 2392–2431.

[14] X. Zhou, M. Sun, G. Y. Li, B.-H. F. Juang, Intelligent wireless com- munications enabled by cognitive radio and machine learning, China Communications 15 (12) (2018) 16–48.

[15] M. Chen, U. Challita, W. Saad, C. Yin, M. Debbah, Artificial neu- ral networks-based machine learning for wireless networks: A tutorial, IEEE Communications Surveys &Tutorials.

[16] N. Ahad, J. Qadir, N. Ahsan, Neural networks in wireless networks: Techniques, applications and guidelines, Journal of network and com- puter applications 68 (2016) 1–27.

[17] T. Park, N. Abuzainab, W. Saad, Learning how to communicate in the internet of things: Finite resources and heterogeneity, IEEE Access 4 (2016) 7063–7073.

[18] Q. Mao, F. Hu, Q. Hao, Deep learning for intelligent wireless networks: A comprehensive survey, IEEE Communications Surveys & Tutorials 20 (4) (2018) 2595–2621.

[19] M. Mohammadi, A. Al-Fuqaha, S. Sorour, M. Guizani, Deep learning for iot big data and streaming analytics: A survey, IEEE Communica- tions Surveys & Tutorials 20 (4) (2018)2923–2960.

[20] X. Li, F. Dong, S. Zhang, W. Guo, A survey on deep learning techniques in wireless signal recognition, Wireless Communications and Mobile Computing 2019.

[21] I. U. Din, M. Guizani, J. J. Rodrigues, S. Hassan, V. V. Korotaev, Ma- chine learning in the internet of things: Designed techniques for smart cities, Future Generation Computer Systems.

[22] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang,

[23] D. I. Kim, Applications of deep reinforcement learning in communi- cations and networking: A survey, IEEE Communications Surveys & Tutorials.

[24] V. Dhar, Data science and prediction, Communications of the ACM56 (12) (2013)64–73.

[25] M. Kulin, C. Fortuna, E. De Poorter, D. Deschrijver, I. Moerman, Data- driven design of intelligent wireless networks: An overview and tutorial, Sensors 16 (6) (2016) 790.

[26] J. McCarthy, Artificial intelligence, logic and formalizing common sense, in: Philosophical logic and artificial intelligence, Springer, 1989, pp. 161–190.

[27] T. Mitchell, B. Buchanan, G. DeJong, T. Dietterich, P. Rosenbloom,

[28] Waibel, Machine learning, Annual review of computer science 4 (1) (1990) 417–433.

[29] C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, L. Hanzo, Machine learning paradigms for next-generation wireless networks, IEEE Wire- less Communications 24 (2) (2017) 98–105.

[30] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, nature 521 (7553) (2015) 436.

[31] A. Mannini, A. M. Sabatini, Machine learning methods for classifying human physical activity from on-body accelerometers, Sensors 10 (2) (2010) 1154–1175.

[32] A. Bulling, J. A. Ward, H. Gellersen, Multimodal recognition of read-ing activity in transit using body-worn sensors, ACM Transactions on Applied Perception (TAP) 9 (1) (2012) 2.

[33] L. Yu, N. Wang, X. Meng, Real-time forest fire detection with wireless sensor networks, in: Wireless Communications, Networking and Mo- bile Computing, 2005. Proceedings. 2005 International Conference on, Vol. 2, IEEE, 2005, pp. 1214–1217.

[34] R. M. Khanafer, B. Solana, J. Triola, R. Barco, L. Moltsen, Z. Alt- man, P. Lazaro, Automated diagnosis for umts networks using bayesian network approach, Vehicular Technology, IEEE Transactions on 57 (4) (2008)2451–2461.

[35] A. Ridi, C. Gisler, J. Hennebert, A survey on intrusive load monitoring for appliance recognition, in: 2014 22nd International Conference on Pattern Recognition (ICPR), IEEE, 2014, pp. 3702–3707.

[36] H.-H. Chang, H.-T. Yang, C.-L. Lin, Load identification in neural net- works for a non-intrusive monitoring of industrial electrical

loads, in: Computer Supported Cooperative Work in Design IV, Springer, 2007, pp. 664–674.
[37] J. W. Branch, C. Giannella, B. Szymanski, R. Wol ff, H. Kargupta, In- network outlier detection in daa wireless sensor networks, Knowledge and information systems 34 (1) (2013) 23–54.
[38] S.Kaplantzis,A.Shilton,N.Mani,Y.A.Şekercioğlu,Detectingselec-tiveforwardingattacksinwirelesssensornetworksusingsupportvecto r machines, in: Intelligent Sensors, Sensor Networks and Information,2007. ISSNIP 2007. 3rd International Conference on, IEEE, 2007, pp. 335–340.
[39] T. J. O'Shea, N. West, M. Vondal, T. C. Clancy, Semi-supervised ra- dio signal identification, in: 2017 19th International Conference on Ad-vancedCommunicationTechnology(ICACT),IEEE,2017,pp.33–38.
[40] I. H. Witten, E. Frank, Data Mining: Practical Machine Learning Tools and Techniques, Second Edition (Morgan Kaufmann Series in Data Management Systems), Morgan Kaufmann Publishers Inc., San Fran- cisco, CA, USA, 2005.
[41] D. Guan, W. Yuan, Y.-K. Lee, A. Gavrilov, S. Lee, Activity recogni- tion based on semi-supervised learning, in: Embedded and Real-Time Computing Systems and Applications, 2007. RTCSA 2007. 13th IEEE International Conference on, IEEE, 2007, pp.469–475.
[42] M. Stikic, D. Larlus, S. Ebert, B. Schiele, Weakly supervised recogni- tion of daily life activities with wearable sensors, Pattern Analysis and Machine Intelligence, IEEE Transactions on 33 (12) (2011) 2521–2537.
[43] T.Huỳnh,B.Schiele,Towardslesssupervisioninactivityrecognitionfro m wearable sensors, in: Wearable Computers, 2006 10th IEEE Inter- national Symposium on, IEEE, 2006, pp. 3–10.
[44] T.Pulkkinen,T.Roos,P.Myllymäki,Semi-supervisedlearningforwlanpositioning, in: Artificial Neural Networks and Machine Learning– ICANN 2011, Springer, 2011, pp. 355–362.
[45] T. Liu, A. E. Cerpa, Foresee (4c): Wireless link prediction using link features, in: Proceedings of the 10th ACM/IEEE International Confer- ence on Information Processing in Sensor Networks, IEEE, 2011, pp. 294–305.
[46] M. F. A. bin Abdullah, A. F. P. Negara, M. S. Sayeed, D.-J. Choi, K. S. Muthu, Classification algorithms in human activity recognition using smartphones, International Journal of Computer and Information Engi- neering 6 (2012) 77–84.
[47] H.H.Bosman,G.Iacca,A.Tejada,H.J.Wörtche,A.Liotta,Ensembles of incremental learners to detect anomalies in ad hoc sensor networks, Ad Hoc Networks 35 (2015)14–36.
[48] R. M. Castro, R. D. Nowak, Minimax bounds for active learning, Infor- mation Theory, IEEE Transactions on 54 (5) (2008) 2339–2353.
[49] S. Hanneke, Theory of disagreement-based active learning, Foundations and Trends R in Machine Learning 7 (2-3) (2014) 131–309.
[50] T. J. OShea, T. Roy, T. C. Clancy, Over-the-air deep learning based radio signal classification, IEEE Journal of Selected Topics in Signal Process- ing 12 (1) (2018) 168–179.
[51] P.SanCheong,M.Camelo,S.Latré,Evaluatingdeepneuralnetworksto classifymodulatedandcodedradiosignals,in:InternationalConferen ce on Cognitive Radio Oriented Wireless Networks, Springer, 2018, pp. 177–188.
[52] C. Liu, K. Wu, J. Pei, A dynamic clustering and scheduling approach to energy saving in data collection from wireless sensor networks., in: SECON, Vol. 5, 2005, pp. 374–385.
[53] A. Taherkordi, R. Mohammadi, F. Eliassen, A communication-e fficient distributed clustering algorithm for sensor networks, in: Advanced Information Networking and Applications-Workshops, 2008. AINAW 2008. 22nd International Conference on, IEEE, 2008, pp. 634–638.
[54] K. Wang, S. A. Ayyash, T. D. Little, P. Basu, Attribute-based cluster- ing for information dissemination in wireless sensor networks, in: Pro ceedingof2ndannualIEEEcommunicationssocietyconferenceonse nsorandadhoccommunicationsandnetworks(SECON05),SantaCla ra, CA,2005.
[55] Y. Ma, M. Peng, W. Xue, X. Ji, A dynamic a ffinity propagation clus- tering algorithm for cell outage detection in self-healing networks, in: Wireless Communications and Networking Conference (WCNC), 2013 IEEE, IEEE, 2013, pp. 2266–2270.
[56] T. C. Clancy, A. Khawar, T. R. Newman, Robust signal classification using unsupervised learning, Wireless Communications, IEEE Transac- tions on 10 (4) (2011) 1289–1299.
[57] N. Shetty, S. Pollin, P. Pawełczak, Identifying spectrum usage byunknown systems using experiments in machine learning, in: Wire- less Communications and Networking Conference, 2009. WCNC 2009. IEEE, IEEE, 2009, pp.1–6.
[58] O. S. Mossad, M. ElNainay, M. Torki, Deep convolutional neural net- work with multi-task learning scheme for modulations recognition.
[59] S. Rajendran, W. Meert, D. Giustiniano, V. Lenders, S. Pollin, Deep learning models for wireless signal classification with distributed low- cost spectrum sensors, IEEE Transactions on Cognitive Communica- tions and Networking 4 (3) (2018) 433–445.
[60] B. Tang, Y. Tu, Z. Zhang, Y. Lin, Digital signal modulation classification with data augmentation using generative adversarial nets in cognitive radio networks, IEEE Access 6 (2018) 15713–15722.
[61] D. Zhang, W. Ding, B. Zhang, C. Xie, H. Li, C. Liu, J. Han, Automatic modulation classification based on deep learning for unmanned aerial vehicles, Sensors 18 (3) (2018) 924.
[62] S. Peng, H. Jiang, H. Wang, H. Alwageed, Y. Zhou, M. M. Sebdani,Y.-
[63] D.Yao,Modulationclassificationbasedonsignalconstellationdiagra ms and deep learning, IEEE transactions on neural networks and learning systems (99) (2018)1–10.
[64] S. Duan, K. Chen, X. Yu, M. Qian, Automatic multicarrier waveform classificationviapcaandconvolutionalneuralnetworks,IEEEAccess6 (2018)51365–51373.
[65] F. Meng, P. Chen, L. Wu, X. Wang, Automatic modulation classifica-tion:Adeeplearningenabledapproach,IEEETransactionsonVehicula r Technology 67 (11) (2018)10760–10772.
[66] Y. Wu, X. Li, J. Fang, A deep learning approach for modulation recog- nition via exploiting temporal correlations, in: 2018 IEEE 19th Interna-tionalWorkshoponSignalProcessingAdvancesinWirelessCommuni - cations (SPAWC), IEEE, 2018, pp.1–5.
[67] H. Wu, Q. Wang, L. Zhou, J. Meng, Vhf radio signal modulation classi- fication based on convolution neural networks, in: Matec Web of Con- ferences, Vol. 246, EDP Sciences, 2018, p. 03032.
[68] M. Zhang, Y. Zeng, Z. Han, Y. Gong, Automatic modulation recogni- tion using deep learning architectures, in: 2018 IEEE 19th International WorkshoponSignalProcessingAdvancesinWirelessCommunication s (SPAWC), IEEE, 2018, pp.1–5.
[69] M. Li, O. Li, G. Liu, C. Zhang, Generative adversarial networks-based semi-supervised automatic modulation recognition for cognitive radio networks, Sensors 18 (11) (2018)3913.
[70] M. Li, G. Liu, S. Li, Y. Wu, Radio classify generative adversarial networks: A semi-supervised method for modulation recognition, in: 2018 IEEE 18th International Conference on Communication Technol- ogy (ICCT), IEEE, 2018, pp.669–672.
[71] K. Yashashwi, A. Sethi, P. Chaporkar, A learnable distortion correc- tion module for modulation recognition, IEEE Wireless Communica- tions Letters 8 (1) (2019)77–80.
[72] M. Sadeghi, E. G. Larsson, Adversarial attacks on deep-learning based radio signal classification, IEEE Wireless Communications Letters 8 (1) (2019) 213–216.

[73] D. Zhang, W. Ding, B. Zhang, C. Xie, H. Li, C. Liu, J. Han, Automatic modulation classification based on deep learning for unmanned aerial vehicles, Sensors 18 (3) (2018) 924.