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A Comprehensive Review of the GNSS with IoT Applications and Their Use Cases with Special Emphasis on Machine Learning and Deep Learning Models

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Abstract— This paper presents a comprehensive review of the Global Navigation Satellite System (GNSS) with Internet of Things (IoT) applications and their use cases with special emphasis on Machine learning (ML) and Deep Learning (DL) models. Various factors like the availability of a huge amount of GNSS data due to the increasing number of interconnected devices having low-cost data storage and low-power processing technologies - which is majorly due to the evolution of IoT - have accelerated the use of machine learning and deep learning based algorithms in the GNSS community. IoT and GNSS technology can track almost any item possible. Smart cities are being developed with the use of GNSS and IoT. This survey paper primarily reviews several machine learning and deep learning algorithms and solutions applied to various GNSS use cases that are especially helpful in providing accurate and seamless navigation solutions in urban areas. Multipath, signal outages with less satellite visibility, and lost communication links are major challenges that hinder the navigation process in crowded areas like cities and dense forests. The advantages and disadvantages of using machine learning techniques are also highlighted along with their potential applications with GNSS and IoT.

Keywords- GNSS, GPS, IoT, RTK, machine learning, deep learning.

I. INTRODUCTION

Global Navigation Satellite System (GNSS) is a satellite navigation system that provides autonomous geospatial position, navigation, and timing services with regional or global coverage [1]. It encompasses popular systems like Global Positioning System (GPS), GLObalnaya NAvigatsionnaya Sputnikovaya Sistema in Russian (GLONASS), Galileo, Beidou, Indian Regional Navigation Satellite System (IRNSS), and other regional and augmented navigation systems [2]. Over the past two decades, GNSS technology has rapidly advanced, becoming more user-friendly and intuitive, enabling wireless connectivity with low power consumption. Its integration with smartphones and other mass-market devices has made it one of the most widely used technologies today [3][4].

On the other hand, the rise of the Internet of Things (IoT) has brought an evolution in applications and devices, enhancing connectivity and interoperability. This has resulted in an exponential increase in the volume of data collected by these interconnected devices [5]. As per the facts, the production of global data is projected to grow from 33 zettabytes in 2018 to 175 zettabytes by 2025. While data centers currently handle 80% of data processing and analysis, the remaining 20% is managed by other computing facilities, smart connected objects, and IoT devices.

Compared to GNSS, which provides specific hardware or object positions, IoT focuses on monitoring and providing real-time information and statistics on device operations. The combination of GNSS and IoT enables the generation of comprehensive and usable interconnected data, paving the way for smarter cities, self-driving cars, tracking devices, and wearable health technologies [6]. Improvements in the position accuracy of IoT devices like smartphones and wearables will expand their usage in the mass market and unlock new consumer applications [7]. The integration of GNSS with IoT

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has led to the deployment of numerous IoT GNSS receivers, including smartphones, and the establishment of permanent GNSS stations worldwide. This vast network of IoT GNSS devices generates a wealth of data, presenting a burgeoning field of scientific interest for applying Machine Learning (ML) and Deep Learning (DL) techniques [8].

To enhance the intelligence and capabilities of IoT applications, ML and DL techniques can be employed to uncover hidden patterns within vast amounts of data. In the case of time-series data like GNSS data, ML and DL models prove to be powerful tools for detecting time-dependent trends and making meaningful correlations to improve the accuracy, continuity, and robustness of the system. ML/DL algorithms have been extensively studied in areas such as classification, prediction, and optimization. These algorithms are trained on specific input data along with their expected output, allowing them to estimate various mathematical parameters. The learned parameters are then applied to new, unexplored data to achieve desired objectives [9]. The choice of ML or DL technique depends on the computational intensity of the problem and the required speed of analysis. Real-time applications, for example, require methods that can track changes in input data and produce results promptly [10]. ML and DL models are revolutionizing the navigation challenges encountered in GNSS, playing a vital role in the advancement of PNT technologies [11][12]. Like any other system, GNSS signals get influenced by many phenomena which may degrade the overall performance of the system. GNSS signals are L band signals travelling long distances with very low power hence are prone to several sources of noise as shown in Fig. 1 [13]. There are two main GNSS observables used for positioning algorithm as input: i) Code phase measurement and ii) Carrier phase measurement [14]. The mathematical equations representing code phase and carrier phase measurements are as follows:

$$\rho = r + c[\delta t_u - \delta t^s] + I_\rho + T_\rho + \varepsilon_m + \varepsilon_\rho \qquad (1)$$

ρ: Pseudorange/code phase measurement, r: the true range, c: speed of light, δt_u: receiver clock offset from GPS time, δt^s: satellite clock offset from GPS time, I_ρ: ionospheric delay, T_ρ: tropospheric delay, ε_m: multipath and ε_ρ: receiver noise.

$$\emptyset = \lambda^{-1}[r - I_\emptyset + T_\emptyset] + {}^{c}/_{\lambda}[\delta t_u - \delta t^s] + N + \varepsilon_\emptyset \qquad (2)$$

∅: carrier phase measurement, λ: wavelength of the carrier signal, r: the true range, c: speed of light, δt_u: receiver clock offset from GPS time, δt^s: satellite clock offset from GPS time, $I_\emptyset$: ionospheric delay, $T_\emptyset$: tropospheric delay, N: integer ambiguity and $\varepsilon_\emptyset$: receiver noise.

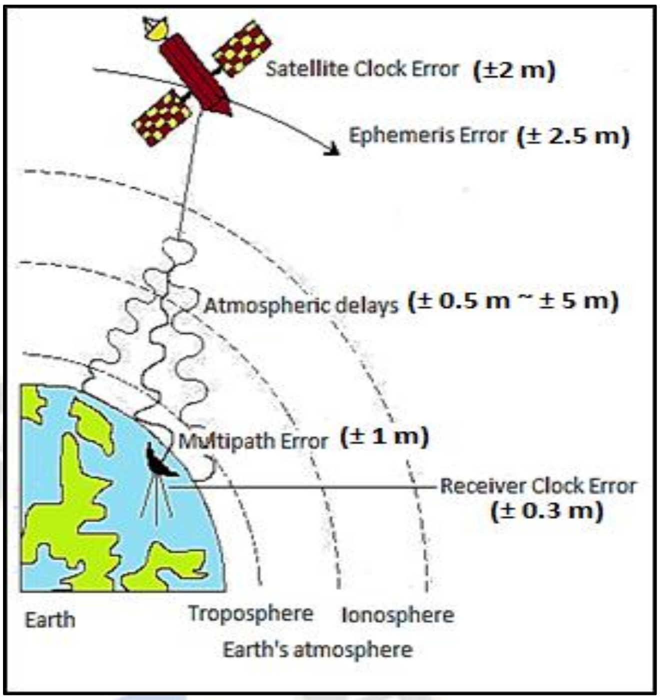

Figure 1. Error Sources in satellite-based navigation system

The effect of these error sources can be reduced significantly by improving the algorithm and integrating the hardware with more sensors to provide accurate inputs [15]. One such technique is known as Differential GPS[16], where the performance of a standalone GNSS receiver is enhanced by an additional receiver which helps in eliminating common errors like satellite clock error and atmospheric delays between the two (identical) receivers, depending upon their relative distances or baseline positioning [17]. An alternate solution is Real-time Kinematics (RTK) which is an extension of DGPS technology that uses carrier phase measurements that are generally more precise in terms of orders of magnitude than the code-phase measurements [18]. This technique may offer centimeter or decimeter-level positioning [19]. However, carrier phase measurements are ambiguous and require initial integer ambiguity to be resolved before being considered as input for the positioning [20]. Nonetheless, these techniques are expensive solutions and come up with their own set of issues like baseline limitations, communication link failure between the two receivers, etc. [21].

IoT devices equipped with GNSS capabilities are not optimized as dedicated GNSS receivers. They are designed to offer services such as Wi-Fi, Bluetooth, and other sensors, with GNSS being just one of their functionalities. Consequently, these devices are not built with high-quality hardware due to cost considerations. For instance, smartphones provide GNSS-based positioning services, but it is not their primary focus. These devices typically feature low-cost chipsets and antennas

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that are linearly polarized, resulting in higher signal loss compared to standard survey-grade GNSS receivers [22].

Furthermore, the quality of signals generated by these devices varies due to differences in their design, sophistication, complexity, and processing methods. As a result, they are more susceptible to interference and multipath issues. In urban areas, the accuracy of GNSS devices is significantly affected by three main factors: multipath effects, signal outages, and communication link failures caused by obstructions such as high-rise buildings, tunnels, trees, and poles [23] as shown in Fig. 2.

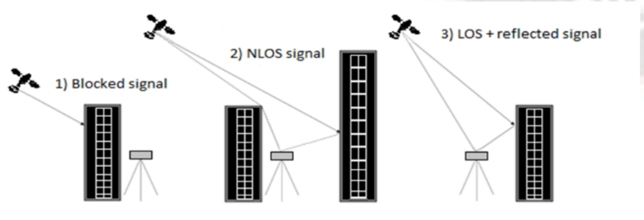

Figure 2. Types of signals during transmission

While using IoT with GNSS, several issues can arise. These issues can impact the performance, reliability, and security of IoT-GNSS applications. Here are some of the key issues to consider:

i. *Signal Interference and Multipath Effects*: GNSS signals can be affected by various sources of interference and multipath reflections, leading to degraded signal quality and accuracy. Signal interference occurs when unwanted signals disrupt the reception and processing of GNSS signals. Multipath effects, on the other hand, occur when GNSS signals are reflected or refracted by obstacles, resulting in multiple signal paths and positional inaccuracies.

   Most commercially available systems for detecting and mitigating multipath effects rely on advanced data processing methods, stochastic modeling, spatial geometry modeling, and specialized hardware designs [24]. These models aim to accurately differentiate between line-of-sight (LOS), multipath, and non-line-of-sight (NLOS) signals, and they are expected to be precise and reliable. However, these solutions face limitations when confronted with the real world.

   Traditional low-grade smartphone receivers cannot effectively address multipath issues, while high-grade receiver designs that can mitigate multipath effects exist but come at a high cost [25]. This poses a challenge for widespread adoption, as cost-effective solutions are necessary to ensure the availability of reliable and accurate positioning for a broader range of applications.

   In recent years, ML and DL methods have emerged as effective tools for addressing these challenges. These techniques empower the development of robust algorithms that enhance the accuracy and reliability of positioning systems. ML techniques leverage historical data to learn patterns and make informed decisions to improve the accuracy of GNSS positioning. For instance, support vector machines (SVM) have been used to classify multipath signals in [26][27][28] [29] [30] [31] [32] while gradient-based decision tree (GBDT) have been applied in [33][34] [35] [36] [37][38] [39] [26]. Studies like [40] [41] [42] [43] [44] demonstrate the usage of k-means clustering to classify multipath signals and [45] illustrates a naïve Bayesian-based technique to do the same. Neural network-based multipath classification and mitigation are shown in [46] [47] [48] [49] [50] [51] [52] [53]. Certain studies even combine multiple techniques to resolve this issue like in [54] [55] [56], the authors have used SVM and NN in combination.

   On the contrary, DL models, particularly deep neural networks, excel at handling complex interference and multipath challenges in GNSS with IoT. DL models automatically learn intricate features from GNSS measurements, enabling robust interference and multipath mitigation. Convolutional neural networks (CNNs) can capture spatial correlations in GNSS signals as demonstrated in [57] [58][59][60] [61] [62][63] [64].

ii. *Limited Power and Computational Resources:* IoT devices, including GNSS-enabled sensors, often have limited power and computational capabilities [65]. This poses a challenge for implementing resource-intensive ML and DL algorithms, which are essential for tasks such as data processing, signal analysis, and positioning. Addressing these challenges is crucial for efficient and real-time operation of GNSS with IoT systems. Researchers have explored techniques such as model compression, quantization, and scarcity to reduce memory footprint and computational requirements of ML models. The paper [66] discusses the challenges and potential solutions for executing machine learning algorithms on resource-constrained IoT devices.

   DL models, with their complex architectures, often demand significant computational power and memory [67]. However, advancements in DL research have led to the development of lightweight models suitable for limited-resource environments. Techniques such as model pruning, knowledge distillation, and low-rank

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approximation have been employed to reduce the complexity of DL models [68].

Furthermore, edge computing, efficient hardware acceleration, and model offloading techniques offer opportunities to offload computation to more powerful resources, enabling efficient processing of ML and DL algorithms [69]. However, it is important to note that while ML and DL techniques provide solutions for handling limited resources, there are trade-offs to consider. The compression and optimization of models may result in a slight decrease in accuracy or performance. Additionally, offloading computation to edge servers or cloud infrastructure introduces latency and dependency on network connectivity.

iii. *Privacy and Security:* GNSS with IoT involves collection and transmission of the location data, raising concerns about privacy and security. This data can potentially be intercepted, tampered with, or misused, posing privacy and security risks [70]. Additionally, ML and DL algorithms can themselves be vulnerable to attacks, such as adversarial perturbations or data poisoning, compromising the integrity of the system [71]. Ensuring the privacy of user location information and protecting against malicious attacks is crucial. The paper [72] presents various privacy-preserving techniques for secure location-based services in IoT. Reference [73]proposed an ML-based privacy protection scheme for GNSS-based location services. Their approach utilized ML algorithms to obfuscate the actual location information while maintaining the required level of utility for location-based services.

Privacy-preserving techniques, secure computation, and encryption methods enable the protection of sensitive location data while maintaining the utility of models [74]. Anomaly detection and intrusion detection systems enhance the security of GNSS with IoT applications. Additionally, defending against adversarial attacks ensures the integrity and reliability of ML and DL models [75]. As the field of ML and DL continues to advance, it is crucial to focus on developing robust privacy and security mechanisms specific to GNSS with IoT applications. Additionally, the development of standardized frameworks and guidelines for privacy-preserving ML and DL in GNSS with IoT would be beneficial.

iv. *Signal Degradation in Urban and Indoor Environments:* Urban environments with tall buildings, narrow streets, and multipath effects, as well as indoor settings with limited satellite visibility, can significantly degrade GNSS signals [76]. The presence of signal reflections, diffractions, and obstructions lead to inaccuracies and multipath effects, impacting positioning accuracy. Overcoming these challenges is crucial for reliable and accurate positioning in urban and indoor environments [77]. The paper [78] provides an overview of various positioning technologies, including GNSS, and discusses the challenges of indoor positioning in IoT applications.

ML and DL methods hold great potential in handling signal degradation in urban and indoor environments in GNSS with IoT applications. Signal quality estimation, map matching, crowd-sourced data utilization, RNNs, CNNs, and transfer learning techniques offer promising avenues for improving positioning accuracy [79]. However, addressing challenges related to data availability, computational resources, model generalization, and sensor fusion is crucial for successful implementation. By advancing research in this field, we can pave the way for reliable and accurate positioning in urban and indoor GNSS with IoT applications.

v. *Localization in Non-Line-of-Sight (NLOS) Scenarios:* The ideal operating environment for GNSS is line-of-sight (LOS), but for a variety of obvious reasons, the signal undergoes reflection or refraction [37]. LOS signals are the direct signals from the satellite to the receiver while the signal reflection received by the receiver is referred to as Non-Line-of-Sight (NLOS) reception [80]. Non-line-of-sight (NLOS) scenarios, such as urban canyons or dense foliage, pose challenges to accurate localization with GNSS. Traditional GNSS techniques struggle to provide accurate positioning in such situations due to signal blockages, multipath effects, and signal reflections. The paper [81] reviews different ML approaches and algorithms for localization in GNSS NLOS environments.

Map-based localization, radio signal fingerprinting, CNNs, RNNs, and GANs are effective techniques to addressing the challenges posed by NLOS conditions. Incorporating contextual information, analyzing spatial and temporal features in GNSS measurements, and generating synthetic data can significantly improve localization accuracy and robustness in NLOS scenarios.

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vi. *Integration of Multiple Sensors:* IoT devices often integrate multiple sensors, such as accelerometers, magnetometers, and gyroscopes along with GNSS receivers. Integrating data from these sensors and fusing them with GNSS measurements can enhance positioning accuracy and robustness along with enabling context-aware applications, including activity recognition, context-aware navigation, and environmental monitoring, contributing to smarter and more efficient IoT systems.

To ensure uninterrupted navigation, GPS is often combined with an Inertial Navigation System (INS) that utilizes accelerometers and gyroscopes to estimate a vehicle's acceleration and improve the overall performance of the navigation system [82]. However, the performance of the system can be compromised in situations where GPS signals are unavailable. GPS signals are vulnerable to environmental factors that can weaken or disrupt their transmissions, such as reduced signal power or signal loss in tunnels, rural areas, interiors, or forested regions [83].

During short periods of GPS outage, the INS can still provide position estimations, mitigating the impact on navigation accuracy. However, as the outage duration increases, the error in the motion sensors accumulates, leading to a significant decrease in location estimate accuracy [84]. To address this issue, ML/DL models are employed to analyze the error patterns of the INS under various conditions. These models help rectify the location error caused by the INS during GPS signal blockages, thereby enhancing navigation accuracy. A Neural network is used to provide seamless navigation in case of GNSS signal outage in [85][86][87] [88][89][90][91] [92][93] [94]. Another method is demonstrated in [31] [95] which uses SVM whereas [96] uses RNN to provide continuous positioning.

Robustness in signal-challenged environments is also achieved by leveraging complementary information from multiple sensors, allowing for accurate positioning even in non-line-of-sight scenarios affected by multipath and interference. Several studies have explored the application of ML and DL models for sensor fusion in GNSS with IoT. The paper [97] discusses sensor fusion techniques and their integration with GNSS in IoT applications. Reference [98]proposed a deep neural network-based sensor fusion framework for GNSS/INS integration. Their model effectively integrated the information from GNSS and inertial sensors to achieve accurate positioning even in challenging environments.

In this section, we have listed and discussed various GNSS combined with IoT applications where ML and DL methods can contribute to improving the performance and meeting the desired results:

i. *Disaster management:* IoT devices equipped with GNSS capabilities are instrumental in environmental monitoring applications [99]. ML algorithms can combine GNSS data with weather measurements to accurately predict weather conditions, improving forecasting capabilities. DL models can process satellite imagery and identify environmental changes, aiding in monitoring deforestation, urban growth, and natural disasters like flood monitoring systems [100], earthquake warning systems [101], and healthcare disaster prediction [6].

ii. *Smart healthcare and wearable devices:* Wearable devices with integrated GNSS capabilities can enable location-based healthcare applications, such as remote patient monitoring and emergency response systems [102][103]. ML and DL methods can analyze sensor data to detect patterns, monitor health conditions, and provide personalized healthcare services [104][105][6].

iii. *Smart cities:* ML and DL models are crucial in smart city applications [106], where GNSS and IoT technologies are integrated to enhance urban services and infrastructure. By analyzing GNSS data, sensor readings, and IoT-generated data, these models enable optimized transportation systems, efficient energy management, smart parking, intelligent traffic management [107][108] and accident detection and classification [109]. ML models can predict traffic congestion patterns based on GNSS data, while DL models can analyze surveillance camera feeds for detecting unusual activities and enhancing security [110] [106].

iv. *Accurate tracking and asset monitoring systems:* By leveraging ML and DL algorithms, organizations can track and monitor their assets in real-time, reducing theft, optimizing operational efficiency, improving route planning and optimizing supply chain management. For example, ML models can predict equipment failures based on GNSS data, enabling proactive maintenance and minimizing downtime [78] [111][112] [113] [114][103].

v. *Precision agriculture:* GNSS technology combined with IoT enables precision agriculture, where farmers can optimize crop management, irrigation, and fertilization based on real-time data[69] [115][110].

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ML and DL methods can analyze the collected data to provide insights for improved decision-making, such as detecting crop diseases, predicting yield, and optimizing resource allocation [116][117][118].

II. CHALLENGES OF INTEGRATING ML/DL WITH GNSS AND IOT

Integrating ML and DL with GNSS and IoT poses several challenges that need to be addressed for successful implementation. These challenges can range from data availability and quality to computational constraints and security considerations. Here, we delve into the key challenges of integrating ML/DL with GNSS and IoT:

i. *Lack of literature:* The limited availability of research on ML/DL modelling for IoT GNSS applications is a common observation. Many studies rely on simulated data or collect real data for short durations, casting doubts on the credibility of the models. Moreover, the experimental data collected in controlled environments often overlooks real-time challenges such as signal loss and poor Dilution of Precision (DOP). As a result, ML/DL solutions developed using such data may not deliver accurate and reliable performance in practical situations.

ii. *Satellite visibility:* The visibility of satellites is a critical factor in global navigation systems like GPS, Galileo, and GLONASS, which depends on the location and time of measurement [119]. This leads to variable sets of GNSS signals in observations due to the Earth's motion and satellite positions. To estimate a position solution, a minimum of four observations is required, and GPS can receive up to 12 signals from its constellation spread. Ensuring ML/DL-based positioning algorithms generate output independent of the measurement order within the observation set is challenging due to the varying numbers and orders of data.

iii. *Data Availability and Quality:* ML/DL algorithms heavily depend on large volumes of high-quality training data, posing challenges in the context of GNSS and IoT [120]. Acquiring diverse and representative datasets that encompass interferences and environmental conditions is complex. Ensuring the quality and accuracy of collected data is crucial for training reliable ML/DL models. Processing noisy and erratic GNSS data from low-cost sensors in IoT devices presents additional difficulties, requiring accurate data preprocessing. Outlier removal, organization, missing value filtering, and refinement GNSS receivers like smartphones capture input signals with approximately 10 dB loss, necessitating extensive preprocessing before ML/DL modelling. Variations between multiple devices in similar conditions make it impractical to capture all potential scenarios during training data collection. Lastly, validating the proper application of a specific ML/DL model in real-world scenarios is also challenging.

iv. *Data labelling and feature selection:* Another difficult aspect is data labeling and feature selection, such as identifying the affected features in the presence of multipath for classifying multipath, LOS, and NLOS signals [37]. This challenge arises from determining the number and selection of prominent features that effectively represent the entire dataset.

v. *Computational Complexity:* ML/DL algorithms, particularly deep neural networks, can be computationally intensive, requiring significant processing power and memory resources. This poses challenges for resource-constrained IoT devices that often have limited computational capabilities and energy constraints. Optimizing ML/DL models for efficient execution on IoT devices is crucial to overcome these computational limitations and striking a balance between accuracy and resource utilization.

vi. *Real-Time Processing:* Many IoT-GNSS applications require real-time processing and decision-making. However, the latency introduced by ML/DL algorithms can be a challenge. Traditional ML/DL models may not meet the real-time requirements of IoT-GNSS systems. Therefore, developing lightweight and efficient ML/DL models, as well as exploring hardware accelerators and distributed processing techniques becomes important for achieving real-time capabilities.

vii. *Generalization and Adaptability:* ML/DL models trained on specific datasets may struggle to generalize to new and diverse scenarios encountered in real-world IoT-GNSS deployments. Environmental variations, changing signal conditions, and evolving user requirements can pose challenges to the adaptability and generalization of ML/DL models. Continual model updating, transfer learning, and domain adaptation techniques are essential to ensure the models' effectiveness across different environments and applications.

viii. *Security and Privacy:* Integrating ML/DL with GNSS and IoT brings security and privacy concerns. ML/DL models can be vulnerable to adversarial attacks, where malicious actors manipulate the input signals or inject malicious data to deceive the system. Moreover, protecting the privacy of sensitive location data collected by IoT-GNSS systems is crucial. Robust security mechanisms, such as secure communication protocols, data encryption, and anomaly detection algorithms, should be implemented to mitigate these risks.

ix. *Interpretability and Trust:* ML/DL models often exhibit black-box behavior, making it challenging to interpret their decision-making processes. This lack of interpretability can undermine the trust and acceptance of IoT-GNSS systems. Ensuring explain ability and transparency of ML/DL models, such as using model visualization techniques or providing confidence measures, can help build trust and facilitate the adoption of ML/DL in IoT-GNSS applications.

x. *Regulatory Compliance:* IoT-GNSS applications need to comply with various regulatory frameworks, such as privacy regulations and spectrum management rules. Integrating ML/DL into these systems requires adherence to legal and ethical guidelines. It is essential to consider the implications of regulatory compliance and ensure that ML/DL algorithms and data processing techniques align with the applicable regulations.

Addressing these challenges requires interdisciplinary collaboration among GNSS experts, data scientists, IoT engineers, and domain-specific stakeholders. Research and development efforts should focus on data collection and curation, model optimization for resource-constrained devices, real-time processing techniques, security and privacy enhancements, interpretability methods, and compliance with regulations. By overcoming these challenges, ML/DL integration with GNSS and IoT can unlock the full potential of intelligent and reliable positioning and navigation systems.

III. CONCLUSION

Overall, ML and DL methods have emerged as powerful tools for addressing various challenges in GNSS with IoT. They have shown great potential in mitigating signal interference and multipath effects, integrating multiple sensors, ensuring privacy and security, handling signal degradation in urban and indoor environments, and providing localization in non-line-of-sight scenarios. These techniques enable improved positioning accuracy, robustness, and efficiency in GNSS-based applications within the IoT ecosystem.

The benefits of applying ML and AI to GNSS in IoT are significant. These methods enable improved positioning accuracy in challenging environments, such as urban canyons or indoor locations, where GNSS signals may be weak or obstructed. ML algorithms can effectively learn and adapt to complex signal conditions leading to enhanced robustness and reliability of GNSS-based systems. Moreover, AI techniques can facilitate intelligent decision-making and optimization in real time, allowing for dynamic adjustments and optimizations of positioning algorithms.

However, there are some limitations associated with applying ML and AI methods to GNSS in IoT. First, ML models often require a substantial amount of training data, which may be difficult to obtain for certain GNSS scenarios or signal conditions. Additionally, the computational complexity of ML algorithms can be high leading to increased power consumption and latency, which may not be suitable for resource-constrained IoT devices. Furthermore, ML models are susceptible to adversarial attacks, where malicious actors intentionally manipulate the input signals to mislead the GNSS positioning system.

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