A Survey of AI/ML Related Standardization Efforts in 5G Mobile Networks (O-RAN and 3GPP)

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Abstract

Using Artificial Intelligence (AI) and Machine Learning (ML) in 5G wireless networks can help Mobile Network Operators (MNOs) improve their service quality while reducing the costs of running and optimizing their networks. This paper surveys the ongoing AI/ML related standardization efforts in Open Radio Access Network (O-RAN) Alliance and the 3rd Generation Partnership Project (3GPP). It highlights the key initiatives aimed at integration and standardization of AI/ML in Radio Access Network (RAN), including the definition of AI/ML workflows, model training, deployment, inference, and model management. The paper also provides an overview of some of the important AI/ML use cases, such as traffic steering, network slicing and RAN slice Service Level Agreement (SLA) assurance, predictive maintenance, and energy savings. Through the analysis of the current standardization efforts and potential future directions, this survey provides a detailed overview of how AI/ML can be applied to 5G RAN and its potential to improve the overall network performance, the quality of user experience, and lowered operational costs.

1. Introduction

The evolution of mobile network technologies, with features such as very high data rates, ultra-low latency connections, machine-to-machine communications, network slicing, and massive antenna arrays, have resulted in a corresponding increase in complexity. Additionally, many Mobile Network Operators (MNOs) are deploying additional base stations to provide good coverage due to the physical distance limitations of higher carrier frequencies that can provide higher data rates. While such higher density of base stations solves the coverage issues, the increased density can create signal interference across base stations, resulting in degraded network performance and poor end user experience.

More base stations also mean higher energy consumption, resulting in higher operating expenses. Mobile Network Operators are already struggling with the investment costs required to upgrade their networks to the latest generation of mobile technologies, such as 5G, and the additional operating expenses due to higher energy bills are making the situation worse.

Combining the complexity of the advanced technology, more challenging network planning to reduce interference, higher energy bills, and many other challenges, Mobile Network Operators are looking for ways to optimize their networks for better performance at a lower cost.

Application of AI/ML technologies is a very promising approach to tackle these challenges. AI/ML can be used to predict network issues before they happen, such as identifying security threats, forecasting potential hardware failures, predicting network traffic utilization levels and potential congestion, detecting anomalies, and many other scenarios. After the prediction of these issues, AI/ML algorithms can take automatic corrective actions to either correct the problems or minimize their impact on the service quality.

In addition to issue prediction and correction, AI/ML algorithms can identify network optimization opportunities, such as energy savings, network configuration parameter optimizations to improve coverage and minimize interference, intelligent load distribution and traffic steering of users between base stations to balance the load on each base station, and more.

Given these benefits, mobile network related Standards Defining Organizations (SDOs), such as 3GPP and O-RAN Alliance have already started and progressed with AI/ML related standardization work. The objective of this paper is to provide an overview of the advancements made in these standards bodies and some of the important AI/ML use cases.

This paper is organized as follows: Section 2 provides an overview of 3GPP and O-RAN Alliance and their roles in standardization of mobile networks. Section 3 captures the three broad categories of mobile network use cases; network planning, network performance monitoring and optimization, fault detection and recovery, and how AI/ML algorithms can be applied to enhance these set of use cases. Section 4 provides a brief overview of supervised, unsupervised, and reinforcement learning AI/ML algorithm types and their applicability to some of the 3GPP and O-RAN use cases. Standardization efforts in O-RAN Alliance and 3GPP are detailed in Section 5 and Section 6. Some of the current challenges and potential future standardization directions are discussed in Section 7 and the paper is concluded with Section 8.

2. Overview of 3GPP and O-RAN Alliance

3GPP is a collaboration between national Standards Development Organizations (SDOs) that creates technical specifications for mobile networks [1]. 3GPP has defined the technical specifications for the architecture and protocols used in different generations of mobile networks, starting with 3rd Generation (3G), followed by 4th Generation (4G), and then with the latest generation of mobile networks; 5th Generation (5G) [2].

The specifications defined by 3GPP cover both the Core Network (CN) and the Radio Access Network (RAN) parts of the mobile network. The CN is responsible for functions such as authentication of users, subscriber management, routing of calls and data sessions, and providing access to external networks such as the Internet. The RAN handles the wireless protocol stacks and the radio resource management functions to provide connectivity of User Equipment (UE) to the Core Network. Through 3GPP's standardization efforts, interoperability and scalability between different network elements from different vendors is achieved.

Similar to 3GPP, O-RAN Alliance is another collaborative standardization effort, made up of many Mobile Network Operators (MNOs) and telecommunications industry players. It is aimed at defining and promoting open, interoperable interfaces and architectures for Radio Access Networks (RAN) [3].

The Alliance focuses on further disaggregating the traditional RAN elements into O-CU-CP, O-CU-UP, O-DU and O-RU, and the introduction of the Non-Real-Time RAN Intelligent Controller (RIC) and the Near-Real-Time RIC to enable a more flexible and efficient network infrastructure, as depicted in Figure 1 below. Some of the core principles include the introduction of intelligence to RAN through the Non-RT and Near-RT RICs, various applications and use cases (called rApps and xApps) that can run on the RIC, and openness across vendors. O-RAN aims to drive the mobile industry towards an ecosystem of innovative, multi-vendor, interoperable, and autonomous RAN, with reduced cost, improved performance and greater agility.

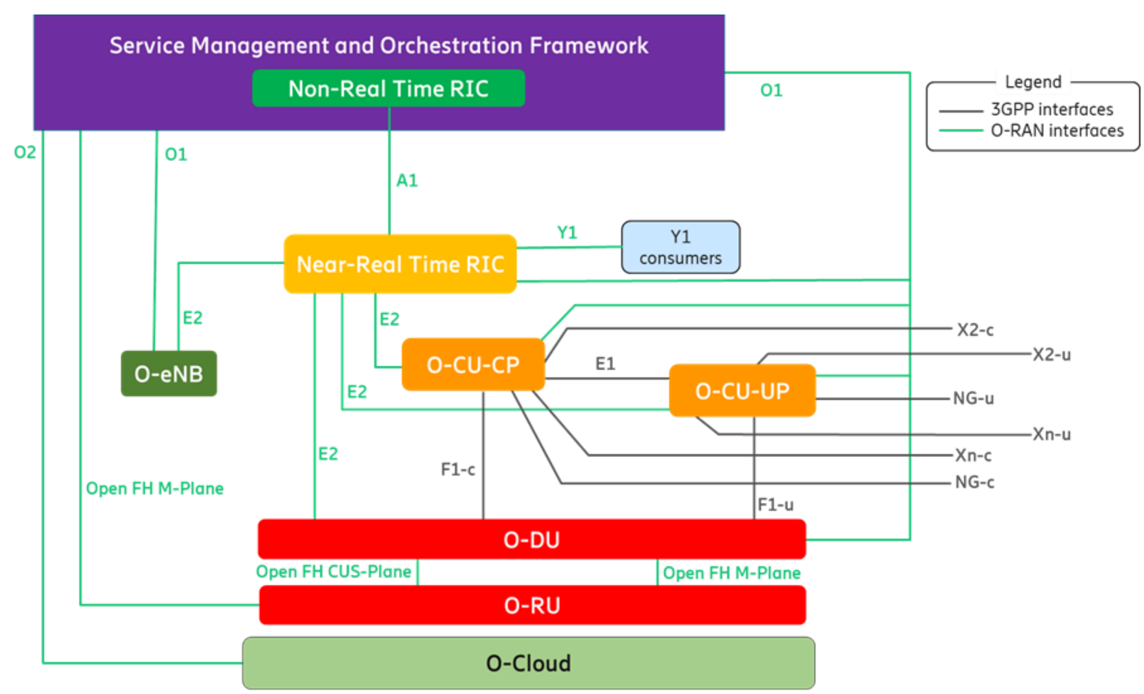

Figure 1: Logical Architecture of O-RAN - Source O-RAN Architecture Description [4]

One important principle of O-RAN Alliance is the alignment with the industry and other SDOs to avoid fragmentation or duplication of efforts. For this purpose, O-RAN architecture and specifications are being built on common RAN standards, especially 3GPP. Such an alignment principle enables O-RAN architecture to be compatible with the existing 3GPP based mobile network deployments as well as being able to incorporate the technological advancements made in 3GPP architecture and standards.

3. Application of AI/ML to RAN use cases

As described in the introduction section of this paper, the application of AI/ML algorithms can provide effective solutions to the challenges MNOs are facing. This section provides some example use cases to elaborate the role and applications of AI/ML in O-RAN and 3GPP RAN networks. These use cases fall into three broad categories: network planning, network performance monitoring and optimization, and fault detection and recovery.

One crucial area where MNOs face significant challenges is network planning. In this phase, MNOs aim to provide the best coverage and service quality to meet the demands of their customers. This is achieved by planning their investments and associated costs; decisions on where to build the radio towers, how much base station hardware is needed, which and how much radio frequencies to use, and how to connect these base stations to their Core Networks. At the same time, they need to balance these investment costs with their revenues for business sustainability and profitability.

Once the network is deployed, the focus shifts to network performance monitoring and optimization. MNOs constantly monitor the service quality and network performance, and take optimization actions as needed. When performance degradations are detected, they investigate the potential root causes and try to optimize the network parameters to restore and improve the service quality.

In addition to performance optimization, MNOs must also address fault detection and recovery. They monitor for unexpected failures, such as hardware failures of the base station components, software bugs causing repeated crashes, loss of power, or loss of transmission links. These and other failures may require expensive on site technician visits to the base station site to replace the faulty components and more importantly loss of service to many customers until the issues are fixed.

While existing tools and products can assist with the above tasks, they are often reactive, detecting issues after they occur and applying network optimization without forecasting the impact of changes. This is where AI/ML offers significant advantages. By leveraging large datasets to learn patterns and predict future behavior, AI/ML algorithms enable a proactive approach. In network planning, AI/ML can forecast resource deployments to balance the service quality and the investment costs. For predictive maintenance, AI/ML can identify patterns before the service degradation or hardware failures, and can take proactive corrective actions. In traffic steering, AI/ML can predict the number of users and their traffic patterns to come up with the expected load levels on the base stations, and forecast the impact of steering users to neighboring base stations for balanced load across the network [5]. Similarly, for network slicing and slice SLA assurance, AI/ML can forecast slice utilization and remaining base station resources to make resource allocation decisions and prevent potential SLA violations [5]. AI/ML can also predict periods of low activity for energy savings, enabling proactive energy-saving measures [5]. Finally, AI/ML pattern identification and forecasting can enhance security use cases [6]. This proactive capability of AI/ML across all three categories; network planning, network optimization, and network fault management, offers significant improvements over the traditional non AI/ML based reactive methods.

4. Types of AI/ML Algorithms and applicability for O-RAN and 3GPP use cases

While there is constant advancement in AI/ML domain and more algorithms are constantly being developed, there are three main categories of Machine Learning algorithms:

- Supervised learning: This category of algorithms learns from labeled data. They can be used for making predictions, such as predicting the numbers of users connected to a base station or expected traffic levels in an interstate highway. They can also be used to classify unlabeled data to a set of labels, which can be very useful for dealing with large sets of real-world data that is not labeled.

- Unsupervised learning: This category of algorithms learns from unlabeled data. They can be used to find patterns and automatically cluster the data into a set of categories. An example application of unsupervised learning is the grouping of customers into a set of categories like loyal customer, fashion enthusiast, etc.

- Reinforcement learning: This category of algorithms learns by interacting with the environment, receiving rewards or penalties for its actions. Training a computer to play a game like chess is a good example of reinforcement learning. The computer tries different moves, and receives rewards or penalties (winning vs losing the game). Through many trial and error attempts, these algorithms learn which actions lead to the best outcomes.

These three main categories of ML algorithms can be utilized for the various use cases captured in Section 3 of this paper. For use cases that need some sort of prediction and forecasting (i.e, prediction of network utilization and traffic levels, forecasting the number of users, etc.) supervised algorithms are very applicable. Some examples of such use cases are traffic steering, QoE optimization and slice SLA assurance [7].

On the other hand, unsupervised learning algorithms are particularly applicable for use cases that rely on identification of hidden patterns. Enhanced security is achieved through the detection of unusual patterns in network traffic and user behavior, enabling the identification of potential threats. Identification of potential faults in the network by clustering data from different network elements can be very useful for use cases like predictive maintenance.

Finally, reinforcement learning can be applied to use cases like dynamic resource allocation of resources based on real-time network conditions and user demands. The algorithm can learn to optimize resource utilization and maximize network capacity by interacting with the environment and receiving rewards or penalties for efficient resource allocation [8].

5. Standardization Efforts in O-RAN

One of the fundamental goals of O-RAN Alliance is to introduce intelligence to the network through RAN Intelligent Controller (RIC). From the beginning, AI/ML has been considered to be an integral part of the RIC and the RIC applications (rApps and xApps).

Since the initial formation of O-RAN Alliance, O-RAN use cases have been defined in Working Group 1 (WG1) Use Case Task Group (UCTG) specifications [9],[5], with majority of these use cases including AI/ML aspects such as data collection, model training, model deployment and inference. As of the latest release of these UCTG specifications, which have been made public in October 2024, 21 out of 26 use cases have AI/ML aspects.

Building up on the definition of many AI/ML based use cases in WG1, O-RAN Working Group 2 (WG2) has published O-RAN's first fully AI/ML focused technical report, "O-RAN AI/ML workflow description and requirements" [10] in July 2021. This report included the definitions of the AI/ML modelling terminology, AI/ML workflows, AI/ML model training and multiple different AI/ML training host and inference host deployment scenarios.

Since then multiple Working Groups (WGs) have been investigating and publishing detailed specifications covering different AI/ML aspects. As of the latest publicly available specifications (October 2024), the status per Working Group is as follows:

5.1 Working Group 1, the “Use Cases and Overall Architecture Workgroup”

As mentioned above, since the formation of the Alliance, all of the O-RAN use cases have been captured in UCTG specifications, specifically in “O-RAN Use Cases Analysis Report” [9] and in “O-RAN Use Cases Detailed Specification” [5].

In these two UCTG specifications, almost every use case has AI/ML aspects, starting with the data collection from RAN for AI/ML training, the deployment of the trained AI/ML model to Non-RT RIC and/or Near-RT RIC, the AI/ML inference on the Non-RT/Near-RT RIC and retraining the AI/ML models if needed. Along with the detailed flow diagrams of the use cases, which includes the AI/ML related phases and steps, the data required for the use cases are captured as well, which can be the basis for data engineers to work on their AI/ML model designs.

Traffic Steering use case for load balancing the users across cells, RAN Slice SLA Assurance use case for monitoring and assurance of slices through resource allocations, and Energy Savings use case for turning off (and as needed, back on) base station cells to conserve energy are some of the high priority use cases documented in these UCTG specifications, along with their AI/ML aspects.

5.2 Working Group 2, the “Non-Real-time RIC and A1 Interface Workgroup”

The O-RAN use cases defined in WG1 UCTG specifications are further detailed for Non-RT RIC and A1 interface specifics in “O-RAN Non-RT RIC & A1/R1 interface: Use Cases and Requirements” [11]. Within this document, almost all of the use cases have AI/ML aspects for the training, deployment and inference of AI/ML models.

The Non-RT RIC architecture, the requirements, and the services of the platform are defined in “O-RAN Non-RT RIC: Architecture” [12]. In this specification, the Non-RT RIC platform requirements, services, functions, and procedures are defined.

This specification starts with the “requirements” in Section 5, then defines the “services” to fulfill these “requirements” in Section 7, followed by the “function” definitions to produce these “services” in Section 8 and then the detailed “procedures” to implement these “functions” in Section 10.

The AI/ML related requirements are defined in section 5.1, including requirements for training, storage and retrieval, performance monitoring, lifecycle management, registration, discovery, and deployment of the AI/ML models.

The services to fulfill the requirements defined in section 5.1 are captured in section 7.7 as "AI/ML workflow services", which includes training, model management and exposure, registration/deregistration, discovery, storage, retrieval, performance monitoring and inference services.

The AI/ML workflow functions to produce these AI/ML workflow services are defined in section 8.7. The detailed procedures to implement these AI/ML workflow functions are defined in section 10.4.

These architectural requirements, services, functions, and procedures are then reflected to the respective Non-RT RIC interfaces; A1, the interface to the Near-RT RIC and the R1, the interface between the rApps and the Non-RT RIC platform.

There are several A1 and R1 interface related specifications to define the general aspects and principles of these interfaces, the transport protocols, the type definitions, and the application protocols, which contain AI/ML related definitions.

5.3 Working Group 3, the "Near-Real-time RIC and E2 Interface Workgroup"

WG3 follows a similar approach as WG2 where the O-RAN use cases defined in WG1 UCTG specifications are further detailed for Near-RT RIC and E2 interface specifics in "O-RAN Use Cases and Requirements" [13]. Similar to WG2 use cases specification [11], almost all of the use cases have AI/ML aspects for the training, deployment, and inference of AI/ML models in WG3 use cases specification as well.

The Near-RT RIC architecture, functionalities, and the interactions between the xApps and the common platform services are provided in "O-RAN Near-RT RIC Architecture" [14]. Within this specification, there are several sections defining the requirements, services, APIs, and procedures for Near-RT RIC platform functionalities.

This specification starts with the "requirements" in Section 5, then defines the "services" to fulfill these "requirements" in Section 6, followed by the "APIs" to utilize these "services" in section 7 and then the detailed "procedures" to implement these "APIs" in Section 9 [14].

Regarding the AI/ML requirements, section 5.1.1 includes a fundamental AI/ML requirement that the "Near-RT RIC platform shall provide AI/ML tools that support for data pipelining, model management, training and inference."

Looking at this requirement, we can see there are four main areas, which are aligned with any generic AI/ML workflow:

- Data pipelining

- Model management
- Training
- Inference

Section 6 defines the full set of Near-RT RIC platform services to fulfill the requirements defined in Section 5. The four main AI/ML areas noted above are then defined in subsections. AI/ML services are covered in subsection 6.2.9 where the “data pipelining” service is defined as the functionality enabling the Near-RT RIC platform with data ingestion and preparation for xApps. The input data to the pipeline and the output data sets that are ready to be consumed by the AI/ML model are noted as well. The next subsection, 6.2.9.1A defines the “model management” services as storage, retrieval and version control of AI/ML models for xApps. “Training” service is defined in 6.2.9.2 as the functionality enabling the training of AI/ML models for xApps. Finally section 6.2.9.3 defines the “Inference” service, which is Near-RT RIC platform offering inference of AI/ML models for xApps.

Each of these four main AI/ML services are then detailed with 17 total service operations in section 6A.2.7.

The AI/ML workflow APIs for xApps to utilize these Near-RT RIC platform AI/ML services are defined in section 7.1.1 and section 9.7 provides the detailed AI/ML procedures and flow diagrams for the implementation of these “APIs”.

5.4 Working Group 10, the “OAM for O-RAN Workgroup”

A number of different AI/ML aspects related to the training and management of AI/ML models have been captured in WG10’s “O-RAN Operations and Maintenance Architecture” specification [15].

One of the primary requirements for AI/ML training, inference, and analysis is the data collection from the RAN. The entities and solutions for such data collection are defined in Section 4.2.2, “O-RAN Measurement Data Collection Use Case” in [15].

AI/ML models have been considered as part of the lifecycle management of applications (i.e., the rApps and xApps) in section 6 of [15], “Application Lifecycle Management (LCM)”, and it has been noted since the applications may or may not contain AI/ML models, the AI/ML model information should be considered as optional in the “App Package”.

AI/ML model training lifecycle and AI/ML model onboarding lifecycle aspects are considered in sections 6.1.2, “App Development Lifecycles” and sections 6.1.3, “App Onboarding Lifecycles” and two functional requirements specific to the identification of deployment and onboarding AI/ML models are captured in section 6.2.4 in [15].

5.5 Working Group 11, the "Security Work Group"

WG11 has published "O-RAN Study on Security for Artificial Intelligence and Machine Learning (AI/ML) in O-RAN" [16], providing detailed AI/ML threat models and their risk assessments. In this report, the 12 threats listed below and the associated risks are captured, potential security controls to protect against those threats are recommended.

1. Input manipulation attacks
2. Data poisoning attacks
3. Membership inference attacks
4. Model stealing
5. Model inversion threats
6. AI supply chain attacks
7. Output integrity attacks
8. Model poisoning
9. Model skewing attacks
10. Transfer learning attacks
11. AI energy-latency attacks
12. Evasion attacks

These 12 specific threat areas are also captured in the overall O-RAN security threats document, "O-RAN Security Threat Modeling and Risk Assessment" [6].

6. Standardization Efforts in 3GPP RAN Groups

Release-18 is the first 3GPP release of 5G-Advanced, which is the middle of the specification cycle between 5G and 6G. Given the importance and the potential benefits of AI/ML, several study and work items have been included in Release-18. Release-18 has been completed in March 2024 and Release-19 work is in progress.

The "Study on Artificial Intelligence (AI)/Machine Learning (ML) for NR air interface" technical report [17], published on December 2023, investigated the advantages of enhancing the air-interface with features to provide better AI/ML support while considering the performance, complexity, and potential standardization impacts.

One key goal noted in this work was the assessment of the performance comparison between the new AI/ML methods against the traditional (non AI/ML) methods, in other words measuring the true benefits and the potential of AI/ML techniques. To achieve this goal, three areas of study were identified as central objectives.

The first goal was the identification of relevant Key Performance Indicators (KPIs) for a specific use case. This process was essential to ensure a set of consistent and measurable metrics to enable accurate comparisons and assessments.

The second goal was the complexity assessment of the associated requirements for implementing the AI/ML algorithms. This assessment included items such as the identification of the required computational power, the memory requirements, and the power consumption implications.

The third goal, and potentially the most important one, was the characterization of the impact on the 3GPP specifications. This goal aimed to enhance the overall understanding of the standardization efforts required in future 3GPP releases to enable the incorporation of AI/ML capabilities for the air-interface.

To achieve these goals and establish a common AI/ML framework definition, three use cases were carefully selected.

The first use case is the “Channel State Information (CSI) feedback enhancement”. The user equipment (UE) measures received signal quality and calculates channel state information (CSI) during communication with the base station (gNB). This information enables the gNB to adjust transmission power. In this study item [17], the enhancement of AI/ML-based algorithms were studied for two different CSI scenarios (spatial-frequency domain CSI compression and time-domain CSI prediction).

The second use case is “beam management”. Utilizing the multiple antenna technologies, the gNB can produce multiple beams towards a UE to improve the connectivity and the data rates. As part of beam management, UE measures the signals of each transmit beam and then tries to find a suitable beam pair through certain calculations, which is a time consuming process. The enhancement of AI/ML-based algorithms were studied with two different scenarios of this use case.

The third use case is “positioning accuracy enhancements”. The position of a UE is calculated by measuring the radio signals and then a complex, non-linear calculation to correlate the UE’s position with these measurements. Since the positioning accuracy of the UE depends on the availability and the quality of direct signals (line of sight signals) from the base station, indoor settings or areas with many physical obstacles like buildings can create accuracy calculation issues. Similar to the other two use cases, the enhancement of the AI/ML based algorithms were studied with two different scenarios of this use case.

In addition to the study of these 3 use cases, this study item investigated several aspects of the common AI/ML framework characteristics as well. The first goal was the identification of various levels of collaboration between the UE and the gNB, which includes the protocol aspects for UE to provide AI/ML capability indication, the configuration and control procedures for model training and inference, the model and the data management. The second goal was the characterization of the lifecycle management of AI/ML models which includes the model training, model deployment, model inference, model monitoring, and model update. The third was the investigation of the datasets needed for training, validation, testing, and inference. The fourth was the identification of a common terminology for AI/ML related functions, procedures, and the interfaces.

The results of this AI/ML study item, as published in [17], will serve as the foundation for AI/ML air interface related specifications. These specifications will continue to evolve through Release-19 and Release-20 for 5G-Advanced and may also be utilized for 6G specifications starting with Release-21 [18].

7. Challenges and Future Directions

While O-RAN Alliance and 3GPP are making good progress with AI/ML related standardization, there are a number of challenges to be tackled, both for further standardization activities, and for actual solution implementations.

One of the key challenges related to research, standardization, and implementation of AI/ML solutions is the lack of real world mobile network data which is critical for offline training and evaluation of AI/ML models before they can be standardized and deployed to the field.

A related challenge, as noted in AI-RAN Alliance's "Integrating AI/ML in Open-RAN: Overcoming Challenges and Seizing Opportunities" whitepaper [19], is "*the diverse and often non-standardized nature of telecom data creates isolated information silos, complicating comprehensive analysis and AI application*", creating significant data quality and standardization issues.

There are ethical and regulatory challenges to be addressed as well. The bias in AI models potentially leading to unfair outcomes like improper prioritization of mobile network traffic [20] and compliance with privacy regulations, such as the General Data Protection Regulation (GDPR) are some of the example challenges.

Finally, the cost of developing and maintaining custom AI/ML models for mobile networks, especially considering the variability of the traffic and user behavior across different sites, different regions, and even different types of base stations served by a Mobile Network Operator, is another major challenge.

3GPP and O-RAN Alliance continue to work on advancing AI/ML solutions for mobile networks. As part of their future work, they can address some of the above challenges by defining standardized mobile network data to overcome the data quality issues, reflecting the solutions for ethical challenges as well as compliance to regulatory requirements into their standards, promoting industry-academic collaborative efforts to reduce the cost of research and development of customized AI/ML models for mobile networks.

8. Conclusion

This paper examined the standardization efforts of 3GPP and O-RAN Alliance regarding the application of AI/ML to mobile networks, highlighting the potential benefits. As discussed in the introduction, MNOs need solutions to the increasing complexity of 5G networks while trying to control their costs. AI/ML offers significant promise in addressing these challenges. This includes big data processing for diagnostics and predictive maintenance, usage forecasting for intelligent traffic steering, RAN slice SLA assurance and energy savings, and anomaly/threat detection for enhanced network security. The key initiatives within O-RAN Alliance and 3GPP have been captured, including the development of specifications for the definition of AI/ML workflows, model training and deployment, model inference, and model management. Furthermore, some important use cases have been provided as examples for the potential of AI/ML to improve the user experience, network performance, and operational efficiency.

While significant progress has been made, there is more work to incorporate AI/ML to mobile networks and many challenges to be solved. Issues such as lack of real world training data for the research, development and standardization of AI/ML models, cost of developing and maintaining custom models, data privacy, model explainability and regulatory compliance requirements require further attention. Future standardization efforts can prioritize these areas to unlock the full potential of AI/ML in 5G and beyond mobile network generations. By addressing these challenges, the standardization bodies can pave the way for the widespread adoption of AI/ML based solutions, enabling MNOs to build and operate more efficient, resilient, and cost effective mobile networks.

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