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Machine Learning Utilization in GNSS—Use Cases, Challenges and Future Applications

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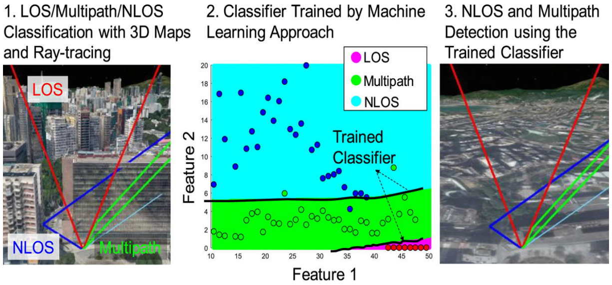
Abstract— **The algorithms and models of traditional global navigation satellite systems (GNSSs) perform very well in terms of the availability and accuracy of positioning, navigation and timing (PNT) under good signal conditions. Research is still ongoing to improve their robustness and performance in less than optimal signal environments. A growing interest in the study of machine learning (ML) and the potential for its application in many fields has also led to several types of research on its utilization in GNSSs. In the field of GNSSs, ML is changing the ways that navigation problems are prevented and resolved, and it is taking on a significant role in advancing PNT technologies for the future. We illustrate this point by reviewing how ML can enhance GNSS performance and usability and also discuss areas of GNSSs in which ML algorithms have been applied. We also highlight the commonly implemented ML algorithms and compare their performance when used in similar GNSS use cases. In addition, the challenges and risks of the utilization of ML techniques in GNSSs are discussed. Insight is given into prospective areas in GNSSs in which ML can be applied for increased performance, accuracy and robustness, thereby providing fertile ground for novel research.**

Keywords— Machine Learning (ML), Deep Learning (DL), Global Navigation Satellite Systems (GNSSs), PNT technologies, GNSS performance.

I. INTRODUCTION

In global navigation satellite systems (GNSSs), there are several sources of errors for satellite-based positioning that affect accuracy and degrade receiver performance, namely, the ionospheric effect, multipath propagation, spoofing and jamming interferences and GNSS-denied environments. Other sources of error in GNSSs include receiver noise and resolution, satellite clock errors and hardware biases [1]. Therefore, it is interesting to see how machine learning (ML) has and can be applied in such cases.

Machine-learning techniques are well suited for real-life problems and are tolerant to data that are imprecise, partially incorrect or uncertain [2]. ML is a very powerful technique in handling time-series data, and it can learn time-dependent patterns across multiple models. Therefore, ML can be found useful in the discovery of unknown and hidden information in GNSS data. The nearly limitless quantity of available data, affordable data storage and the growth of less expensive and more powerful processing has propelled the growth of ML. Compared to statistical methods, ML methods enable us to identify tricky dependencies in datasets for which exploratory analysis has not enabled the proper determination of the shape of the underlying model. The aim in ML is not to provide an explicit formula for the distribution of the data; rather, an algorithm is trained to detect the relationships among the features of the data on its own, directly from the data. Learning methods makes it possible to avoid the assumptions involved in many statistical methodologies. A demonstration of the concept of training using a machine-learning approach is shown in Fig. 1. It shows an ML model trained to classify a GNSS signal as line of sight (LOS)/multipath/non-line of sight (NLOS).


1. LOS/Multipath/NLOS Classification with 3D Maps and Ray-tracing

2. Classifier Trained by Machine Learning Approach

3. NLOS and Multipath Detection using the Trained Classifier

Fig. 1. Demonstration of the concept of training using a machine-learning approach [3].

This paper presents some major applications in GNSSs in which ML has been utilized to provide a novel solution or a new service. The different ML algorithms, methods and solutions used in the primary literature are compared to show how they are used. The rest of the paper is organized as follows: Section II presents the review process and the research questions that are discussed. In Sections III through V, the research questions used are discussed, while Section VI discusses the challenges and risks of using ML algorithms in GNSSs. Section VII presents the conclusions and future directions.

II. FEASIBILITY ASSESSMENT

To facilitate the use of ML algorithms in GNSSs, it is necessary to review their performance and usage in the extant literature. This review began with a systematic search for applications of ML in GNSS use cases of digital libraries, leading to the retrieval of 182 papers. A total of 47 of these papers were deemed relevant and required full-text screening for detailed information on the application of ML in a GNSS. The search phrase used to identify the primary studies was *"GNSS AND (machine learning OR deep learning OR artificial intelligence OR random forest OR support vector machine OR decision tree OR neural network OR regression)"*. The four electronic databases used for the search were IEEE Xplore, ScienceDirect, Google Scholar and the Web of Science. We restricted the search to articles published from 2000 to 2020.

Two other papers ([43 and [50]) were added based on recommendations from reviewers. The following research questions (RQs) were identified to guide the review:

RQ1. To which GNSS use cases have ML algorithms been applied and in what are other prospective areas of GNSSs could ML algorithms be utilized?

RQ2. Which ML algorithms are utilized in GNSSs and are there ML algorithms that significantly outperform the others?

RQ3. What are the challenges and risks of using ML algorithms in GNSSs?

These research questions are discussed in Sections III through V, respectively.

III. MACHINE LEARNING UTILIZATION IN GNSS USE CASES

The use of ML in GNSSs is promising, as it has proven useful in various studies. Here, we discuss the ML techniques implemented in the primary studies. The ML techniques described include decision trees (DTs), gradient-boosting decision trees (GBDTs), logistic regression (LR), long short-term memory (LSTM), naïve Bayes (NB), Gaussian process regression (GPR), deep learning (DL) models (neural networks, or NN), extreme learning machines (ELMs), support vector machines (SVM) etc. The algorithms were used for classification, clustering, forecasting and anomaly detection depending on the GNSS application. ML cannot completely replace GNSS physical models, but the use of ML/DL together with traditional GNSS has been promising and has become more popular among researchers, as discussed in the following subsections.

A. GNSS Signal Acquisition

The signal acquisition process estimates if a particular satellite signal is present or not in the received signal, and it also gives a rough estimate of its associated code delay and Doppler frequency if present [4]. This acquisition process is implemented by all GNSS receivers [5], [1]. This process is achieved through the evaluation of a cross-ambiguity function (CAF), usually in a discrete-time domain. The CAF is a two-dimensional function that is related to the correlation between the received signal and local code for every possible delay/Doppler pair. The CAF, which can be considered an image, has certain characteristics that can be used to distinguish the presence or absence of a signal from a specific satellite. This knowledge can be used to train a data-driven model, such as a multi-layer perceptron (MLP), which is a neural network architecture with moderate complexity that has been widely used in ML studies, or a convolution neural network (CNN), which is able to capture complex non-linear phenomena, at the expense of much greater complexity when compared to MLPs [4].

B. Signal Detection and Classification

Most of the solutions already in the market that implement multipath detection and mitigation are designed using stochastic modelling, spatial geometry modelling, advanced techniques in data processing, or new special hardware designs [6]; however, this is not the case for all receivers, for example, low-cost receivers and GNSS-enabled smartphones. In the detection and classification of the characteristics of an acquired signal, the model needs to be able to accurately and reliably classify the LOS, multipath and NLOS signals. However, when there is an event outside the statistical models (too complex to be modelled with classical statistics and that does not fit the mathematical assumptions used to develop the models), these solutions become ineffective. ML methods enable us to throw off assumptions required in the statistical methodology. In [7], [6], [8], [9] and [10], ML methods, such as logistic regression (LR), support vector machines (SVMs), naïve Bayes (NB), decision trees (DTs), CNNs and recurrent neural networks (RNNs), have been implemented. An artificial neural network (ANN) model capable of processing the structure of the autocorrelation function (ACF) was used for the detection of evil waveforms (EWF) in [11]. In [12] and [13], a robust gradient-boosting decision tree (GBDT) and DT-based classifier were employed, respectively, for GNSS signal reception classification that made use of the carrier-to-noise-density ratio (C/N0), pseudo-range residuals and satellite elevation angle as the input features to improve the performance of the signal classification at the receiver.

C. Earth Observation and Monitoring

GNSSs have been used in understanding the atmospheric effects of earthquakes by analysing the ionospheric behaviour before and after them through the determination of the total electron content (TEC) using GNSS data [14]. TEC is a representation of the electron density in the signal trajectory between the satellite and the receiver on the earth's surface. In [14], vertical total electron content (VTEC) data from the National Oceanic and Atmosphere Administration (NOAA) along with ionospheric disturbance information were used for training an ANN for the prediction and detection of earthquakes and the determination of their magnitude. Hurricane detection and prediction are based on the categorization of the maximum wind speed that can be estimated from the reflected GNSS signals, but to be able to track the hurricane efficiently, a large amount of measurement data is required. This is where a deep learning algorithm such as CNN is used, as seen in [15]. Similarly, in [16], a CNN model based on classification was used for sea ice detection, while a regression-based CNN was applied in sea ice concentration (SIC) estimation from TechDemoSat-1 GNSS reflectometry delay-Doppler maps (DDMs). DL has also been useful in other cases, such as environmental remote sensing, which includes land cover mapping, aerosol monitoring and the prediction of agricultural yield, snow cover, ocean colour parameters etc. [17].

D. GNSS Navigation and Precise Positioning

Nowadays, GNSS is successfully implemented to achieve precise positioning in both indoor and outdoor environments [18], [19]. Such precise positioning is essential for safe operations [20], [21]. For indoor positioning, GNSS is applied in areas like warehouse management [22], automated manufacturing [23] etc. In the case of outdoor positioning, GNSS is also suitable for tracking and tracing in various sectors, such as intelligent transportation systems (ITSs), autonomous vehicles [24], supply chain and logistics [25], port operations [26] etc. Achieving accurate and precise positioning is achieved by minimizing errors in both indoor and outdoor positioning.

ML has been applied in location-based services (LBS) with the aim of improving GNSS navigation and positioning in several scenarios. In [27], the least-squares support vector machine (LSSVM) technique was used to enhance the accuracy of Kalman filtering (KF). This enhanced model is called LSSVM-enhanced KF (LSSVM-KF). The KF relies on the quality of the observations as well as the dynamic model; therefore, LSSVM-KF adaptively estimates the dynamic modelling bias from the historical information and then uses the bias estimate to compensate the dynamic model. The dynamic model bias is treated as a time-variant ambiguous function by the algorithm, which is trained with the LSSVM [27]. Also, ML has been applied in ITSs to estimate the GNSS position error by aiding motion sensor units in providing a more accurate position estimate during periods of outage or blockage of the GNSS signal. In [28], a DT and SVM were implemented to choose the best feature for classifying the input data at every iteration and for the selection of features that were most relevant for the location error estimation.

E. Indoor Navigation

Scenario recognition is essential for seamless indoor localization and robust positioning in complex environments. In [29], the influence of multi-constellation GNSS measurements on scenario recognition performance was studied using a hidden Markov model (HMM) algorithm. This work was based on the recognition of four scenarios (deep indoor, shallow indoor, semi-outdoor and open outdoor). The results from the scenario recognition showed a significant improvement with the increase in the number of constellations received by the smartphones. However, when the user was switching between indoor and outdoor environments, the observed variables (such as the number of visible satellites) did not respond to this change of environment immediately, as the change to the current scenario was rather slow. This caused the result of scenario recognition to lag behind the true value, and it is a challenge to effectively shorten this transition delay during scenario recognition. A scenario recognition algorithm based on an RNN, which showed better results in terms of accuracy, adaptability to new environments and real-time performance, was implemented to meet this challenge.

F. Ionospheric Scintillations and Tropospheric Wet Delay

In a GNSS receiver, signal acquisition and tracking can be severely impacted by strong scintillation, resulting in GNSS performance degradation in accuracy and continuity. It is difficult to predict and model scintillation because there are different reasons for the occurrence of this phenomenon, for example, solar activity, magnetic storms, local electric fields, conductivity, wave interaction etc. [30]. A DT model in [31] and an SVM in [30] are examples of ML algorithms employed for the detection of scintillation. The time delay of a GPS (L1 and L2) signal in the ionosphere is an example of propagation path delay, and it depends on the TEC of the atmospheric layer. This delay contributes to a potential source of error in time measurements and can produce an error range in tens of meters. In [32], Gaussian process regression (GPR) was used in comparison to an auto regressive moving average (ARMA) model and ANN model to implement the forecasting of low-latitude ionospheric conditions, and in [33], a single frequency correction algorithm based on a GNSS global ionosphere map (GIM) vertical TEC (vTEC) and fully connected neural networks (FC-NN) was used to estimate GNSS single-frequency ionospheric delay. [34] is another study on GNSS atmosphere delays in which ML has been employed. In [35], an ANN model was implemented to predict tropospheric wet delay based on meteorological and GNSS data.

G. GNSS Security—Spoofing and Jammer Attacks

Mitigation against spoofing attacks has been achieved at the pseudorange level, with receivers employing receiver autonomous integrity monitoring (RAIM) by the discovery of an inconsistent set of five or more pseudoranges to allow the receiver to identify an unsophisticated spoofer that broadcasts one or more false signals with no attempt to achieve believable consistency. However, in response to efforts to defend against spoofing, advanced forms of GNSS spoofing have been conceived, for example, a spoofing method called “in the wild”, which is an actual malicious spoofing attack [36]. Therefore, ML has been implemented to detect and defend against spoofing; for example, in [37], one- and two-hidden-layer neural networks with various numbers of hidden neurons were implemented to detect GPS spoofing signals by making use of different features, such as pseudo-range, Doppler shift and signal-to-noise ratio (SNR), to perform the classification of GPS signals. While [38] used an MLP neural network classifier trained by particle swarm optimization (PSO). Other ML algorithms used to detect jamming and spoofing include RNN based on long short-term memory (LSTM), classification SVM (C-SVM) with principal component analysis (PCA), and SC-SVM, as seen in [39], [40] and [41], respectively. In the case of GNSS jamming, in [42], SVM and CNN models were used for the detection and classification of the jammer signal. In [43], ML is used to protect users against Secure Code Estimation and Replay (SCER) attacks on Galileo OS-NMA making use of the analysis done on the features extracted from the victim’s Search Space. This ML technique is, however, complementary to the Navigation Message Authentication (NMA) techniques meaning that it will not offer any guarantee the navigation message was not modified if the ML is used separately without the NMA technique. The features extraction used is based on fitting the correlation peaks in the search space as 2D Gaussians and detecting radio frequency interferences (RFIs) during a time analysis window. The detection used in this paper is based on simply finding outliers with the assumption that an Automatic Gain Controller (AGC) is present. Using algorithms based on Decision Trees (DT, ADA Boost, and Random Forest) gave the best results when signal C/N0 is above 30dBHz. Other algorithms implemented were Nearest Neighbour, and RBF SVM algorithm with the accuracy decreasing when the location of the peaks is introduced, particularly for high C/N0. While Linear SVM showed that as the C/N0 improves the results also improve, and give values similar to that of the Decision Trees when C/N0 is greater than 30 dBHz.

H. GNSS/Inertial Navigation Systems (GNSS/INS) Integration

Several technologies that are essential to reducing positioning errors are now being researched [28]. Nowadays, a GNSS is interfaced with inertial navigation systems (INS) along with some filtering techniques with the objective of improving the overall positioning system [44]. Usually, a combination of an INS with various filters is used to calculate the accurate position. In such a situation, a GNSS outage of shorter duration does not have much effect on estimating accurate positioning. However, if the outage becomes longer, then the accuracy of the positioning decreases significantly [45]. Therefore, it is a common concern for a longer GNSS outage that makes for inaccurate precision positioning. In the case of a longer outage, the application of machine-learning algorithms can help to maintain positioning accuracy [28].

The Kalman filter (KF) is widely used in navigation as a data-fusion algorithm. In the integration of GNSS/INS, when a GNSS cannot normally supply measurement updates, the filter time will be increased. In such cases, the divergence of strap-down inertial navigation system (SINS) or INS error occurs quickly without GNSS information correction. This could be detrimental depending on the use case, such as in the concealment of unmanned underwater vehicles (UUVs) and unmanned aerial vehicles (UAVs). In [46], a backpropagation neural network (BPNN)-aided integrated navigation method based on vehicle motion learning was proposed. In [47], a recurrent neural network (RNN) in comparison with an extreme learning machine (ELM) and extended Kalman filter (EKF) was employed, while [48] used an NN model to design a neural network-assisted GNSS/SINS calibration system. A CNN-based adaptive Kalman filter was designed and discussed in [49]. In [50], ML is integrated with 3DMA (3D modelled assisted GNSS) to achieve high accuracy in urban environments. This is done using ML/AI algorithm together with Google’s vast database of 3D building models, the asymmetric NLOS propagations are modelled in order to correct NLOS pseudorange errors. This was shown to reduce Wrong-Side-of-Street occurrences from GNSS in phones up to 50 to 90%.

In general, when a GNSS is active, the ML model is used to learn the divergence characteristics of the INS error under several basic conditions, depending on the area of application (vehicles, UAV etc.). If there is a disturbed GNSS signal, the ML model is used to correct the position error of the INS in order to improve navigation accuracy.

I. Satellite Selection

Location accuracy is the result of two main factors, namely, the satellite location-dependent geometric dilution of precision (GDOP) and the pseudorange measurement inaccuracies [51]. The benefit of multi-constellation GNSS is that there are more visible satellites to improve user positioning performance. However, due to some issues, such as low-cost receivers having limited tracking receiver channels (four or five channels) and power consumption (also applicable to sophisticated receivers having up to 12 channels), it is usually not possible, beneficial or desirable to use all satellites in view for positioning [52]. Instead, an optimal subset is generally selected from all the possible visible satellite combinations with the aim of minimizing either the GDOP or weighted GDOP (WGDOP), as in the case of [53]. The GDOP is computed from the trace of the inverse of the measurement matrix of the contributing satellites [54]. Other selection criteria used in studies include elevation angle, C/N0 and range errors. In [53], an end-to-end DL network for satellite selection based on the PointNet [55] and VoxelNet [56] networks were proposed. The satellite selection procedure is converted to a satellite segmentation problem that has two class labels, one for selected satellites and the other for satellites not selected. In [54], the functional relationships between the entries of a measurement matrix and the eigenvalues of its inverse are learned using a neural network, and the model is able to give the GDOP values without the need to compute the inverse of a matrix.

IV. What are Other Prospective GNSS Areas in Which ML Algorithms Could Be Utilized?

There are other GNSS areas in which ML can be utilized, including space applications, such as robotic exploration in space and situation awareness for space debris analysis. ML models could be used in fault detection, altitude determination of space vehicles, flight control etc. Also, ML algorithms could be proposed to estimate products similar to international GNSS service (IGS) products using the IGS observation data model to correct GNSS position error. Furthermore, ML algorithms could be proposed to emulate some of the output of a satellite-based augmentation system (SBAS) processing facility and predict the performance of SBASs in the context of a single frequency, single constellation (SFSC) and/or dual-frequency multi-constellation (DFMC) operation. These are areas that have seen much interest, especially in the latest European Space Agency (ESA) invitations to tender. They could also be used to detect signal diffraction, which has seen less research. This effect occurs when GNSS signals are partially obstructed but not totally blocked. Signal diffraction is usually statistically modelled into the navigation algorithms, in which they are mitigated by smoothing techniques that adapt poorly. This makes these solutions ineffective, especially when there is an event too complex to be modelled with classical statistics and does not fit the mathematical assumptions used to develop the statistical model.

There are well-known models to estimate the precise position of a GNSS receiver (e.g., tropospheric and ionospheric models) under simple scenarios with good line of sight, but there are high non-linearities if the receiver experiences multipath effects (e.g., urban scenarios, which have seen a high amount of research) or high signal dynamics (e.g., a rocket launch—in the domain of space applications). It would be interesting to use deep learning in the later problem. ML could also be applied to space applications (space debris analysis, robotic exploration in space, cube satellites etc.). We have seen from this review that artificial neural networks assisting Kalman filter positioning in order to determine the measurement noise covariance and process noise covariance of the Kalman filter have been promising and can be applied in other scenarios.

V. Are There ML Algorithms that Outperform the Others?

From the review done, ML algorithms were implemented in several GNSS use cases. It was observed that a GBDT-based algorithm achieved a classification accuracy higher than distance weighted k-nearest neighbour (KNN), traditional DT and an adaptive network-based fuzzy inference system (ANFIS) [12] for GPS signal reception classification (LOS/NLOS/multipath). In [13], the proposed DT-based classifier obtained a higher accuracy than the KNN and SVM classification techniques. The DL models have also been seen to perform much better; for example, [8], [9] and [11] showed good performance using CNN models. The next ML model with significant performance was an NB prediction model, as seen in [7], in which the model performed better than logistic regression, SVM and traditional DT, according to their studies. Another ML model with significant performance was the SVM in various forms (SVM, LSSVM-KF, C-SVM), as seen in [27], [28] and [38], respectively.

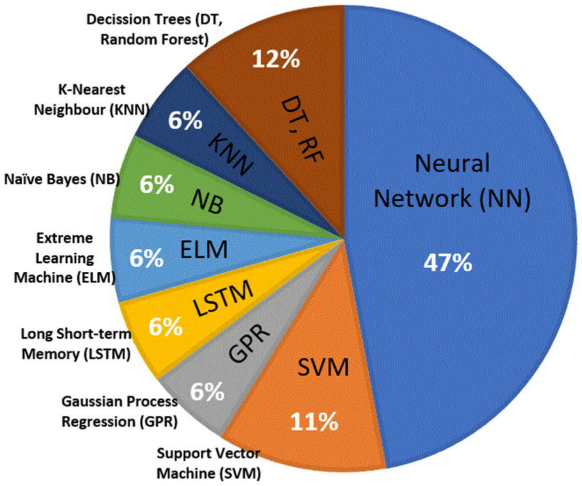


Fig. 2. A summary of the ML algorithms mostly utilized in GNSS.

As illustrated in Fig. 2, it was also noticed that the algorithms utilized in the GNSS use cases examined with better performance mostly included SVMs, 11%; DTs (GBDT), 12%; and NN (or DL) models, 47% [30], [31], [32], [34], [33], and [35]. The distribution of the DL models used based on the literature reviewed is illustrated in Fig. 3.

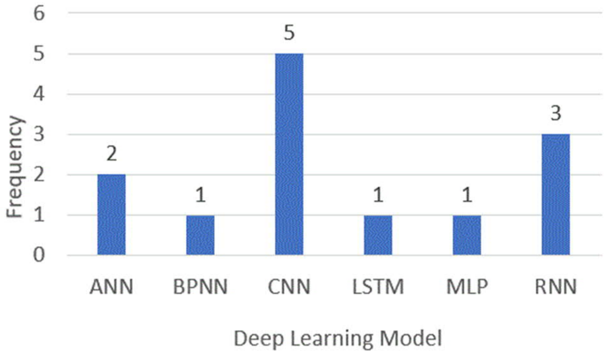


Fig. 3. Distribution of the use of deep learning models in the GNSS studies examined.

From Fig. 3, we can see that CNN was implemented five times, followed by RNN and ANN with frequencies of three and two, respectively.

VI. CHALLENGES AND RISKS OF USING ML ALGORITHMS IN GNSSS

A primary source of risk is the data used to train the ML model. It is therefore important to ensure the reliability, integrity, representativeness and security of the training data being used. Otherwise, it is possible to produce false predictions and a bad ML model. Furthermore, "false correlation" is a risk that can occur when features are completely independent of each other and exhibit very similar behaviour by chance. This can provide a false conclusion that they are somehow connected. An example is when a high C/N0 value is incorrectly attributed to multipath propagation, even though high C/N0 values can also occur during normal LOS situations. ML algorithms are dependent on the data used for training and learning. Therefore, it is especially important to ensure the privacy and confidentiality of the data used for building or training the ML models. Otherwise, data extraction attacks could be launched by hackers that jeopardize the entire ML system. Since most ML systems take advantage of an already trained ML model, a generic model can be tweaked to meet a specific need by conducting specialized training. Therefore, what is referred to as a transfer learning attack can affect the task-specific ML model derived from the generic model. Other risks include a non-representative sample used for training data, developers' bias, system parameters, feedback loops, overfitting/underfitting, misinterpretation of the resultant models and contaminated reference data or data bias.

Lastly, because ML/DL algorithms may be hard to understand and explain (a "black box" effect, that is, a lack of transparency in some algorithms), for example, how the weighted coefficients within a neural network are arranged to arrive at the correct answers, this may lead to difficulty in validating and explaining results to stakeholders in order to allow such models to be applied in real-life scenarios.

VII. CONCLUSIONS AND FUTURE WORK

Machine learning has been an enabling technology for many industrial applications in areas such as image recognition, classification, early anomaly detection and prediction. This review has shown that the utilization of ML in GNSSs has been an area of increasing research interest with positive prospects for future research and application.

The most common use cases for ML in GNSS, according to the recent research, include signal acquisition, NLOS/multipath/evil waveform (EWF) detection, signal reception classification (LOS/NLOS/multipath signal classifier), earth observation/monitoring, GNSS positioning error estimation, indoor navigation, characterization of GNSS ionospheric amplitude scintillation, detection of GNSS ionospheric scintillations/forecasting ionospheric time delay, GNSS phase scintillations, estimation of GNSS single frequency ionospheric delay, prediction of tropospheric wet delay, detection of GNSS spoofing attacks and jammer classification, GNSS/INS integration, and satellite selection etc.

We showed that among all ML methods, DL models (NNs) were the techniques that had been widely used by researchers most lately and provided the best results, followed by DTs and SVMs.

The challenges and risks in using ML in GNSSs were discussed and include a broad, but admittedly, selective sample of training data, developers' biases, system parameters, feedback loops, overfitting/underfitting, misinterpretation of the resultant models and contaminated reference data or data bias. The security of the training data and models was also identified as a risk, as they could be potentially manipulated by hackers.

Finally, we proposed other prospective areas of GNSSs to which ML algorithms could be applied, such as (but not limited to) space applications (space debris analysis, robotic exploration in space, cube satellites etc.), predictions of IGS products through the use of IGS data, SBAS performance prediction, GNSS hardware error detection/compensation, live tracking and tracing for supply chain and logistics and smart port operation.

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