A Systematic Review of Machine Learning Techniques for GNSS Use Cases

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In terms of the availability and accuracy of positioning, navigation, and timing (PNT), the traditional Global Navigation Satellite System (GNSS) algorithms and models perform well under good signal conditions. In order to improve their robustness and performance in less than optimal signal environments, many researchers have proposed machine learning (ML) based GNSS models (ML models) as early as the 1990s. However, no study has been done in a systematic way to analyze the extent of the research on the utilization of ML models in GNSS and their performance. In this study, we perform a systematic review of studies from 2000 to 2021 in the literature that utilizes machine learning techniques in GNSS use cases. We assess the performance of the machine learning techniques in the existing literature on their application to GNSS. Furthermore, the strengths and weaknesses of machine learning techniques are summarized. In this paper, we have identified 213 selected studies and ten categories of machine learning techniques. The results prove the acceptable performance of machine learning techniques in several GNSS use cases. In most cases, the models using the machine learning techniques in these GNSS use cases outperform the traditional GNSS models. ML models are promising in their utilization in GNSS. However, the application of ML models in the industry is still limited. More effort and incentives are needed to facilitate the utilization of ML models in the PNT context. Therefore, based on the findings of this review, we provide recommendations for researchers and guidelines for practitioners.

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I. INTRODUCTION

THE growing complexity and dependency on global navigation satellite system (GNSS) technologies have increased the need for delivering high-performance GNSS solutions in terms of performance parameters, such as accuracy, availability, continuity, and integrity, at lower costs. Another additional performance indicator is the "Time To First Fix (TTFF)," which is used by some receiver manufacturers. GNSS performance prediction is a very important and essential activity to be carried out before the system is deployed so that the performance of the navigation system can be estimated, and the maintenance efforts and downtime can be significantly reduced. The early detection of faults and errors may lead to the timely correction of these faults [1].

There are various performance parameters addressed in the literature. These performance parameters as well as error/fault data can be used to develop and evaluate models used for the detection and correction of GNSS errors. These models can be used for estimating and predicting GNSS performance required by an application relying on a GNSS system in order for it to perform adequately.

There are some significant sources of errors for satellite-based positioning namely the ionospheric and troposphere effects, multipath, clock drift, receiver noise, interference, and hardware biases [2]. Ionospheric content interferes with GNSS signals, thereby, inducing errors for users when making calculations of their position from such signals. In addition, because GNSS was designed to operate in ideal line-of-sight (LOS) conditions, it has been observed to be highly influenced by the signals arriving at the receiver with multipath propagation in locations having a high possibility of reflection or refraction of the signal, such as urban areas. The GNSS signals are also vulnerable to radio frequency interference (RFI), due to their very low power at the Earth's surface. There are areas where GNSS signals are denied or not available (GNSS-denied environments) and this affects or even hinders the calculation of the user's position. All these can have a severe degrading effect on receiver performance [2].

The GNSS performance degradation is an area where machine learning (ML) finds its application as it deals with a nearly limitless quantity of data GNSS provides. ML has been used in many research works to propose and provide solutions to tackle GNSS challenges.

When compared to statistical methods, ML techniques enable us to identify tricky dependencies in data for which exploratory analysis has not allowed the proper determination of the shape of the underlying model [3]. The aim of using ML is not to generate an explicit formula for the distribution of the data. Rather, ML can be used to train an algorithm to learn the relation between the input features and the output. Furthermore, it is used for studying inter-relationships between features of a dataset. For example, if the features are continuous variables, you can use covariance to find their inter-relationship. Covariance is a measure of how much a feature is dependent on another. This learning method makes it possible to allow relaxation of the assumptions needed as seen in many statistical methodologies. Furthermore, the use of ML in GNSS context has seen increased interest by also several industries, such as Google's DeepMind AI, which learns to navigate cities without a map. When this is achieved in a real-world practical setting, it means artificial intelligence (AI) can recognize both objects and the type of the object, and relate them to the physical environment at various scales and distances [4]. Google has also found a new way to update its maps, by combining deep learning with Street View. This is done by combining the location data from Street View car's GNSS with address information and business names extracted from imagery. This could help in effectively mapping an entire city without any pre-existing knowledge of the layout or nomenclature [5]. In February 2020, Apple applied to the Federal Communications Commission for a license to install GPS testing equipment on its headquarters campus. It is thought that this move is related to the application filed by Apple Inc. with the U.S. Patent Office in August 2019, describing the company's "Machine Learning Assisted Satellite Based Positioning" [6]. Therefore, with this increased interest by industry and researchers alike in ML utilization in GNSS, we decided to make a systematic literature review (SLR) to analyze and compare the different ML algorithms, methods, and solutions used in the literature, as it can facilitate the development of new and efficient solutions in the utilization of ML techniques in GNSS. We perform a systematic review of studies between 2000 and 2021 to analyze and cite examples from the identified literature.

The rest of this article is organized as follows. Section II presents the methodology used in this systematic review. In Section III, we present and discuss the results of the review process. The implications for research and practice are presented in Section IV. While Section V describes the limitation of this article. Finally, Section VI concludes this article.

II. MATERIALS AND METHODS

In the planning, conducting, and reporting of the systematic review performed in this article, a process was adopted from [8], as illustrated in Fig. 1.

In the planning stage, the review protocol was developed, which includes the following steps:

1) identifying the research questions;

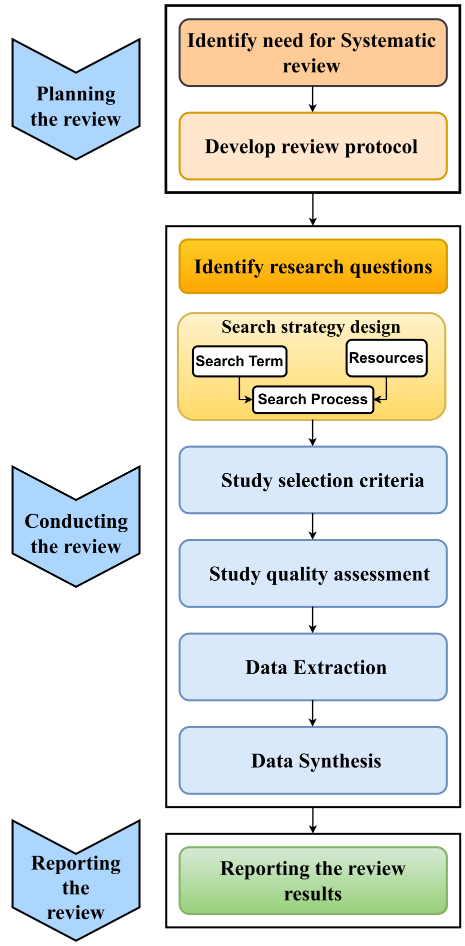

Fig. 1. Systematic review process adapted from [8].

2) design of the search strategy;
3) criteria for study selection;
4) quality assessment of the study;
5) data extraction;
6) data synthesis process.

Afterward, the results are then used in reporting the review.

The first step was the formation of the research questions that covered the issues to be addressed in the SLR. In the second step, the search strategy was described including the identification of search words and phrases and the selection of data sources from where the search will be performed in order to identify the candidate studies. The third step is used to determine the relevant studies. In this step, the criteria for the inclusion and exclusion of studies in the relevant study are performed. The fourth step scans the reference of the relevant papers for additional relevant studies, and then the quality assessment criteria are applied to the total relevant papers to derive the final selected papers used for the SLR. The fifth step involves the design of data extraction forms to collect the required information from the final selected papers in order to answer the research questions and in step six, we devise methods for data synthesis. The review protocol was developed through frequent meetings and consultations with senior researchers and professors.

TABLE I
Research Questions

#RQs	Research questions	Motivation
RQ1	Which ML algorithms have been applied to GNSS?	Identify the ML algorithms that have been used in GNSS. Practitioners and researchers can use the identified ML techniques as candidate solutions in their work.
RQ2	To which GNSS use cases have ML algorithms commonly been applied?	Identify GNSS use cases to which ML algorithms have been utilized. Practitioners can use this information to decide if their work requires the consideration of using an ML technique.
RQ3	What are the GNSS data sets used in the ML algorithm?	Identify GNSS data sets used in ML algorithms.
RQ4a	Do ML algorithms outperform non-ML algorithms?	In some of the existing studies, the proposed ML algorithms are compared with traditional non-ML GNSS algorithms in terms of estimation accuracy. RQ4a, therefore, aims to verify if ML algorithms perform better than non-ML algorithms. Estimation accuracy is the primary performance metric for ML models. The four aspects of estimation accuracy are accuracy metric, accuracy value, data set used for model construction, and model validation method.
RQ4b	Are there ML algorithms that significantly outperforms other ML algorithms?	Investigate which ML algorithms consistently outperform other ML algorithms. Therefore, RQ4b aims to identify the ML algorithms with relatively good performance.
RQ5	What are the strength and weaknesses of ML models applied to GNSS?	This aims at identifying the pros and cons of utilizing ML algorithms in GNSS. Having a full understanding of the characteristics of the candidate ML models, practitioners can make rational decisions on choosing the ML models that favor the GNSS use case in focus.
RQ6	What are the methods used for evaluation or validation of the ML algorithms?	List out the methods used for evaluation or validation of the ML algorithms to determine their accuracy and performance.

This review protocol helps in reducing the possibility and risk of research bias in the SLR. The following sections describe the research questions used and the steps taken during the period the SLR was conducted.

A. Research Questions (RQs)

This SLR is performed with the aim of providing and assessing results obtained from the studies done on the utilization of ML techniques in GNSS. This article extensively reviews studies between 2000 and 2021. From the final selected studies, first, we identify the different ML algorithms applied to GNSS (RQ1). Second, we identify GNSS use cases in which ML techniques are commonly used (RQ2). In the third research question (RQ3), the GNSS datasets used in ML techniques are identified. In RQ4a, the performance of ML techniques with traditional GNSS parameters/techniques is compared. This was done with the aim of determining if ML techniques are better than the traditional GNSS parameters/techniques. In RQ4b, the assessment of whether an ML technique outperformed other ML techniques in order to determine if an ML technique is consistently better than other ML techniques was addressed.

In research question RQ5, the strengths and weaknesses of different ML techniques are discussed to provide GNSS experts and researchers guidance regarding the selection of an appropriate ML technique based on the context of the GNSS application. Finally, in RQ6, the different methods used for the evaluation or validation of the ML algorithms are discussed. Furthermore, future guidelines are provided to GNSS technology experts and researchers regarding the application of ML techniques in GNSS. Table I presents more details on the research questions addressed in this SLR.

In Table XI in Appendix B, a summary of the ML algorithms utilized in GNSS and the GNSS use case they were applied to has been presented. Other details include year of publication, data type, the ML validation method, and the paper type (journal/conference).

B. Search Strategy

The search strategy comprises search terms, literature resources, and search process, which are detailed one by one as follows:

1) *Search Terms:* We formed sophisticated search terms by incorporating alternative terms and synonyms using the Boolean expression "OR" and combining main search terms using "AND." The following general search terms were used for the identification of literature:

GNSS AND "deep learning" OR GNSS AND "machine learning" OR GNSS AND "artificial intelligence" OR GNSS AND "random forest" OR GNSS AND "decision tree" OR GNSS AND "support vector machine" OR GNSS AND "neural network" OR GNSS AND "regression"

2) *Literature Resources:* After identifying the search terms, relevant digital portals were selected. The selection was restricted by the availability of digital portals at the home universities. The following electronic databases were used for the search. We also used relevant studies from The Institute of Navigation (ION).[1]

1) IEEE Xplore
2) Google Scholar
3) ScienceDirect
4) Crossref
5) Scopus
6) Institute of Navigation (ION)

We restricted the search from 2000 to 2021 to capture the ML and GNSS-related studies for the most recent two decades. The initial search to identify the literature for the review was performed after which the candidate studies were determined from the full-text papers by removing duplicate and irrelevant papers. The search was limited to only publications in journals and conferences. However, we included one paper from 1995 because we found it to be very relevant to our review process.

3) *The Search Process:* To facilitate the use of ML techniques in GNSS, it is necessary to systematically review the performance of these ML techniques and their usage from existing literature and studies. To the best of the authors' knowledge, there is no systematic review that focuses on ML techniques utilized in GNSS use cases except for our conference publication presented at the 2021 International Conference on Localization and GNSS (ICL-GNSS) [7].

To achieve this aim, we extensively searched through some relevant digital libraries to identify studies to answer the research questions. The final selected studies were selected based on the quality assessment of the studies and their relevance. Fig. 2 illustrates the stages involve in this SLR.

1) *Search phase 1:* Search each electronic database separately and then go through each paper title and abstract to check its relevance based on the search

[1][Online]. Available: https://www.ion.org

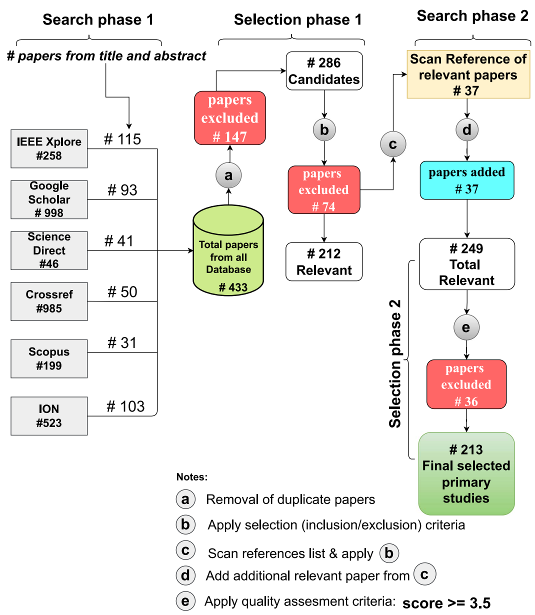

Fig. 2. Stages in the systematic review process.

term (*i.e., # papers from title and abstract*). Afterward, gather the returned papers for each electronic database together and remove duplicate papers to form a set of candidate papers.

2) *Search phase 2:* Scan the reference lists of the relevant papers to find extra relevant papers and then, if any, add them to the set of relevant papers.

C. Study Selection

Search phase 1 resulted in 433 retrieved papers. Since not all of the retrieved papers would provide the information useful to address the research questions raised by this review, further filtering is needed to identify the relevant papers. This is the aim of the study selection. Specifically, as illustrated in Fig. 2, the study selection process consists of two phases. It is important to note that in each selection phase, two researchers conducted the selection independently. If there were any disagreements between them on the selection criteria, a group meeting involving all researchers was held to make a decision.

1) *Selection phase 1:* Apply the inclusion and exclusion criteria (defined below) to the candidate papers so as to identify the relevant papers, which provide potential data for answering the research questions.
2) *Selection phase 2:* Apply the quality assessment criteria (defined in the next section) to the relevant papers so as to select the papers with acceptable quality, which are eventually used for data extraction.

The final literature to study was selected after following the criteria for inclusion and exclusion listed below, which had been refined through pilot selection. We carried out the study selection by reading the titles, abstracts, or full text of the papers.

Inclusion Criteria:

1) Studies utilizing ML techniques in GNSS use cases.
2) Studies combining ML and non-ML techniques in GNSS application.
3) Studies utilizing ML techniques for GNSS/non-GNSS integration such as inertial navigation system (INS), ultra-wideband (UWB), and wireless fidelity (Wi-Fi).
4) Comparative studies that compare different ML models or compare the ML model with the non-ML model in GNSS use cases.
5) Only journal versions of papers will be included: for studies with both conference versions and journal versions.
6) Only the most complete and latest paper will be included for duplicate publications of the same study.

Exclusion Criteria:

1) Studies based only on non-ML techniques applied to GNSS.
2) Studies using ML techniques in a context other than in GNSS.
3) Studies based on ML techniques used with only non-GNSS techniques, such as INS, UWB, and WIFI.
4) Similar studies, that is, studies by the same author in conference as well extended versions in the journal. However, if the results were different in both studies, they were retained.
5) Review studies (mini-reviews), editorials, news.
6) Short communications, encyclopedia, book chapters, case reports, conference info.

Using the above steps, we identified 212 relevant studies for inclusion in the SLR process. We then used search phase 2 to include more papers from the reference lists of the relevant studies, which produced an extra 37 studies. Therefore, a total number of 249 relevant studies were identified for further processing and analysis.

D. Quality Assessment Criteria

We formed a quality questionnaire for assessing the relevance and strength of the relevant studies. The quality criteria were developed by considering the suggestions given in [9]. Table II presents the quality assessment questions. The questions are ranked 1 (yes), 0.5 (partly), and 0 (no). The final score is obtained after adding the values assigned to each question. A study could have a maximum score of 6 and a minimum score of 0.

Two independent researchers ranked the quality questions for each relevant study and consulted other researchers in case of any disagreement. Finally, after thorough reviews, discussions, and brainstorming sessions, a final decision about the inclusion/exclusion for each study was made. To ensure the reliability of the findings of this review, we considered only the relevant studies with acceptable quality, i.e., with quality scores equal to or greater than 3.5, for the

TABLE II
Quality Assessment Questions

#Q	Quality factors	Yes	Partly	No
Q1	Are the ML algorithm used in the research clearly described?			
Q2	Are the GNSS use cases to which the ML algorithms are utilized clearly defined?			
Q3	Are the data set for model construction clearly defined and are the evaluation or validation methods for the ML algorithms mentioned?			
Q4a	Are there any comparison done between non-ML vs ML?			
Q4b	Are there any comparison done between ML vs other ML?			
Q5	Are the strengths and weaknesses of the ML algorithms specified?			

TABLE III
Data Extraction Form

ID
Authors
Paper Title
Year of Publication
DOI
Machine Learning Technique Used (RQ1)
Study Application (Uses case) (RQ2)
Data Category (Real or Simulated)
Data Used (RQ3)
Performance (ML vs. non-ML) (RQ4a)
Performance (ML vs. ML) (RQ4b)
Strength and Weakness (RQ5)
Validation Method (RQ6)
Results
Paper Abstract
Digital Library
Paper Type (Type)
Publication Venue

subsequent data extraction and synthesis. Accordingly, we further dropped 36 papers with a quality score of less than 3.5 in selection phase 2 (see Fig. 2). Finally, after the application of the quality assessment criteria stated in selection phase 2 to the total number of relevant studies, we identified 213 papers as the final selected studies used for this SLR. The quality scores of all 213 selected studies are presented in Table VII in Appendix A. These 213 studies were then used in the data extraction form. The more detailed list of these 213 selected papers can be found in the data extraction form in Table XI in Appendix B.

E. Data Extraction and Data Synthesis

A form is filled out for each of the final selected studies. The purpose of using the data extraction form is to determine which research question was satisfied by a final selected study. We summarized author's name, title, publishing details, dataset details, independent variables (metrics), and the ML techniques. The details of which specific research questions were answered by each final selected study were present in the data extraction card. These data extraction cards were used to collect information from the final selected studies. Two independent researchers collected the information required for each final selected study from the data extraction card. The two researchers then matched their results and if there is any disagreement between the two, other researchers are consulted to resolve these disagreements. The resultant data are saved into a excel file for further use during the data synthesis process. Table III shows the data extraction form used to collect the data from the selected studies.

The basic objective while synthesizing data is to accumulate and combine facts and figures from the final selected studies in order to formulate a response and resolve the research questions [10]. Collection of a number of studies that state similar and comparable viewpoints and results help in providing the research evidence for obtaining conclusive answers to the research questions. We scrutinized and evaluated both the quantitative data, which include values of various performance metrics like area under the receiver operating characteristic (ROC) curve (AUC), prediction accuracy, and qualitative data, which include strengths and weaknesses of the ML methods, categorization of various ML methods, feature subselection methods, and datasets used. We utilize a number of techniques to synthesize data collected from our final selected studies. In order to answer the research questions, we used visualization techniques, such as line graphs, box plots, pie charts, and bar charts. We also used tables for summarizing and presenting the results.

F. Threats to Validity

The three main threats to the validity of the process implemented in this review are presented from the following standpoints: bias from study selection, possible inaccuracy in the data extraction process, and publication bias. Therefore, based on the research questions and the aim of this review, the search terms were generated. It was noticed that some studies used different terms in titles that may not be related to the research questions or aim of our review process. As a result, it is possible that there were biases in the search strategy. The study selection process was performed by two independent researchers. However, some relevant studies that were found may have been excluded during the selection phase, but it was a minimal number of records.

The inclusion and exclusion criteria were used to select the studies to meet the aim of the review. These criteria were agreed on by all the authors to meet the scope of the study. Another possible threat to the validity of this review is publication bias. Based on this, it is more likely that positive results on ML models will be published than negative results, or researchers may put forward their methods as outperforming other ML or non-ML methods. This can therefore lead to an overestimation of the performance of ML models. However, this may be limited by the inclusion of studies that did not implement new ML models, but just did comparisons between ML models and other models.

TABLE IV
Publication Type Distribution

Paper Type	Number of Studies	Percentage
Journal	123	57.75
Conference	87	40.85
PhD thesis	1	0.47
Msc thesis	1	0.47
Book-Chapter	1	0.47
Total	**213**	**100**

TABLE V
Quality Levels of Relevant Studies

Quality level	# Of studies	Percent
Very high (5 <= score <= 6)	46	18.47
High (3.5 <= score <= 4.5)	167	67.07
Medium (2.5<= score <= 3)	14	5.62
Low (1.5<= score <= 2)	19	7.63
Very low(0 <= score <= 1)	3	1.20
Total	**249**	**100**

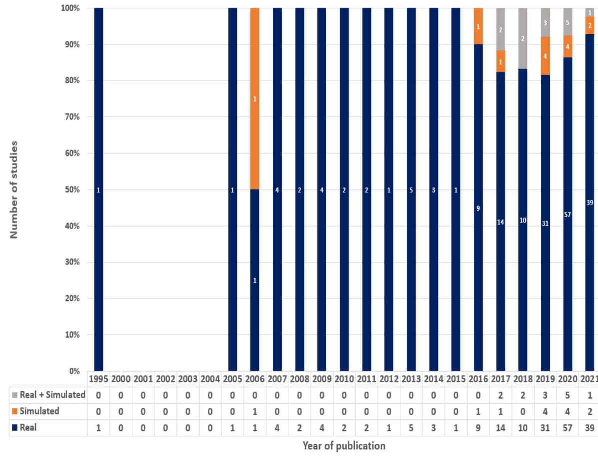

Fig. 3. Distribution of the studies over publication year.

To reduce the inaccurate data extraction bias, a specialized card was utilized for data extraction (see Table III). In addition, the study selection process was undertaken in its entirety by two independent researchers (extractor and checker) with other researchers resolving disagreements by discussion among all researchers.

III. RESULTS AND DISCUSSIONS

In this section, the findings of this review are presented and discussed. We begin by presenting an overview of the selected studies. We then report and discuss, one by one in separate sections, the findings of the review based on the research questions. We interpret the review results not only within the context of the research questions but also in a broader context that is closely related to the research questions. Furthermore, some related works are also presented to support the findings.

A. Overview of the Final Selected Studies

In this review, we identified 213 primary studies that applied ML in GNSS use cases (see Table VIII). These papers were published between 2000 and 2021.

A total of 122 (57.55%) papers were published in journals, 87 (41.04%) papers were published in conference proceedings, and 3 (1.42%) papers (one Ph.D. thesis, one M.Sc. thesis, and one book chapter (see Table IV). The publication venues of the selected studies are presented in Table VI while the distribution of the studies over publication year is shown in Fig. 3.

From Fig. 3, it is interesting to see how the number of publications has been expanding over the years. The types of the selected studies belong to experiment research except for one survey research [7], and one case study research was found [11]. Although most of the selected studies used one form of validation dataset to validate ML models, it does not follow that the validation results sufficiently reflect the real situations in the industry. In fact, the lack of sufficient case studies and surveys from the industry may imply that the application of ML techniques in GNSS is still immature.

Regarding the quality of the selected studies, we used the quality score of the study which must be equal to or above 3.5 (with a perfect score for the quality assessment being 6), before it is included in the review. As shown in Table VII, about 85.14% (213 of 249) of the selected studies are in high- or very high-quality level.

B. Types of ML Techniques (RQ1)

From the selected studies, we were able to identify some of the main types of ML techniques that had been applied to GNSS use cases. They are listed as follows:

1) Decision tree (DT)
2) Random forest (RF)
3) Regression analysis (linear/logistic)
4) K-nearest neighbor (KNN)
5) K-means clustering
6) Naive Bayes (NB)
7) Extreme learning machine (ELM)
8) Gaussian process regression (GPR)
9) Support vector machine (SVM)
10) Neural networks (NNs) a.k.a. artificial neural network (ANN)

a) Recurrent neural network (RNN)
b) Long short-term memory (LSTM), a special kind of RNN
c) Convolutional neural network (CNN)
d) Multilayer perceptron (MLP)
e) Back propagation neural network (BPNN)
f) Deep neural network (DNN)
g) General regression neural network (GRNN)
h) Radial basis function neural network (RBF-NN)
i) Bidirectional recurrent neural networks (BRNN)
j) Deep belief network (DBN)
k) Time-delay neural network (TDNN).

Among the above-listed ML techniques, NNs, DTs, and SVMs were the three most frequently used techniques; they together were adopted by about 84% of the selected studies, as illustrated in Fig. 4. The top three algorithms

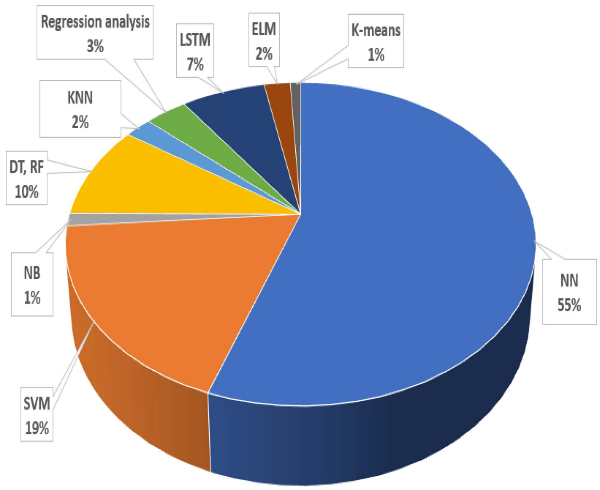

Fig. 4. Summary of ML algorithms mostly utilized in GNSS.

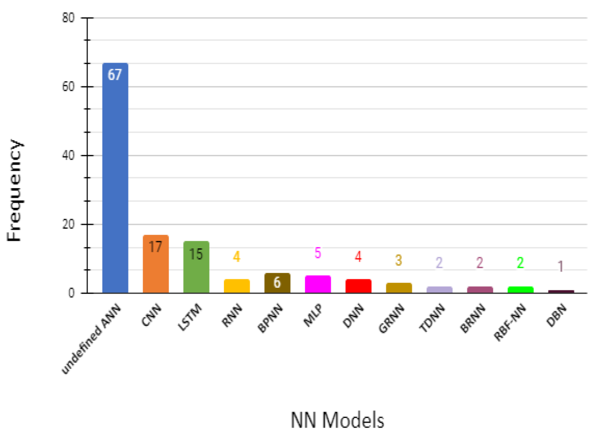

Fig. 5. Distribution of the NN model's terminologies as used in the selected studies.

have the following percentages: NNs (55%); SVMs (19%); DTs (10%). Considering only the selected ones, this shows that DL models have been utilized the most in GNSS out of all ML models. The distribution of the NN models as shown in Fig. 5 is based on the terminologies used in the reviewed literature. This shows that ANN (58%), CNN (15%), and LSTM (18%) have been used more frequently by researchers in various GNSS applications. Note that "undefined ANN" is used to categorize the ANN models where the author of the selected paper was not specific on the category of the ANN used. Fig. 5 is used to represent the number of times these NN model terminologies are used in the selected papers. We present the terminologies used in the selected papers. From this, we can see that, for example, MLP, BPNN, and DNN are all related but have been counted separately based on their reference in the selected papers used for the review.

MLP is known as the foundation architecture of DNNs. However, notice that MLP and DNN are separated in Fig. 5. This is done in this article in other to keep track of how the NN models' terminologies are being used. For example, although DNNs could be seen as a subset of MLP, they are different in their structure. The structure of both MLP and DNN consists of an input layer, hidden layers, an output layer, an activation function, and a set of weights and biases. However, DNN has a higher number of hidden layers stacked together for processing and learning from data, while MLP has few numbers of hidden layers. Similarly, LSTM is a special kind of RNN that is suitable for classification, processing, and prediction using time series data. This is because time series can have lags of unknown duration between important events. LSTMs were designed to take care of the vanishing gradient problem that can be experienced when training traditional RNNs. It is difficult to train RNNs that require long-term memorization, but LSTM performs better with these kinds of datasets as it has more additional special units that can hold information longer.

C. GNSS Use Cases for ML Algorithm (RQ2)

ML utilization in GNSS is becoming more popular among researchers. The ML algorithms were used for classification, clustering, forecasting, and anomaly detection depending on the GNSS use case. In this section, we present some of the GNSS use cases in which ML algorithms have been utilized based on the selected studies used in this review.

1) *GNSS Signal Acquisition:* Signal acquisition is the process of assessing the presence of GNSS signals and providing a rough estimate of the parameters of the incoming signal: the Doppler frequency and the code delay. It is the first step performed by a GNSS receiver. The outcome of this process decides 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 [12]. This acquisition process is implemented by all GNSS receivers [2]. This process is achieved through the evaluation of the cross ambiguity function (CAF), usually in a discrete-time domain. CAF is a 2-D function that is related to the correlation between the received signal and local code for every possible delay/Doppler pair. The CAF can be assumed to be an image and has certain traits that can be utilized in identifying the presence or absence of the signal from a specific satellite. With this knowledge, a data-driven model can be trained such as 1) an MLP, which is an NN architecture with moderate complexity been widely applied in ML literature; and 2) a Convolution Neural Network (CNN), having the ability to recognize complex nonlinear phenomena, at the expense of a much larger complexity compared to MLPs [12].

2) *Signal Detection and Classification:* The detection and classification of GNSS signals are very useful as it helps to differentiate the various types of signals based on how they are being affected or not by the environment or media of propagation. GNSS signals can be classified into, for example, LOS, non-line-of-sight (NLOS), and multipath [13]. A multipath signal is a GNSS signal bouncing off a reflective surface prior to reaching the GNSS receiver antenna. This means multipath interference occurs when an RF signal from a transmitter arrives at a receiver through two

or more routes. Multipath is one of the major sources of a GNSS error that lead to unacceptable pseudorange errors and affects positioning. Multipath causes distortions of GNSS signals; therefore, it needs to be detected, excluded, or corrected. NLOS signals are reflected signals arriving at a receiver even when the LOS signal is blocked. Detecting the characteristics of the acquired signal enables the system to decide how to treat the signal based on the evaluated effect it would have on the GNSS positioning solution. New designs of receivers can help mitigate against multipath to some extent but this is not the case for all receivers, for example, low-cost receivers and GNSS-enabled smartphones. Most of the market-ready solutions currently available for multipath detection and mitigation are based on stochastic modeling, spatial geometry modeling, advanced techniques in data processing, and special hardware designs [3]. These models need to be able to accurately and reliably classify LOS, multipath, and NLOS signals. However, when there is an outside event that is too complex to be modeled and that does not fit the mathematical assumptions used to develop the statistic model, these solutions become ineffective. ML methods enable us to relax assumptions attached to the statistical methodology. In [14] (SVM), [15] (LSTM), [16] (DT, SVM, and KNN), [17] (SVM, NN), [18] (CNN), [19] (SVM), and [13] [gradient-boosting decision tree (GBDT), DT, KNN, and adaptive network-based fuzzy inference system (ANFIS)], ML have been applied to signal detection and classification. An ANN model capable of processing the structure of the autocorrelation function (ACF) was used for the detection of evil waveforms (EWFs) in [20] (ANN). EWFs are a rare perturbations occurring at the stage of signal generation. Detecting this type of distortion postcorrelation traditionally involves hand-crafted structure tests on a densely sampled ACF. These are designed for specific scenarios; therefore, they lack flexibility compared to data-driven methods. In [13], compared with DT, KNN, and ANFIS, a robust GBDT was employed for GNSS signal reception classification. It made use of the carrier-to-noise-density ratio (C/N0), pseudorange residuals, and satellite elevation angle as the input features to improve the performance of the signal classification at the receiver. Similarly, in [16], compared with SVM, and KNN, a DTs-based classifier has used the satellite elevation and C/N0-R-L ratio as the input features to improve the performance of the signal classification at the receiver. While in [21], GNSS interference signal recognition based on CNN and fusion time–frequency features was implemented. The accurate detection and classification of GNSS signals can help in the improvement of the GNSS positioning accuracy especially in urban areas where the GNSS signals are heavily impacted by the environment [19].

3) *Earth Observation and Monitoring:* Earthquakes detection—ML algorithms have been used in Earth observation and monitoring applications, such as in [22], where an alternative ML approach to the prediction and detection of earthquakes and the determination of their magnitude has been proposed. Results show that the ANN process achieved an accuracy of 85.71% in validation assessment to predict the earthquake approximately 3 h before the seismic event. Other techniques applied to the monitoring of earthquakes include seismographic stations, Interferometric Synthetic Aperture, strong-motion measurements, and gravity measurement [23]. Hurricane tracking—ML has also been applied to hurricane tracking using a convolutional neural network (CNN) in [24]. The trained CNN regression model has achieved accuracy with less than 1.5 pixels errors in x and y coordinates, i.e., 0.2% error on average.

Sea ice detection/sensing/thickness estimation—ML-aided sea ice monitoring methods make use of spaceborne global navigation satellite system-reflectometry (GNSS-R) data. These data collect information about sea ice concentration (SIC), sea ice thickness (SIT), etc. In [25], sea ice detection/sensing/thickness estimation is done using an NN. On average, using this method, the accuracy for sea ice detection is about 98.4%. It was found that when GNSS-R delay-Doppler maps (DDMs) data are adequately preprocessed, CNNs and NNs share similar accuracy; otherwise, the former outperforms the latter. Furthermore, it was concluded that CNNs were more tolerant to the data format changes than ANNs [26]. In [27], support vector regression (SVR) and CNN are used. Comparisons showed good consistency between the derived and reference SIT, with correlation coefficients of 0.95 and 0.90 and root mean square differences of 5.49 and 7.97 cm for SVR and CNN, respectively. While in [28], among NN, CNN, and NN-FS, the NN-FS (FS means feature selection) showed the best performance, and it was the closest to that of SVM-FS. Through experiment, it was found that SVM-FS produced fewer false alarms compared to NN-FS during the analysis of false detection of ice under different sea conditions in terms of wind speed. In [29], DT- and RF-based methods have been used and achieved an overall accuracy of 97.51% and 98.03%, respectively, in the Arctic region and 95.46% and 95.96%, respectively, in the Antarctic region. Furthermore, a regression NN is used in [30] to train thin ice and full-range models having a mean absolute error (MAE) of 6.5 and 23 cm, respectively.

In the estimation of snow depth (SD), a DBN was used in [31]. The results showed that the DBN SD retrieval model estimates SD more accurately than linear methods and CNN models. Specifically, R increased from 0.81 to 0.85, MAE decreased from 11.15 to 9.55 cm, and root mean square error (RMSE) decreased from 17.96 to 15.40 cm.

Soil moisture (SM), wind speed retrieval, and vegetation water content (VWC)—SM retrieval is a vital activity in various applications such as hydrology and agriculture. GNSS-R is a new type of remote sensing technology also used for SM retrieval. In [32], random forest (RF) was used for GNSS-R SM retrieval. While in [33] RF, SVM, gradient boosting DT (XGBoost), and ANN was used. The XGBoost model performed best with an RMSE of 0.052 cm. The proposed algorithm can be applied to other training and testing problems that could benefit from it such as hydrology and agriculture where accurate SM estimates play an important role. Another study that used the XGboost ML-aided method in GNSS-R SM retrieval/estimation is seen in [34]. The results showed a good correlation with the statistical analysis of ground-truth measurements.

Other ML-based methods include Bayesian regularization neural network (BRNN) used in [35]. RF and SVM used in [36], SVM used in [37], ANN in [38], and ANN, RF, and SVM in [39].

For GNSS-R wind speed retrievals and estimation, NN was used in [40], [41], [42], and [43]. When compared to an LS-based approach, the derived model shows a significant improvement of 20% in the RMSE. While for wind speed retrievals from cyclone global navigation satellite system (CYGNSS), ANN was used in [44]. The comparison highlights that the ANN approach outperforms the baseline approach for both low and high wind speeds (ANN RMSD improves by 15%) and removes most of the geographical biases between baseline winds and wave-watch 3 model winds seen in monthly maps of wind speeds. The ANN improvement increases for increasing wind speed [44]. Similar accuracy was found in [45] and [46], where ANN outperforms the traditional approach for wind speed retrieval. In [47], RF was used in down-scaling GNSS-R-based VWC, which is recognized as an important parameter in vegetation growth study. The results showed that the RF model outperformed the traditional methods of multiple linear regression (MLR) and kriging interpolation in the cross-validation results (R of MLR is only about 0.4, and that of the cross-validation of kriging interpolation is only 0.3). Using the RF method, the results decreased a lot with R decreasing by 0.2 and RMSE increasing by 0.015 for cross-validation results. Similarly, in [48], RF-method, BPNN, and GRNN were used in monitoring the variation of VWC. Among the three ML methods, the results of RF were the best, followed by those of GRNN and BPNN [48].

Other areas of Earth monitoring—An RF algorithm has also been used in the prediction of dam displacement [49]. While in [50], SVR was used in monitoring the urban heat island effect, which has been widely studied because of its impacts on the environment and human well-being.

Other areas of Earth monitoring in which ML has been applied include using GNSS position time series to predict the land subsidence or upheave in an area. This is done by predicting the next GNSS position time series using algorithms like MLP, Bayesian NN (BNN), RBF, KNN, GRNN, SVR, GP, and classification and regression trees (CART) [51], [52], [53]. Another Earth monitoring application is the nowcasting of severe weather events and summer storms from the combination of vertically integrated water vapor with vertical profiles of wet refractivity derived from GNSS tomography. In [54], RF was used.

ML models have been applied to other environmental remote sensing applications such as landslide monitoring/prediction, estimating nearshore water depths, weather forecast by monitoring and forecasting precipitable water vapor (PWV), and forecast hourly intense rainfall [11], [55], [56], [57], [58], [59], [60], [61], [62].

4) *GNSS Navigation and Precise Positioning:* Location-based services can be utilized in many aspects, namely, tracking, health care monitoring, and intelligent transport systems (ITS). ML has also been applied in this area with the aim of improving GNSS navigation/positioning in several scenarios. GNSS outage for very short periods may not represent a relatively big problem for a position estimate, as an INS can be integrated to produce position estimates. However, a long outage period means the bias error from motion sensors will start to increase and position estimate accuracy is significantly reduced as well [63]. Therefore, long GNSS signal outages could harm vehicles' position estimates and become a risk for ITS and its users. Nowadays, GNSS is successfully implemented to achieve precise positioning in both indoor and outdoor environments [64], [65]. Such precise positioning is essential for safe operations [66], [67]. ML has been applied in ITS 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 [63]. For land vehicle navigation applications, an ANN model and an efficient hybrid methodology based on Dempster–Shafer theory augmented by an SVM (DS-SVM) were implemented in order to effectively fuse GNSS and INS data [68]. Kalman filtering (KF) is used for linear systems and extended KF (EKF), i.e., linearized KF can be implemented but may cause filter divergence under high dynamic conditions. In [68], test results indicate that the proposed DS-SVM algorithm effectively compensated and reduced positional inaccuracies over the regular ANN model and traditional KF/EKF methods during GNSS availability and outage conditions for low-cost inertial sensors.

In [69], LSTM is used to achieve a GNSS network-based real-time kinematic improvement. The GNSS sensor only provided the RMSE of about 3.8 m compared to the LSTM model, which significantly improved to about 0.45 m. GNSS position error estimation is done in order to improve the positioning accuracy after error correction. In [63], DT and SVM were implemented, with the average RMSE for SVM being around 31% less than the one seen in the best results in RMSE for DTs (28 versus 41 cm). Features considered in training the models included elevation, azimuth, constellation type, and carrier-to-noise ratio.

In [70], fully connected NNs (FCNNs) and LSTM are combined and used to predict the GNSS satellite visibility and pseudorange error in an urban area based on the available GNSS measurements. These combined networks achieve satisfactory performance on both satellite visibility and pseudorange error predictions, which have 80.1% overall accuracy and a 4.9-m average difference from the labeled pseudorange error (reference). A least-squares SVM (LSSVM) technique is used in [71] for GNSS navigation with dynamic model real-time correction. The results show that the proposed LSSVM-KF algorithm can adequately adapt to time-variant dynamics and performs well for real-time correction. In [72], a new ML-based architecture [LR, linear discriminant analysis (LDA), SVM, KNN, CART, and Gaussian Naive Bayes (NB)] combines classical observables for local hazard detection, with the outcome of advanced Receiver Autonomous Integrity Monitoring

(RAIM) in order to find out if a given point of a railway is suitable for safe and reliable use of GNSS for train positioning. The results show that the setup of the classifier can be driven by the features of the electromagnetic environment on which the train shall operate. Using the daily records taken by the GNSS receivers, the map of the local hazards and the effects of their combinations can be learned. This can mitigate the risks derived by significant changes in the environment (for example, constructing new buildings along a railway) or by the activation of new RF sources (such as new 5G RAN nodes). ML models have been applied to other positioning and navigation applications, such as regional mapping of the geoid [73] and human mobility analysis on large-scale mobility data, which has contributed to multiple applications, such as urban and transportation planning, disaster preparation and response, tourism, and public health [74]. Other applications include location prediction using GPS trackers to, for example, locate missing people with dementia [75], improving GNSS Positioning from smartphones [76], [77], [78], [79], improving GPS code phase positioning accuracy in urban environments [80], improving accuracy of differential GPS correction prediction in the position domain [81], and improving kinematic GNSS positioning accuracy with low-cost GNSS receiver in urban environments [19]. Another study used the combination of Genetic Algorithms (GA) and NNs for exploring the navigation satellite constellation design tradespace to speed up the constellation performance computation and for an improved GNSS integrity [82]. In [83], a wavelet neural network (WNN) is employed for orbit approximation to obtain a continuous orbit function. This is because the orbit function is essential in positioning and navigation tasks. Therefore, the advantage of continuity is that it can also be used during GNSS signal interruptions.

5) *GNSS-Denied Environments and Indoor Navigation:* The foundation for a context-adaptive system is scenario recognition and it is a major contributor to seamless indoor and outdoor positioning technology. This allows the system to “understand” its environment, and then apply the appropriate strategies to achieve accurate, continuous, and reliable positioning in the different scenarios [84]. Scenario recognition is essential for seamless indoor localization and robust positioning in complex environments. RNN-based scenario recognition with multiconstellation GNSS measurements on a smartphone was implemented in [85]. Here, a complex environment was divided into four categories (deep indoor, shallow indoor, semioutdoor, and open outdoor) and the influence of multiconstellation satellite signals on scenario recognition performance based on a hidden Markov model algorithm was analyzed in detail prior to the application of RNN for the scenario recognition. The experimental results show high recognition accuracy in both isolated scenarios and transition environments, with an overall accuracy of 98.65%.

In the case of situation and context awareness, Guinness [86] implemented an ML-based approach [SVM, ANN, LR, BN, DT, NB, instance-bases learning with parameter *k* (IBk)], and locally weighted learning (LWL) for sensing mobility contexts using smartphone sensors. The aim is to develop techniques that continuously and automatically detect a smartphone user’s mobility activities, including walking, running, driving, and using a bus or train, in real time or near-real time ($<$5 s). The main aim of this study was to investigate if an ML algorithm exists that can produce a classifier having both high performance (with respect to class prediction rate) and low computational complexity. The results show that several existing ML algorithms achieved performance above 95% accuracy; however, DT algorithms were the only ones that also had relatively low computational complexity (for classification) [86].

In indoor navigation, NLOS and multipath are caused by indoor furniture and flat surfaces of the walls and ceilings, and it is quite severe. Since detecting NLOS and multipath is a classification problem, deep learning can be used to tackle this problem. In [87], a deep learning approach [NLOS and multipath detecting network (NMDN)] is used for indoor NLOS and multipath detection. The datasets used are generated by a GNSS software receiver using an intermediate frequency signal collected from an indoor pseudolite system. This method is compared with two SVMs, which are the traditional methods for classification, and shows an improvement of up to 45% in overall classification accuracy. In [88], NN fingerprinting and GNSS data fusion are done to improve localization in an indoor environment. The NN-based positioning fusion model was able to reduce the positioning error by up to 49%, having submeter accuracy in the uncertainty-free scenarios and 1.75 m mean positioning error in the 5-dB uncertainty case.

6) *GNSS Anomaly Detection and Atmospheric Effects:* GNSS has been used recently in the understanding of the atmospheric effects on the Earth because of the analysis of the ionospheric behavior. This ionospheric behavior can be derived through the determination of the total electron content (TEC) derived from GNSS data processing. TEC is a representation of the electron density in the signal trajectory between the satellite and the receiver on the Earth’s surface. A good understanding of the tropospheric wet delay and ionospheric scintillation effects on GNSS signals has been of great interest both in the fields of science and industry. Ionospheric scintillation is the rapid fluctuation of the amplitude and phase of radio frequency signals (for example, GNSS), propagating through the ionosphere. In GNSS receivers, signal acquisition and tracking can be heavily impacted by strong scintillation, resulting in degradation in accuracy and continuity of GNSS performance. 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, and wave interaction to name a few [89].

Ionosphere analyses: ML models have been employed for the detection of scintillation, as illustrated in [89] using SVM-based algorithm. It used cross-validation to determine the optimal hyperparameters with a detection accuracy is 96%, which is increased by 1.5% compared to the previous implementation. In [90], the overall accuracy in the validation performance is around 92%, which demonstrates the good performance of the SVM detector on phase scintillation detection.

In [91], Ridge Regression, Long short-term memory (LSTM), Classification Neural Network, Autoencoder Classification Neural Network, and LSTM Autoencoder Classification Neural Network were implemented, and compared. The results showed that the durability of the LSTM Autoencoder Classification Neural Network model over the span of a year can predict irregularities up to 3 hours in advance with an accuracy of 92%. Other studies include [92] and [93] using ANN model, [94], [95] and, [96] using DT model, [97], [98], [99], and [100] using SVM model, [101] and [102] using RBF SVM model (RBF-SVM), and [103] using an NN model.

The time delay of the GPS (L1 and L2) signal in the ionosphere is one of the propagation path delays 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. ML algorithms have been used to predict ionospheric time delays from GNSS observations like in [104] and [105] using an NN model. It used an extrapolation methodology combining two types of input data, observed TEC, and environmental parameters. The NN method yielded the best accuracy when compared to the least square regression (LSR) model and bi-harmonic spline (BHS), which is a pure spatial extrapolation method.

Others include [106] and [107] using GPR, and [108] using SVM. Prediction of tropospheric wet delay from GNSS observations has also been performed using ML algorithms like in [109], [110], [111], [112], and [113] using ANN, and [114] using BP NN.

Tropospheric analyses: In [115], ANN has been used to precisely identify interfered radio occultation (RO) events from GNSS RO measurements widely used in the prediction of weather, climate, and space weather, particularly in the area of tropospheric analyses. The estimation of tropospheric wet delay is of great importance for real-time weather forecasting applications. The characteristics and effects of ANN in tropospheric analyses can be validated by comparing the predicted zenith wet delay values using ANN with the values estimated from GNSS observations and meteorological data. ANN is useful in finding hidden relationships between features in a dataset, such as the relationship between the GNSS signal delay and PWV as in the case of tropospheric analyses. It has the ability to learn, recall, and generalize from the given data by suitable assignment and adjustment of weights. Due to significantly reduced computation time compared to the traditional SVM method, ANN is useful for real-time RO applications, such as extreme weather prediction or data assimilation [115].

7) *GNSS Security: Spoofing and Jammer Attacks:* A user device receiving false signals and believing it to be authentic could prompt dangerous behavior due to the false position or timing fixes. An example was mentioned in [116], where GPS spoofing was used to misdirect a hovering drone into an unplanned dive and to steer a yacht off course. Therefore, defenses against spoofing are aimed at detecting an attack in order to warn the attacked receiver that its navigation fix and clock offset are unreliable. The second reason for defense against spoofing is to recover a reliable navigation and timing solution. This has been achieved at the pseudorange level with receivers employing RAIM by using an inconsistent set of five or more pseudoranges to allow the receiver to detect an unsophisticated spoofer that broadcasts one or more false signals with no attempt to achieve a believable consistency. However, in response to increased efforts to defend against spoofing, advanced forms of GNSS spoofing have been conceived and interest in GNSS spoofing has increased with an example of such spoofing called "in the wild," which is an actual malicious spoofing attack. Various defense strategies that have been developed to deal with self-consistent spoofing have been beaten by these advanced spoofings [116]. Therefore, we have seen researchers attempting to use ML to detect and defend against spoofing attacks, for example, in [117] using the ANN model. Using features such as pseudorange, PR, Doppler shift, etc., an increase in the ANN model detection performance is observed. For one feature, the highest accuracy of 73.2% is achieved with the pseudorange. With two features (pseudorange and Doppler shift), the best performance with an accuracy of 92.6%, a probability of detection of 85.2%, and a probability of false alarm of 0% is obtained. As the number of features increases, the accuracy also increases. Another application is the C/N0 abnormity detection method for GPS antispoofing using an ANN model [20].

In [118], using MLP trained with particle swarm optimization (PSO), the simulation results showed that spoofing attack detection improved approximately 4 and 2% in comparison with the results achieved through classification based on Bayes-optimal rule and multihypothesis Bayesian classifier mentioned in the literature review. The feature vector used by this method includes received signal power and correlation function distortion. It uses these features to try to classify received signals as jammed, spoofed, multipath, or interference-free signals.

While in [119], using RNN based on LSTM, the error of the forecasting model over the testing dataset is in the order of 0.0006%. The model is able to detect GPS anomalies using signal imperfections, Doppler shift deviations higher than 4 Hz, and detecting mobile spoofing devices at higher speeds of 2.5 km/h.

In [120] SVM classification (C-SVM) with principal component analysis (PCA) was implemented. The overall success rate of the proposed approach was 97.8%, and the cross-validation error was slightly higher. Using PCA, the relations among the selected variables were analyzed. These variables include lock time, pseudorange, carrier Doppler frequency, receiver clock bias, receiver clock drift, C/N, code variance, multipath correction, carrier multipath correction, full carrier phase [cycles], carrier variance, and spoofing indication.

Research has also been done on the use of ML to detect and classify interferences and jammer signals in order to defend against jammer attacks. Types of jamming signals include audio jamming, narrow-band jamming, pulse jamming, sweep jamming, spread spectrum jamming, and the combination of each two of the above jamming signals. Jammer signals are a type of interference signal; therefore, the detection and classification of GNSS interference signals can help identify if the interference is an intentional and malicious (jammer or spoofing signal) attack or if it is unintentional, which can still cause GNSS positioning errors.

For intentional jammer attacks, studies have been conducted using ML to detect and classify GNSS interference such as in [121] using a twin SVM algorithm (TWSVM) for real-time interference monitoring. Implementing SVM in the interference monitoring of GNSS signals meets the requirement of objectivity and accuracy. However, the training speed of standard SVM does not satisfy the requirement of being in real time for interference monitoring. The experimental results indicate that the TWSVM model [121] is faster than the standard SVM in training speed (the training speed of TWSVM is at the millisecond level and the classification speed of TWSVM is at the microsecond level) and can be used in practice.

While for unintentional attacks like solar radio bursts that interfere with the GNSS signal, the SVM algorithm was used for the detection of the interference. In [122], SVM and CNN were used for jammer signal classification in GNSS bands. The results showed that with a small library of images and not excessively complex parameters/network layer architectures, a high mean classification accuracy was obtained for SVM (94.90%) and CNN (91.36%). It used a dataset[2] composed of 61 800 different images and containing different jammer types including the no-interference scenario and also used randomly generated parameters for these interference types.

While in [18], CNN is used for jammer signal classification. Here, the proposed CNN method has both robustness and good accuracy in jamming signals classification. This is seen in the results for single jamming signal classification, the proposed CNN method correctly classifies almost 100% of jamming signals. While for coexisting situations (more than one jamming signal), the lowest classification accuracy is up to 92%. Other studies include [123] using LSTM with CNN, [124] using LR, KNN, NB, DT, and SVM algorithms, [125] using a multilayer NN, and [126] using SVM.

8) *GNSS/INS Integration:* KF is widely used as a data-fusion algorithm in navigation. The integration of GNSS and non-GNSS systems, such as INS, makes use of KF for its GNSS/INS calibration systems. When GNSS cannot supply measurement updates normally, the filter time would be increased. In such cases, the divergence of INS error is fast without GNSS information correction. This could be detrimental depending on the use case, such as the concealment of unmanned underwater vehicles and unmanned aerial vehicles (UAVs). ML algorithms have been used in several studies to mitigate such scenarios. In general, when 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 the navigation accuracy.

In [127], the BPNN algorithm was used for GNSS/INS integration to overcome the GNSS outages. The simulation experiments used BPNN to compensate for the KF algorithm. The results showed an improved accuracy of the integrated navigation when GNSS is unavailable. The proposed method is able to maintain low-level deviations for about 9 min. Within this short navigating mission without a GNSS signal, the reliability and feasibility of the UAV can be verified. Similarly, in [128], the BPNN algorithm was used for GNSS/INS integration. The results show that the BPNN model can efficiently predict the increment of position and compensate for the accumulation of INS errors during GNSS outages.

In [129], a CNN-based adaptive KF is implemented to achieve the GNSS/INS integration. The estimator can output the system noise covariance matrix by windowed inertial measurements. The experimental results show that the proposed algorithm has a better performance (three times lower RMSE value) compared to classical KF and Sage–Husa adaptive filter in highly dynamic conditions. While a CNN-LSTM method is used in [130], here the results of the CNN-LSTM model compared with the EKF navigation method, show significant improvement in the navigation accuracy and the alignment time. It has a final attitude accuracy better than 0.2°, an alignment time of 10 s, and a position accuracy better than 3 m. This can meet the requirements of low-cost vehicle flexibility. While in [131], an ensemble learning algorithm (ELM) is used for INS/GPS navigation. To validate the performance of the proposed method, the results are compared with an adaptive network-based fuzzy inference system (ANFIS) and an EKF method. The result of ELM outperforms ANFIS and EKF by approximately 50% and 70%, respectively. This suggests a promising prospect for the use of ELM in the field of positioning in the absence of GPS signals using low-cost MEMS-based inertial sensors.

NN models have also been implemented to mitigate the GNSS signal outage in GNSS/INS integration in [132]. The study uses an NN model to do online learning of the system behavior during the time intervals when there are no satellite outages. It then takes advantage of this learning by applying it during periods of outages. The fixed velocity (stationary) results showed that the MAE after a 30-s outage was about 400 m without the NN model, but after the NN model was used for error compensation, it was approximately 100 m. For a constant-velocity trajectory, the position accuracy was about 500 m without NN error corrections and close to 100 m with the NN error corrections applied.

An SVM-based GNSS/INS integrated was utilized in [133] for land vehicle navigation. Here, the proposed

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SVM-based GNSS/INS integrated provided a 45%–73% improvement on rms positioning compared with the KF approach. It also outperformed BPNN by 8%–32%, and ELM by 46%–67% on rms positioning. The positioning improvements in maximum position accuracy were 26%, 66%, and 78% compared with KF, BPNN, and ELM methods, respectively.

GNSS can also be integrated into other devices such as cameras [134] using the CNN algorithm. The RMSE errors obtained remain low even at high added bias values of 100 and 200 m. The highest RMSE values were observed at low/medium biases because it is more difficult to detect and exclude low biases than high biases. Other ML-based GNSS/INS integration studies include [135] using RNN, [136] using RBF-NN, and [137], [132], [138], [139], and [140] using NN models.

9) *Satellite Selection:* Location accuracy is a result of two main factors namely, the satellite location-dependent geometric dilution of precision (GDOP) and the pseudorange measurement inaccuracies [141]. Generally, the more visible satellites available the better the positioning performance. The benefit of multiconstellation GNSS is that more visible satellites can be used to improve user positioning performance. However, not all satellite would contribute to the positioning performance because of some GNSS error like satellite clock error or high C/NR, etc. [142]. Therefore, selecting the optimal sets of satellites from all possible visible satellite combinations is important. This selection is done with the aim of minimizing either GDOP or weighted GDOP (WGDOP) as a criterion. Other selection criteria used in researches include elevation angle, C/NR, and range errors. ML has been applied in this kind of study to implement an ML-based satellite selection algorithm as seen in [143] using PointNet and VoxelNet networks, and [144] using an NN model. The study by Simon et al. [144] was one of the earliest research (from our database search in Section II) that utilized DL algorithm for satellite selection. Usually, a satellite subset is chosen by minimizing a quantity known as geometric dilution of precision (GDOP). However, in [143], the satellite selection algorithm is a satellite segmentation problem, having a specified input channel for each satellite and two class labels, one for selected satellites and the other for those not selected. The satellite segmentation algorithm is used to ensure that a fixed number of satellites with the minimum GDOP or WGDOP value can be segmented from any feeding order of input satellites. Whereas, in [144], an NN model is used to predict the GDOP without the usual resource consuming computation of the trace of the inverse of the measurement matrix. The NN model does this by learning the functional relationships between the entries of a measurement matrix and the eigenvalues of its inverse.

10) *LEO Satellites: Orbit Determination and Positioning:* The application of GNSS to the precise orbit determination (POD) of low-Earth-orbit (LEO) satellites has been beneficial in the development of many new space applications in the area of navigation, telecommunication, remote sensing, and Earth observation systems. These applications can benefit from the precise tracking of satellites orbits using onboard GNSS receiver data. With recent advancements, GNSS receivers have been designed to meet the POD requirements and have been implemented on many satellites, depending on the objectives of their missions, requiring accurate knowledge of their orbits. The performance of the POD process can be affected by the measurement environment, the technique used, and the mission application of the satellite. Furthermore, besides accuracy, the need to reduce the latency in achieving a precise solution has been of interest. This is beneficial to many end-user applications as it provides faster access to the required orbit solutions [145]. ML for orbit determination of LEO satellites has been implemented by some studies [146], [147], [148], [149]. In [146] and [149], TDNN, which is a type of feed-forward NN (FFNN), and LSTM are used for simultaneous tracking and navigation with LEO satellites. An NN is implemented in [147] and [148] to mitigate GNSS multipath for LEO positioning applications. It was noticed that very limited studies have been done on the use of ML for POD of LEO satellites. This may be due to the fact that most studies related to GNSS navigation are based on improving positioning accuracy and mitigation of GNSS errors. Additionally, LEO satellites with GNSS receivers have only recently emerged, and thus not many studies have yet focused on their POD via GNSS accounting for little number of research on LEO satellites using ML models and GNSS.

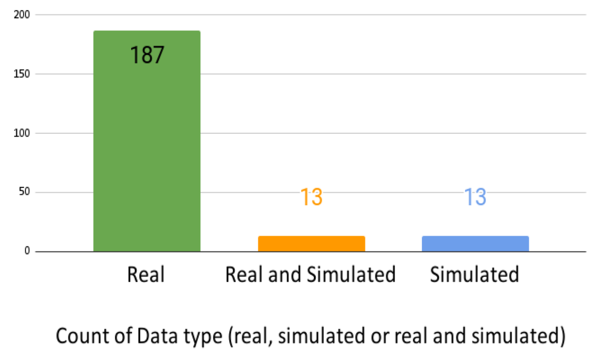

Fig. 6. Datasets for ML utilization in GNSS.

D. Datasets Used by the ML Models (RQ3)

A variety of datasets have been used in ML utilization in GNSS studies. Fig. 6 shows the percentage of studies using different datasets. Some of the data used were simulated data [150], [151] while others were real data [23], [152], [153]. The utilized datasets can be publicly available (for free) or private in nature not shared by researchers; therefore, results on such datasets cannot be verified and such studies are not replicable. The major category of datasets used and their sources are as follows.

1) *Simulated data:* These datasets include, CU SeNSe Lab [154], and a customized software-defined radio (SDR)-based GNSS data grabber and software receiver [155].

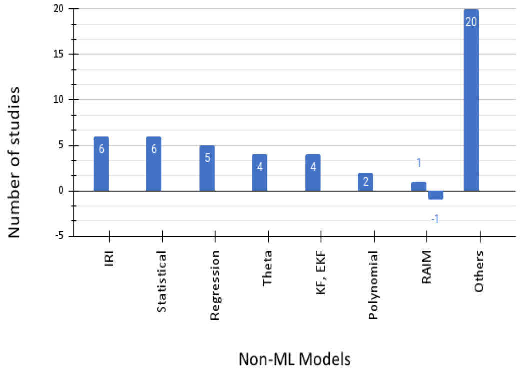

Fig. 7. ML versus non-ML (bars above zero line indicate that ML models are more accurate, while the bars below zero line indicate that non-ML models are more accurate).

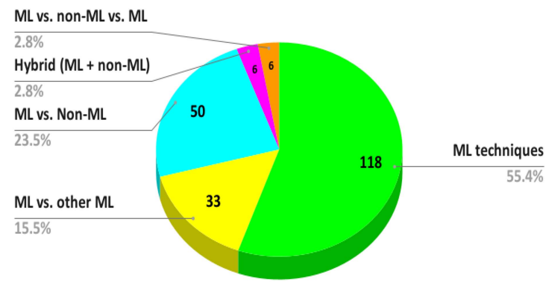

Fig. 8. Utilization of ML in GNSS.

2) *Real data:* These datasets include GNSS raw data from smartphones (it also include data collected by individuals.) [156], vertical total electron content (VTEC) data from the National Oceanic and Atmosphere Administration [23], and GPS data over International GNSS Service (IGS) stations [152], [153].
3) *Combining real and simulated data:* The combination of real and simulated data are used [3], [120], [157].

Different kinds of devices were used for the collection of the data used for research. These include low-cost receivers such as u-blox, smartphones, and high-end receivers, for example, Trimble, Novatel, and Javad Triumph VS receivers. The type of research determined the location for data collection. These locations include open sky environments (LOS), urban canyon (multipath/NLOS prone), indoors (GNSS-denied environment), and laboratory-generated data.

In GNSS, even with the same equipment and the same data collection path, the data collected at different times should be regarded as different dataset due to the change in satellite's geometry. Therefore, in the GNSS field, it is rare to see researchers use the same dataset for different objectives or even more, the same objective. However, in research, replicability is important; therefore, it would be a good practice to create a database where researches can store their research data for easy access in order for other researchers to be able to replicate their results. This way, the ML model used can be trained and evaluated by other researchers making use of the shared data.

E. ML Versus Non-ML Models (RQ4a)

In some of the selected studies, ML models versus non-ML models performance were compared (as seen in Fig. 7). The ML models have been compared with several conventional non-ML models: regression model [14], [80], [101], [158], [159], brute force approach [143], traditional statistical approaches [60], [94], [160], [161], [162], [163], classical KF [129], Bayes-optimal rule [118], least square (LS)-based approach [40], Saastamoinen model [110], autoregressive model and a traditional LEO propagation model (EKF-STAN) [146], conventional wind speed retrieval method [43], maximum-likelihood power-distortion (PD-ML) [164], BERNESE 5.2 [114], CYGNSS [44], hydrostatic-seasonal-time model [49], statistical theta method [51], [52], [53], [165], MAPGEO2004 geoid model [73], GNSS-IR SM [58], autoregressive and autoregressive moving average [166], ERA-Interim—a global atmospheric reanalysis (now ERA5 reanalysis) [107], empirical linear algorithms (LRM and LLM) [59], International Reference Ionosphere (IRI) 2016 model [167], NeQuick and IRI-2001 global TEC model [168], [169], [170], EKF-based integration scheme [171], CODE Global Ionospheric Maps (GIMs) [172], autoregressive integrated moving average (ARIMA), and quadratic polynomial models [173], LSR and BHS [105], linear interpolation method and inverse distance weighted interpolation method [112], KF [138], [139], polynomial model [93], [174], IRI-2001 model [175], conventional systems (RAIM) [126], [176], EGNOS [103], and IRI-2012 model [177].

In Fig. 7, we present the studies that compared the performance of ML with non-ML models. Majority of the studies concluded that ML models outperformed non-ML models except for one study (GNSS/INS integration [126]), where the SVM model has a similar performance to conventional systems (RAIM), but suffers from faster degradation due to the tightly coupled fusion algorithm. Specifically, Fig. 8 shows that 23.47% (50 of 213) of studies did a comparison between non-ML and ML models [14], [31], [40], [43], [44], [45], [51], [52], [53], [58], [59], [60], [73], [80], [93], [94], [103], [105], [107], [110], [112], [114], [126], [129], [130], [131], [138], [139], [143], [146], [158], [159], [160], [161], [162], [163], [164], [165], [166], [168], [169], [170], [171], [172], [173], [174], [175], [176], [177], [178].

The percentage of studies that made comparison between ML and other ML models was 15.49% (33 of 213) [12], [13], [16], [17], [26], [27], [28], [29], [33], [36], [39], [56], [63], [68], [77], [86], [87], [91], [108], [115], [122], [123], [124], [135], [179], [180], [181], [182], [183], [184], [185], [186], [187]. Whereas 55.39% (118 of 213) of the studies did not do any comparison but presented the result of ML model(s) used [3], [11], [15], [18], [19], [20], [21], [22], [24], [25], [30], [32], [34], [35], [37], [38], [41], [42], [46], [47], [48], [50], [54], [55], [57], [61], [62], [69], [70], [72], [74], [75], [76], [78], [79], [81], [83], [85], [88], [89], [90], [92], [95], [96], [97], [98], [99], [100], [102],

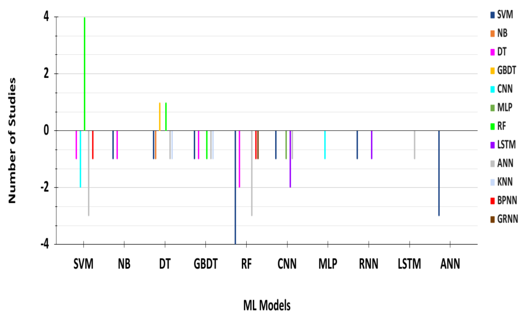

Fig. 9. Comparison between ML models (bars above zero line indicate that models in vertical axis are more accurate, whereas the bars below zero line indicate that models in horizontal axis are more accurate).

[104], [106], [109], [111], [113], [117], [119], [120], [121], [125], [127], [128], [132], [133], [134], [136], [137], [140], [144], [147], [148], [157], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201], [202], [203], [204], [205], [206], [207], [208], [209], [210], [211], [212], [213], [214], [215], [216], [217], [218], [219], [220], [221], [222], [223], [224], [225], [226], [227], [228], [229], [230], [231], [232], [233].

Furthermore, 2.82% (6 of 213) of studies compared one or more non-ML model with one or more ML model [49], [71], [101], [167], [234], [235], while 2.82% (6 of 213) of studies implemented a hybrid between ML and non-ML algorithm [82], [118], [149], [236], [237], [238]. These hybrid implementation studies claim their performance is better than ML only and non-ML only implementations. The comparison of the utilization of ML in GNSS are presented in Fig. 8.

F. ML Versus Other ML Models (RQ4b)

For the comparisons between different ML models, we compared the accuracy of many ML models applied to the same use case. This comparison is done for studies that implemented more than one ML model for a particular GNSS use case. All ML models applied to a specific GNSS use case are analyzed for comparison based on accuracy. In general, five significant comparison results can be found from the selected studies. First, RF, GBDT, CNN, RNN, and ANN are more accurate than LSTM and SVM respectively. Some studies showed that DT, GBDT, and RF-based classifier obtained a higher accuracy than KNN, CNN, ANN, and SVM respectively. Another ML model with significant performance was the SVM in its various forms (SVM, LSSVM-KF, and C-SVM) performing better than CNN, ANN, and DT. These performance comparisons between ML models are provided in Fig. 9.

The reasons for some ML models such as DT, GBDT, and RF performing better than NN models (ANN, CNN, and LSTM) may be due to the following:

1) Very few studies conducted experiments to compare ML with other ML models for the same GNSS use case.
2) All the GNSS use cases demonstrating the superiority of NN models over other ML models come from the studies of NN models; therefore, it is possible that some of them have a bias toward NN model and these studies may be overly optimistic.
3) The use cases used for this comparison differ slightly from each other and as a result, the type of ML algorithm used varies and it may not be beneficial to do a cross-comparison of ML model across GNSS use cases.

Furthermore, for ML models that are rarely compared with each other, it is difficult to determine which is more accurate.

G. Strength and Weakness of ML Models Applied to GNSS (RQ5)

Given the various GNSS use cases, we may have to concern ourselves with selecting the appropriate ML models for a specific GNSS use case. By investigating the characteristics of the candidate ML models (to be more precise, the ML techniques), such concern can be addressed. The aim is to identify the strengths and weaknesses of the ML techniques. To this aim, we have extracted the strengths and weaknesses of ML techniques and synthesized them based on the type of the ML technique. The different studies assessed the ML techniques in different ways and from different aspects based on the GNSS use case the ML model was applied to, therefore, we decided to synthesize in general, the common strengths and weaknesses that were mentioned by at least two studies (see Table IX). The list comprises of the most common algorithm from the selected studies. However, in Table X, we present the strength and weaknesses as mentioned by some of the authors of the selected studies.

The topics about model selection, model application, and model combination, which are closely related to the characteristics of ML techniques and estimation contexts have been discussed in some existing works. With respect to model selection, a tree-form framework to select appropriate ML models was proposed [239]. The design of the framework is based on criteria, such as dataset size, uncertainty, causality, and applicability. These preliminary criteria can be extended to include more criteria related to ML models. With respect to applying ML models to GNSS use cases, no study has proposed a framework or procedure; however, Zhang and Tsai [240] proposed a general procedure for applying ML models that consists of the following steps: problem formulation, problem representation, data collection, domain theory preparation, performing the learning process, analyzing and evaluating learned knowledge, and dealing with the knowledge base. This procedure is also applicable to GNSS-related tasks. In the aspect of model combination, MacDonell and Shepperd [241] stated that the combination of a set of diverse techniques can improve estimation accuracy in cases where no dominant technique can be found. In [242], an SLR was conducted where it was also found that combining models would usually produce better estimates than when the models are used individually. Other studies [243] have provided strong support for this possibility although in the field of software development effort. Studies have presented the opinion that combining two or more ML techniques may potentially enhance the power of the estimation model. This can hold true in the field of GNSS, as shown in [77].

Although ML techniques have been proved in some studies to be effective for some GNSS use cases (contexts), they do not always perform well on all GNSS use cases. This implies that an absolutely "best" ML model (technique) does not appear to exist, and the performance of a particular ML model depends heavily on the contexts it applies to. Therefore, in order to choose appropriate ML techniques and apply them to real-world GNSS use case efficiently, the characteristics of the candidate ML techniques as well as the contexts of the GNSS use case needs to be well understood. In [244], it was noted that selecting the best estimation method "in a particular context" is more beneficial than selecting the "best" estimation method in general.

H. Evaluating/Validating ML Models (RQ6)

Since ML model is data-driven, both building the model and its validation rely extremely on the training data. Therefore, when evaluating the estimation accuracy of an ML model, the training dataset on which the model is built and validated, must be taken into account, as well as the employed validation method. Various historical datasets were used to build and validate the ML models identified in this review. The most frequently used datasets together with their relevant information has been presented in the previous sections.

Regarding the type of data used for evaluating the model, the studies made use of either simulated data, real data, or semisimulated data to evaluate the model depending on the GNSS use case. The real data were collected using high-grade GNSS receivers to be used as reference/ground truth. In some studies where GNSS ground truth/reference data are not available (for example, indoor applications), predefined known trajectories were used. During the trajectory recording, stops are made at certain way-points and the current location is recorded as a reference point (ground truth). For the studies that used simulated data, the simulation was done to be used as the accurate reference data for the model evaluation. The aim of testing with simulated data is to validate the proposed method in a well-controlled environment, where all the parameters (for example, multipath/direct-only signals) can be manually defined and clearly labeled.

With respect to validation methods, the metric explains the performance of an ML model. The chosen metrics influence how the performance of ML algorithms is measured and compared. They influence how we weigh the importance of different characteristics in the results. Furthermore, the ML model may give satisfying results when evaluated using a metric like *accuracy score* but may have poor results when evaluated against other metrics such as "*logarithmic loss*" or any other such metric. Hence, it is very much important to choose the right metric to evaluate the ML model. The metric used depends on if it is a classification, regression, or clustering problem. Some examples of classification, regression, and clustering metrics are listed as follows.

1) *Classification Metrics:*
   a) Accuracy.
   b) Logarithmic loss.
   c) ROC, AUC.
   d) Confusion matrix.
   e) Classification report.
2) *Regression Metrics:*
   a) MAE.
   b) Mean Squared Error.
   c) RMSE.
   d) Root mean squared logarithmic error.
   e) R square.
   f) Adjusted R square.
3) *Clustering Metrics:*
   a) Silhouette score.
   b) Rand index.
   c) Adjusted rand index.
   d) Mutual information.
   e) Calinski–Harabasz index.
   f) Davies–Bouldin index.

From the selected studies, Holdout, n-fold cross-validation ($n > 1$), and comparison with another algorithm were mostly used. Specifically, the numbers (percentages) of the studies that used these three validation methods are 2 (3.84%) for Holdout, 20 (38.46%) when compared with another algorithm, and 30 (57.69%) for n-fold cross-validation. Furthermore, accuracy metric should also be considered in evaluating the ML models. Different metrics measure the accuracy from different aspects and effort estimation accuracy can be measured using various metrics. It was found from the selected studies that RMSE, mean square error (MSE), ROC curves, and Standard-Deviation (StD) were the most popular accuracy metrics. Specifically, the numbers (percentages) of the studies that used these three metrics are 45 (56.25%) for RMSE, 7 (8.75%) for MSE, 9 (11.25%) for ROC, and 12 (15%) for StD.

More details can be seen in Table XI in Appendix B. It was also seen that when evaluating an ML model, we can make use of other well established model or methods for the evaluation.

IV. IMPLICATIONS FOR RESEARCH AND PRACTICE

This review has found that the studies on the application of ML techniques such as FFNN, RBF-NN, DBN, and SVR to GNSS use cases are still limited. Some ML techniques have not even been applied in the GNSS domain. Researchers are therefore encouraged to explore the possibilities of using the unapplied ML techniques to new GNSS use case context. In order to identify these unapplied ML techniques and to use them more efficiently in GNSS, researchers should keep track of the related disciplines like ML, artificial intelligence, data mining, and statistics. Because these disciplines can provide valuable insights and methods to address GNSS challenges.

High-quality historical GNSS dataset with detailed descriptions of features and data collection process is essential for building and validating ML models. This review has shown that, on one hand, most of the available GNSS datasets are GNSS observations. On the other hand, some of the studies used simulated GNSS datasets. These data varied and their means of collected also varied from study to study. To address this and thereby promote ML utilization in GNSS research, we suggest that researchers share their GNSS datasets in the research community after the removal of confidential information.

In the comparison of different ML models for GNSS use cases, the limited number of relevant studies and the nonuniform experimental designs may account for inconclusive and/or unclear results. Therefore, aside from performing more research and experiments, it will benefit the research community if a uniform experimental framework for evaluating the performance of different ML models utilized for a particular GNSS use case is developed. Without the use of such a uniform framework, the comparison results for different ML models may vary when using different datasets, or different experimental approaches even for the same GNSS use case.

In the case of the implications for practitioners, this review has found that very few of the selected studies focus on industry practice, for example, [76], [77], [78]. This may be evidence that the application of ML models in the real world of the GNSS industry is still quite limited. Therefore, we suggest that practitioners should cooperate with researchers to investigate the possibility of applying the promising ML models in their practices. For example, RF, SVM, CNN, and ANN have been investigated most extensively in academia; therefore, these can first be taken into consideration by practitioners, as a useful complement to the existing traditional GNSS model. However, because of the limited number of studies comparing ML models and traditional GNSS (non-ML) models found from this review, we recommend using both ML and non-ML models in parallel at the early stage of practice, which has been shown to have promising accuracy by some studies [82], [118], [149], [236], [237], [238]. The replacement of the non-ML (traditional GNSS) models with ML models can only be considered when the ML model performs significantly and consistently better than the existing traditional GNSS model.

This review has shown that different ML techniques are beneficial to different GNSS use cases. Therefore, prior to decision making concerning choosing an ML model to implement, practitioners need to know the contexts of the GNSS use case; in addition, they need to understand the characteristics of the ML models of interest. Usually, the degree to which the GNSS use case matches the characteristics of the chosen ML model can have a direct and significant impact on the performance of the ML model. This means that given the estimation contexts of a GNSS use case, we have to select ML models appropriate for the contexts. This concern can be addressed by investigating the candidate ML models or, more precisely, the ML techniques based on their characteristics, mainly reflected by the strengths and weaknesses of the ML techniques. The characteristics of the ML techniques are mainly associated with four types of estimation contexts namely: 1) small dataset, 2) outliers, 3) categorical features, and 4) missing values. For example, DT is prone to overfitting on small training dataset, while ANN and DT cannot deal with missing values. Second, ANN cannot deal with categorical features in their standard forms but will work as long as the categorical features have been quantified (or to avoid misleading information for methods using distance metrics, the categorical features should be encoded to suitable form, of which one-hot-encoding is often used). Third, similarly, ANN and DT cannot deal with missing values in their standard forms but will work as long as the missing values have been imputed.

In addition to the characteristics summarized above, there are some other distinct characteristics of ML techniques, which may be considered when choosing appropriate ML models. These are as follows: DT are intuitive and are easy to understand, while ANN has the ability to learn complex functions; however, it requires a large amount of data for training and may suffer from overfitting, with weak explanatory ability; BNN is capable of learning causal relationships. The topics about model selection, model application, and model combination have been discussed by existing works [239]. These topics are closely related to the characteristics of ML techniques and estimation contexts. With respect to model selection, a tree-form framework to select appropriate ML models was proposed in [239]. The framework is designed using criteria such as dataset size, uncertainty, causality, and applicability. These are preliminary criteria and can, therefore, be extended to include more criteria related to ML models. Furthermore, this framework was done for selecting the appropriate ML techniques for the prediction of software development costs. However, it can still be adapted to GNSS use cases as the characteristics of ML are the same irrespective of the field of application.

V. LIMITATIONS OF THIS REVIEW

This review considered accuracy metrics (e.g., RSME) and validation when evaluating the performance of ML models or comparing ML models with other models. Accuracy metrics are the most important metrics and were used by most of the studies. However, besides accuracy metrics, other performance metrics, such as generalization ability and interpretability, were ignored in this review. These may also be important, especially when selecting appropriate models for given GNSS use case. However, the summarized strengths and weaknesses of ML models, i.e., the outcomes of RQ5, are helpful to identify the appropriate ML models, which may alleviate this limitation to some extent. Another limitation in this review is that only 50 out of the 213 selected studies compare non-ML and ML techniques. Thus, the non-ML versus ML comparison is not definitely conclusive. Furthermore, while comparing different ML techniques, each of the selected study made use of different experimental settings including datasets, feature reduction methods, and preprocessing methods. This review has revealed contradictions in some results of the comparisons between ML models and conventional non-ML models and between different ML models; therefore, it is difficult to establish which model is more accurate for a GNSS use case. To improve the chances of identifying the model which is more accurate for a GNSS use case, the comparison of the ML algorithms should be done on common grounds. Some of the comparison parameters may include: time complexity (how much time the algorithm takes), space complexity (how much memory an algorithm needed to run in terms of the input size), sample complexity (number of training examples needed to train the network in order to guarantee a valid generalization), bias-variance tradeoff, online and offline, parallelizability, parametricity, etc. [245]. The authors will consider these parameters in future work. Furthermore, it would be important to use the same data. Section III-D shows that there are plenty of different datasets used by different researchers. Therefore, we suggest the development of a common test bench to study the utilization of ML algorithm in GNSS. Another limitation is the insufficient number of studies reporting the desired comparisons, which may have led to these inconsistencies. In general, drawing conclusions from a large number of studies is more likely to be reliable. There is also a possibility that although we have exhaustively searched all the stated digital libraries, we may have missed a suitable study. In conducting this review, we have assumed that all the studies are impartial, and where this is not the case, it then poses a threat to this study.

Some of the mentioned strengths and weaknesses of the approach used in the studies were retrieved directly from the selected studies (see Table IX). This means that it is possible that some of them may just represent the authors' opinions and, therefore, may be unreliable. To increase the reliability of the synthesized results for RQ5, we take only the synthesized strengths and weaknesses supported by two or more selected studies. Therefore, care has to be taken in dealing with any inferences drawn from these synthesized results.

TABLE VI
Publication Venues of Selected Studies

Publication Venue	**Paper Type**	**# Studies**	**Percentage**
The Institute of Navigation	Conference	44	20.66
Remote Sensing	Journal	15	7.04
Sensors	Journal	12	5.63
Advances in Space Research	Journal	9	4.23
GPS Solutions	Journal	5	2.35
arXiv	Journal	5	2.35
International Geoscience and Remote Sensing Symposium	Conference	5	2.35
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	Journal	5	2.35
Advancing Earth and Space Science	Journal	5	2.35
IEEE Access	Journal	4	1.88
IEEE/ION Position, Location and Navigation Symposium (PLANS)	Conference	3	1.41
International Conference on Localization and GNSS (ICL-GNSS)	Conference	3	1.41
IEEE Transactions on Geoscience and Remote Sensing	Journal	3	1.41
The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	Conference	3	1.41
Geodesy and Geodynamics	Journal	3	1.41
Journal of Atmospheric and Solar-Terrestrial Physics	Journal	3	1.41
International Conference on Intelligent Transportation Systems (ITSC)	Conference	2	0.94
Journal of Sensors	Journal	2	0.94
IEEE Transactions on Aerospace and Electronic Systems	Journal	2	0.94
IEEE Geoscience and Remote Sensing Letters	Journal	2	0.94
International Conf. on Sensing, Measurement Data Analytics in the era of Artificial Intelligence (ICSMD)	Conference	2	0.94
Remote Sensing of Environment	Journal	2	0.94
Materials Today: Proceedings	Journal	2	0.94
IEEE Internet of Things Journal	Journal	2	0.94
Applied Soft Computing	Journal	2	0.94
NAVIGATION, Journal of the Institute of Navigation	Journal	2	0.94
Information Fusion	Journal	2	0.94
Neurocomputing	Journal	1	0.47
ITS World Congress	Conference	1	0.47
IET Radar, Sonar Navigation	Journal	1	0.47
University of Nottingham	PhD thesis	1	0.47
International Conf. on Technology Management, Operations and Decisions (ICTMOD)	Conference	1	0.47
International Conf. on Signal Processing, Communications and Computing (ICSPCC)	Conference	1	0.47
Advanced Information Management, Communicates, Electronic and Automation Control Conf. (IMCEC)	Conference	1	0.47
IEEE Annual Consumer Communications Networking Conference (CCNC)	Conference	1	0.47
KTH ROYAL INSTITUTE OF TECHNOLOGY	Msc Thesis	1	0.47
RFI Workshop - Coexisting with Radio Frequency Interference (RFI)	Journal	1	0.47
Defence Technology	Journal	1	0.47
Asia-Pacific Conf. on Intelligent Robot Systems (ACIRS)	Conference	1	0.47
International Conf. on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT)	Conference	1	0.47
International Computer Conference, Computer Society of Iran (CSICC)	Conference	1	0.47
International Conf. on Computer Applications Information Security (ICCAIS)	Conference	1	0.47
Acta Astronautica	Journal	1	0.47
Engineering Science and Technology, an International Journal	Journal	1	0.47
Measurement	Journal	1	0.47
International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)	Conference	1	0.47
International Conf. on Acoustics, Speech and Signal Processing (ICASSP)	Conference	1	0.47
International Conf. on Signal, Information and Data Processing (ICSIDP)	Conference	1	0.47
IEEE Intelligent Vehicles Symposium (IV)	Conference	1	0.47
Global Oceans 2020: Singapore – U.S. Gulf Coast	Conference	1	0.47
European Navigation Conference (ENC)	Conference	1	0.47
IEEE Aerospace Conference (50100)	Conference	1	0.47
International Conf. on Artificial Intelligence in Information and Communication (ICAIIC)	Conference	1	0.47
IEEE Sensors Journal	Journal	1	0.47
Cognitive Communications for Aerospace Applications Workshop (CCAAW)	Conference	1	0.47
Systems of Signal Synchronization, Generating and Processing in Telecommunications (SYNCHROINFO)	Conference	1	0.47
International Symposium onTelecommunications (IST)	Conference	1	0.47
Forum on Cooperative Positioning and Service (CPGP)	Conference	1	0.47
European Signal Processing Conference	Conference	1	0.47
IEEE International Conf. on Wireless for Space and Extreme Environments (WiSEE)	Conference	1	0.47
International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)	Conference	1	0.47
IEEE Sensors Journal	Journal	1	0.47
Animals	Journal	1	0.47
Satellite Navigation	Journal	1	0.47
Journal of Hydrology	Journal	1	0.47
Wireless Personal Communications	Journal	1	0.47
Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography	Journal	1	0.47
Leibniz International Proceedings in Informatics (LIPIcs)	Journal	1	0.47
International Journal of Remote Sensing	Journal	1	0.47
ISPRS International Journal of Geo-Information	Journal	1	0.47
IOP Conference Series: Materials Science and Engineering	Conference	1	0.47
Mechatronics	Journal	1	0.47
Journal of Geodesy	Journal	1	0.47
International Association of Geodesy Symposia book series	book-chapter	1	0.47
Applied Sciences	Journal	1	0.47
Advances in Artificial Neural Systems	Journal	1	0.47
International Journal of Electronics	Journal	1	0.47
International Journal of Computer Applications	Journal	1	0.47
Alexandria Engineering Journal	Journal	1	0.47
IEEE Aerospace and Electronic Systems Magazine	Journal	1	0.47
International Conference on Automation and Computing (ICAC)	Conference	1	0.47
Iranian Journal of Electrical Electronic Engineering	Journal	1	0.47
International Conference on Robotics and Biomimetics (ROBIO)	Conference	1	0.47
International Symposium on Signal Processing and Information Technology (ISSPIT)	Journal	1	0.47
Annals Geophysics (AG)	Journal	1	0.47
Studia Geophysica et Geodaetica	Journal	1	0.47
Others	Journal	5	2.35
Total		**213**	**100**

VI. CONCLUSION

This systematic review investigated ML utilization in GNSS. The type of ML technique, the performance accuracy of the ML model, the comparison between different models (including ML model versus non-ML model, and ML model versus other ML model), and the GNSS contexts (use case) in which the ML models were presented. An extensive literature search for relevant studies published in the period 2000–2021 have been performed and which identified 213 primary studies (referred to as "selected studies") that are pertaining to the six research questions (RQs) raised in this review.

The principal findings of this review are summarized as follows.

1) *RQ1*—The ML algorithms that have been applied in GNSS use cases are presented in Table XI in Appendix B. Among them, RF, SVM, ANN, and

TABLE VII
Quality Levels of Relevant Studies

ID	Authors	Q1	Q2	Q3	Q4a	Q4b	Q5	Score
S1	Simon et al.	1	1	0	0	1	1	4
S3	Machado et al.	1	1	1	0	1	0	4
S4	Bhatt et al.	1	1	0.5	0	1	0	3.5
S5	Socharoentum et al.	1	1	1	0	1	0	4
S6	Z. Zhou et al	1	1	1	1	1	1	6
S7	Jiao et al.	1	1	1	0	1	0	4
S9	Favenza et al.	1	1	0.5	0.5	0.5	0	3.5
S10	Y. Quan	1	1	1	0	1	0	4
S11	Yang et al.	1	1	0.5	0	1	0	3.5
S12	L.-T. Hsu	1	1	1	0	1	1	5
S14	Suzuki et al.	1	1	1	0	1	0.5	4.5
S15	Jiao et al.	1	1	1	0	1	0	4
S16	B. GUERMAH et al.	1	1	1	0	1	0	4
S18	Y. Liu et al.	1	1	1	0	1	0	4
S19	Y. Quan et al.	1	1	1	0	1	1	5
S20	P. Huang et al.	1	1	1	1	1	0	5
S21	Gogliettino et al.	1	1	1	0.5	0.5	0.5	4.5
S22	Zhidong Zhang et al	1	1	1	0	1	0	4
S23	Z. Liu et al.	1	1	1	0	1	0	4
S25	H.-U. Kim and T.-S. Bae	1	1	1	0	1	1	5
S26	N. Linty et al.	1	1	0.5	0	1	0.5	4
S27	M. R. Manesh et al.	1	1	1	0	1	0.5	4.5
S28	ALEJANDRO KURATOMI	1	1	1	0	1	0	4
S29	Q. Liu et al.	1	1	1	0	1	0	4
S30	R. Morales Ferre et al.	1	1	1	0	1	0.5	4.5
S31	A. LOUIS	1	1	0.5	0	1	0	3.5
S32	K. Lamb et al.	1	1	1	0	1	1	5
S33	S. Semanjski et al.	1	1	1	0	1	1	5
S34	R. Orus Perez	1	1	1	0	1	1	5
S35	R. Sun et al.	1	1	1	0	1	1	5
S36	D. Brum et al.	1	1	1	0	1	0	4
S37	H. Dai et al.	1	1	1	0	1	1	5
S38	Z. Zou et al.	1	1	1	0.5	1	1	5.5
S39	Chang et al.	1	1	0.5	0.5	0.5	0	3.5
S40	E. Munin et al.	1	1	1	0	1	0.5	4.5
S42	Li et al.	1	1	0.5	0.5	0.5	0.5	4
S43	Borhani-Darian et al.	1	1	1	0	1	0	4
S44	P. Borhani-Darian et al.	1	1	1	0	1	0	4
S45	S. Tohidi et al.	1	1	0.5	0.5	0.5	0	3.5
S46	Munin et al.	1	1	1	0	0.5	0	3.5
S47	M. Alshaye et al.	1	1	1	0	1	0	4
S48	Yunxiang Liu et al.	1	1	1	0	1	0	4
S49	L. Mallika I et al.	1	1	1	0	1	0	4
S50	Suzuki et al.	1	1	1	0	1	0	4
S51	M. O. Selbesoglu	1	1	1	0	1	0	4
S52	Y. Xia et al.	1	1	1	0	1	0	4
S53	Q. Yan et al.	1	1	1	0	1	0.5	4.5
S54	R. Calvo-Palomino et al.	1	1	1	0	1	0	4
S55	Haiyu et al.	1	1	1	0	0.5	0	3.5
S56	S. Semanjski et al.	1	1	1	0	1	0	4
S57	S. Semanjski et al.	1	1	1	0	1	0	4
S58	F. Dovis et al.	1	1	0.5	0	1	0	3.5
S59	Y. Jia et al.	1	1	1	0	1	0	4
S60	E. I. Adegoke et al.	1	1	1	0	1	0	4
S61	Y. Jia; et al.	1	1	1	0	1	0	4
S62	Q. Yan et al.	1	1	1	0	1	0	4
S63	M. Asgarimehr; et al.	1	1	1	1	1	0	5
S65	L. Miotti et al.	1	1	1	1	1	0	5
S67	Y. Liu et al.	1	1	1	0	1	0	4
S68	T. Mortlock et al.	1	1	1	1	1	0	5
S69	L. Mengying et al.	1	1	1	0	1	0	4
S71	A. Lwin et al.	1	1	1	0	0.5	0	3.5
S73	S. J. Cho et al.	1	1	1	0	1	0	4
S74	J. Wang et al.	1	1	1	0	1	0	4
S75	X. Chu et al.	1	1	1	0	1	0	4
S76	G. Zhang et al.	1	1	0.5	0	1	0	3.5
S77	D. R. Kartchner et al.	1	1	0.5	0	1	0	3.5
S79	R. Klus et al.	1	1	1	0	1	0	4
S80	M. Y. Klimenko et al.	1	1	0.5	0.5	0.5	0	3.5
S82	Y. Liu et al.	1	1	1	1	1	0.5	5.5
S84	A. Hu et al.	1	1	0.5	0	1	0	3.5
S86	A. R. Kazemi et al.	1	1	0	0.5	1	0.5	4
S87	Y. Yang et al.	1	1	0.5	1	1	0	4.5
S88	Q. Yan et al.	1	1	1	0	1	0	4
S89	J. -. De Boer et al.	1	1	0.5	0	1	1	4.5
S90	J. Reynolds et al.	1	1	1	1	1	1	6
S91	R. Imam et al.	1	1	1	0	1	0	4
S92	S. Li et al.	1	1	0.5	0	1	0	3.5
S93	Y. Su et al.	1	1	0.5	1	1	0	4.5
S94	Z. Ã–ZDEMÄ°R et al.	1	1	0.5	0	1	0	3.5
S95	W. Ye et al.	1	1	1	0	0.5	0	3.5
S98	Y. Luo et al.	1	1	0.5	0.5	1	0.5	4.5
S99	Y. Wang et al.	1	1	1	1	1	0	5
S100	Q. Yan et al.	1	1	1	0	1	0	4
S101	L. Cong et al.	1	1	1	0	1	0	4
S102	L. He et al.	1	1	1	0	1	0	4
S103	J Mendez-Astudill et al.	1	1	1	0	1	0	4
S104	M Kiani et al.	1	1	1	1	1	0	5
S105	M Kiani et al.	0.5	1	0.5	1	1	0	4
S106	Liu et al.	1	1	0.5	0.5	0.5	0	3.5
S107	ES Fogarty et al.	1	1	1	0	1	0	4
S108	K Maschera et al.	1	1	1	0	1	0	4
S110	M Łoś et al.	1	1	1	0	1	0	4
S111	Y Jia et al.	1	1	1	0	1	0	4
S112	M Kiani et al.	1	1	1	1	1	0	5
S113	Alessandro Neri et al.	1	1	0.5	0	0.5	0.5	3.5
S114	Y Zhu et al.	1	1	1	0	1	0	4
S115	Y Liu et al.	1	1	1	0	1	0	4
S116	H Xu et al.	1	1	1	0	1	0	4
S117	V Senyurek et al.	1	1	1	0	1	0	4
S118	Y Jia et al.	1	1	1	0	1	0	4
S119	Q Yuan et al.	1	1	1	0	1	0	4
S121	A Lwin et al.	1	1	1	0	0.5	0	3.5
S122	H Liu et al.	1	1	1	0	1	0	4
S124	J Wang et al.	1	1	1	1	1	0	5
S125	N Liu et al.	1	1	1	0	1	0	4
S126	HU Kim et al.	1	1	1	0	1	0	4
S127	S Li et al.	1	1	1	0	1	0	4
S130	M Kaselimi et al.	1	1	1	0	1	0	4
S131	K Kasantikul et al.	1	1	1	0	1	0	4
S132	J Hu et al.	1	1	1	0	1	0	4
S132	J Hu et al.	1	1	1	0	1	0	4
S133	Dongchan et al.	1	1	0.5	0	0.5	1	4
S134	V Otugo et al.	1	1	1	0	1	0	4
S136	X Zou et al.	1	1	1	0	1	0	4
S137	O Eroglu et al.	1	1	1	0	1	0	4
S138	M Kiani et al.	1	1	1	1	1	1	6
S139	E. Piccolomini et al.	1	1	1	0	1	0	4
S140	M. Moses et al.	1	1	1	0	1	0	4
S141	Veronez et al.	1	1	1	1	1	0	5
S142	Y Liang et al.	1	1	1	0	1	0	4
S144	Y Shi et al.	1	1	1	0	0.5	0	3.5
S143	M Zeybek et al.	1	1	1	1	1	0	5
S145	L Zhao et al.	1	1	0.5	0	1	0	3.5
S146	M Kaselimi et al.	1	1	1	1	1	1	6
S147	S Miyazawa et al.	1	1	1	0	0.5	0	3.5
S148	Shamshiri et al.	1	1	1	1	1	1	6
S149	Surisetty et al.	1	1	1	1	1	0	5
S150	Mutchakayala et al.	1	1	1	0	1	0	4
S151	Wojtusiak et al.	1	1	1	0	1	0	4
S152	Osah et al.	1	1	1	0	1	0	4
S153	Salar et al.	1	1	1	0	1	0	4
S155	Xia et al.	1	1	1	1	1	0.5	5.5
S156	Li et al.	1	1	1	0	1	0	4
S157	Mohammed et al.	1	1	1	0	1	0	4
S158	Okoh et al.	1	1	1	1	1	0	5
S159	Rafatnia et al.	1	1	1	1	1	0	5
S160	Sahu et al.	1	1	1	1	1	0	5
S161	Sivavaraprasad et al.	1	1	1	1	1	0	5
S162	Ferreira et al.	1	1	1	1	1	1	6
S163	P. Prešeren et al.	1	1	1	0	1	1	5
S164	Rahimi et al.	1	1	1	1	1	0	5
S165	Kemal Tütüncü et al.	1	1	1	1	1	1	6
S166	R.E. Guinness et al.	1	1	1	0	1	0	4
S167	N. Yamaga et al.	1	1	1	1	1	0	5
S168	Q. Yuan et al.	1	1	1	0	1	0	4
S169	L. Li et al.	1	1	1	0	1	0	4
S170	B. Huang et al.	1	1	1	1	1	0.5	5.5
S171	M. Kim et al.	1	1	1	1	1	0	5
S172	B. Zhang et al.	1	1	1	0	1	0	4
S173	C. Herbert et al.	1	1	1	0	1	0	4
S174	Taro Suzuki et al.	1	1	1	0	1	0	4
S175	Marco Mendonça et al.	1	1	1	0	1	0	4
S179	Selbesoglu et al.	1	1	1	1	1	0	5
S180	Mohamad Orabi et al.	1	1	1	0.5	0.5	0	4
S181	Yu Jiao et al.	1	1	1	0	1	0	4
S183	Hany Ragabet et al.	1	1	1	0	1	0	4
S185	J. Merwe et al.	1	1	0.5	0	1	0	3.5
S186	Yung-Cheng et al.	1	1	1	0.5	1	0	4.5
S187	Hamad Yousif et al.	1	1	1	0.5	0.5	0.5	4.5
S188	J. Wang et al.	1	1	0.5	0.5	0.5	0	3.5
S190	T. Désert et al	1	1	1	0.5	1	0.5	5
S191	Li He et al	1	1	0.5	0	1	0.5	4
S192	W. Vigneau et al.	1	1	1	0	1	0.5	4.5
S194	Ramos-Bosch et al.	1	1	1	0	1	0	4
S195	Chengquan Xu et al.	1	1	1	0.5	1	0	4.5
S196	Heekwon No et al	1	1	1	0	1	0.5	4.5
S197	Qiming Zhong et al	1	1	1	0	1	0.5	4.5
S198	Chengjun Guo et al	1	1	1	0	1	0	4
S199	N. HARBAOUI et al	1	1	1	0	1	0	4
S200	S. Kozhaya et al	1	1	0.5	0	1	0	3.5
S201	Adyasha Mohanty et al	1	1	1	0	1	0	4
S202	Kahn-Bao Wu et al	1	1	1	0	1	0	4
S203	A. Kanhere et al	1	1	1	0	1	1	5
S204	A. Siemuri et al	1	1	1	0	1	0	4
S207	G. Caparra et al	0.5	1	1	0	0.5	0.5	3.5
S208	N. Ziedan	1	1	1	0	0.5	0	3.5
S209	A. Gomez et al	1	1	1	0	1	0	4
S210	Lei Liu et al	1	1	1	0	0.5	0	3.5
S211	Yunxiang Liu et al	1	1	0.5	0	1	0	3.5
S213	Quoc-Huy Phan et al	1	1	1	0	0.5	0	3.5
S214	Azami Hamed et al	1	1	1	0	1	0	4
S215	Nadali Zarei	1	1	0.5	0	1	0.5	4
S216	A. Noureldin et al	1	1	0.5	0	1	0	3.5
S217	Yu Jia et al	1	1	1	0	1	0.5	4.5
S218	E. Abdolkarimi et al	1	1	0.5	0	1	0	3.5
S220	A. Elnaggar	1	1	1	0.5	0.5	0	4
S221	Yiming Quan et al	1	1	1	0	1	0	4
S222	Habarulema et al	1	1	1	0.5	0.5	0.5	4.5
S223	J. Habarulema et al	1	1	1	0	0.5	0.5	4
S224	R. Sharaf et al	1	1	1	0	1	0	4
S225	C. Pikridas et al	1	1	0.5	0	1	0	3.5
S226	P. Benevides et al	1	1	1	0	1	0	4
S227	G. Panice et al	1	1	0.5	0.5	1	0	4
S228	Rui Sun et al	1	1	1	0.5	0.5	0	4
S229	Mosavi et al	1	1	1	0	0.5	0	3.5
S231	Li Jing et al	1	1	0.5	0	0.5	0.5	3.5
S232	Yimin Zhou et al	1	1	1	0	1	0	4
S233	Guangcai Wang et al	1	1	0.5	0	1	0	3.5
S234	Fangni Lei et al	1	1	1	0	1	0	4
S235	Zhengxie Zhang et al	1	1	1	0	1	0	4
S236	Li et al.	1	1	1	0	1	0	4
S237	Wu et al	1	1	0.5	0	1	0	3.5
S238	Savas et al	1	1	0.5	0.5	0.5	0.5	4
S239	Liu et al	1	1	1	0	1	1	5
S241	David et al	1	1	1	0	0.5	1	4.5
S242	Huang et al	1	1	1	0	1	1	5
S243	Yilmaz et al	1	1	0.5	0	1	0	3.5
S244	Habarulema et al	1	1	1	0	0.5	0	3.5
S245	Sabzehee et al.	1	1	1	0	1	0	4
S246	Leandro et al	1	1	1	0	1	1	5
S247	Wang et al	1	1	0.5	0	1	1	4.5
S248	Lyu et al	1	1	1	0	1	1	5
S249	Shafiee et al	1	1	1	0	1	1	5

TABLE VIII
Selected studies

ID	Authors	Research Questions Addressed (#RQ)						Ref.	ID	Authors	Research Questions Addressed (#RQ)						Ref.
S1	Simon et al.	1	2			4b	5	[144]	S127	S Li et al.	1	2	3		4b		[209]
Q3	Machado et al.	1	2	3		4b		[189]	S130	M Kaselimi et al.	1	2	3		4b		[210]
S4	Bhatt et al.	1	2	3		4b		[68]	S131	K Kasantikul et al.	1	2	3		4b		[45]
S5	M. Socharoentum et al.	1	2	3		4b		[180]	S132	J Hu et al.	1	2	3		4b		[179]
S6	Z. Zhou et al.	1	2	3	4a	4b	5	[71]	S133	Dongchan et al.	1	2	3		4b	5	[211]
S7	Jiao et al.	1	2	3		4b		[97]	S134	V Otugo et al.	1	2	3		4b		[92]
S9	Favenza et al.	1	2	3	4a	4b		[94]	S136	X Zou et al.	1	2	3		4b		[212]
S10	Y. Quan et al.	1	2	3		4b		[3]	S137	O Eroglu et al.	1	2	3		4b		[38]
S11	Yang et al.	1	2	3		4b		[190]	S138	M Kiani et al.	1	2	3	4a	4b	5	[166]
S12	L.-T. Hsu et al.	1	2	3		4b	5	[191]	S139	E Loli Piccolomini et al.	1	2	3		4b		[15]
S14	Suzuki et al.	1	2	3		4b	5	[192]	S140	M Moses et al.	1	2	3		4b		[213]
S15	Jiao et al.	1	2	3		4b		[98]	S141	MR Veronez et al.	1	2	3	4a	4b		[73]
S16	B. GUERMAH et al.	1	2	3		4b		[16]	S142	Y Liang et al.	1	2	3		4b		[57]
S18	Y. Liu et al.	1	2	3		4b		[89]	S143	Y Shi et al.	1	2	3	4a	4b		[58]
S19	Y. Quan et al.	1	2	3		4b	5	[158]	S144	M Zeybek et al.	1	2	3		4b		[11]
S20	P. Huang et al.	1	2	3	4a	4b		[143]	S145	L Zhao et al.	1	2	3		4b		[214]
S21	Gogliettino et al.	1	2	3	4a	4b	5	[159]	S146	M Kaselimi et al.	1	2	3	4a	4b	5	[167]
S22	Zhidong Zhang et al.	1	2	3		4b		[193]	S147	S Miyazawa et al.	1	2	3		4b		[74]
S23	Z. Liu et al.	1	2	3		4b		[137]	S148	Shamshiri et al.	1	2	3	4a	4b	5	[107]
S25	H.-U. Kim and T.-S. Bae	1	2	3		4b	5	[69]	S149	Surisetty et al.	1	2	3	4a	4b		[59]
S26	N. Linty et al.	1	2	3		4b	5	[95]	S150	Mutchakayala et al.	1	2	3		4b		[215]
S27	M. R. Manesh et al.	1	2	3		4b	5	[117]	S151	Wojtusiak et al.	1	2	3		4b		[75]
S28	ALEJANDRO KURATOMI	1	2	3		4b		[63]	S152	Osah et al.	1	2	3		4b		[216]
S29	Q. Liu et al.	1	2	3		4b		[87]	S153	Salar et al.	1	2	3		4b		[217]
S30	R. Morales Ferre et al.	1	2	3		4b	5	[122]	S155	Xia et al.	1	2	3	4a	4b	5	[168]
S31	A. LOUIS	1	2	3		4b		[194]	S156	Li et al.	1	2	3		4b		[46]
S32	K. Lamb et al.	1	2	3		4b	5	[195]	S157	Mohammed et al.	1	2	3		4b		[111]
S33	S. Semanjski et al.	1	2	3		4b	5	[120]	S158	Okoh et al.	1	2	3	4a	4b		[169]
S34	R. Orus Perez	1	2	3		4b	5	[104]	S159	Rafatnia et al.	1	2	3	4a	4b		[172]
S35	R. Sun et al.	1	2	3		4b	5	[13]	S160	Sahu et al.	1	2	3	4a	4b		[170]
S36	D. Brum et al.	1	2	3		4b		[22]	S161	Sivavaraprasad et al.	1	2	3	4a	4b		[171]
S37	H. Dai et al.	1	2	3		4b	5	[135]	S162	Ferreira et al.	1	2	3	4a	4b	5	[173]
S38	Z. Zou et al.	1	2	3	4a	4b	5	[129]	S163	P. Pavlovčič Prešeren et al.	1	2	3		4b	5	[83]
S39	Chang et al.	1	2	3	4a	4b		[82]	S164	Rahimi et al.	1	2	3	4a	4b		[60]
S40	E. Munin et al.	1	2	3		4b	5	[181]	S165	Kemal Tütüncü et al.	1	2	3	4a	4b	5	[239]
S42	Li et al.	1	2	3	4a	4b	5	[161]	S166	R.E. Guinness et al.	1	2	3		4b		[86]
S43	Borhani-Darian et al.	1	2	3		4b		[182]	S167	N. Yamaga et al.	1	2	3	4a	4b		[160]
S44	P. Borhani-Darian and P. Closas	1	2	3		4b		[12]	S168	Q. Yuan et al.	1	2	3		4b		[186]
S45	S. Tohidi and M. R. Mosavi	1	2	3	4a	4b		[118]	S169	L. Li et al.	1	2	3		4b		[218]
S46	Munin et al.	1	2	3		4b		[196]	S170	B. Huang et al.	1	2	3	4a	4b	5	[174]
S47	M. Alshaye et al.	1	2	3		4b		[24]	S171	M. Kim et al.	1	2	3	4a	4b		[105]
S48	Yunxiang Liu et al.	1	2	3		4b		[183]	S172	B. Zhang et al.	1	2	3		4b		[61]
S49	L. Mallika l et al.	1	2	3		4b		[106]	S173	C. Herbert et al.	1	2	3		4b		[30]
S50	Suzuki et al.	1	2	3		4b		[197]	S174	Taro Suzuki et al.	1	2	3		4b		[17]
S51	M. O. Selbesoglu	1	2	3		4b		[109]	S175	Marco Mendonça et al.	1	2	3		4b		[240]
S52	Y. Xia et al.	1	2	3		4b		[85]	S179	Mahmut Oguz Selbesoglu et al.	1	2	3	4a	4b		[112]
S53	Q. Yan and W. Huang	1	2	3		4b	5	[26]	S180	Mohamad Orabi et al.	1	2	3	4a	4b		[163]
S54	R. Calvo-Palomino et al.	1	2	3		4b		[119]	S181	Yu Jiao et al.	1	2	3		4b		[90]
S55	Haiyu et al.	1	2	3		4b		[198]	S183	Hany Ragabet et al.	1	2	3		4b		[219]
S56	S. Semanjski et al.	1	2	3		4b		[238]	S185	J. Rossouw van der Merwe et al.	1	2	3		4b		[124]
S57	S. Semanjski et al.	1	2	3		4b		[199]	S186	Yung-Cheng et al.	1	2	3	4a	4b		[138]
S58	F. Dovis et al.	1	2	3		4b		[200]	S187	Hamad Yousif and Ahmed El-Rabbany	1	2	3	4a	4b	5	[164]
S59	Y. Jia et al.	1	2	3		4b		[32]	S188	Jianguo Jack Wang et al.	1	2	3	4a	4b		[139]
S60	E. I. Adegoke et al.	1	2	3		4b		[201]	S190	T. Désert et al	1	2	3	4a	4b	5	[103]
S61	Y. Jia et al.	1	2	3		4b		[33]	S191	Li He et al	1	2	3		4b	5	[20]
S62	Q. Yan and W. Huang	1	2	3		4b		[27]	S192	W. Vigneau et al.	1	2	3		4b	5	[147]
S63	M. Asgarimehr et al.	1	2	3	4a	4b		[40]	S194	Pere Ramos-Bosch et al.	1	2	3		4b		[148]
S65	L. Miotti et al.	1	2	3	4a	4b		[110]	S195	Chengquan Xu et al.	1	2	3	4a	4b		[175]
S67	Y. Liu et al.	1	2	3		4b		[41]	S196	Heekwon No et al	1	2	3		4b	5	[220]
S68	T. Mortlock and Z. M. Kassas	1	2	3	4a	4b		[146]	S197	Qiming Zhong et al	1	2	3		4b	5	[221]
S69	L. Mengying et al.	1	2	3		4b		[99]	S198	Chengjun Guo et al	1	2	3		4b		[21]
S71	A. Lwin et al.	1	2	3		4b		[35]	S199	Nesrine HARBAOUI et al	1	2	3		4b		[222]
S73	S. J. Cho et al.	1	2	3		4b		[184]	S200	Sharbel E. Kozhaya et al	1	2	3		4b		[149]
S74	J. Wang et al.	1	2	3		4b		[202]	S201	Adyasha Mohanty et al	1	2	3		4b		[134]
S75	X. Chu et al.	1	2	3		4b		[42]	S202	Kahn-Bao Wu et al	1	2	3		4b		[223]
S76	G. Zhang et al.	1	2	3		4b		[70]	S203	Ashwin V. Kanhere et al	1	2	3		4b	5	[76]
S77	D. R. Kartchner et al.	1	2	3		4b		[123]	S204	Akpojoto Siemuri et al	1	2	3		4b		[77]
S79	R. Klus et al.	1	2	3		4b		[88]	S207	Gianluca Caparra et al	1	2	3		4b	5	[78]
S80	M. Y. Klimenko et al.A. V. Veitsel	1	2	3	4a	4b		[203]	S208	Nesreen I. Ziedan	1	2	3		4b		[79]
S82	Y. Liu et al.	1	2	3	4a	4b	5	[43]	S209	Annabel R. Gomez et al	1	2	3		4b		[91]
S84	A. Hu et al.	1	2	3		4b		[115]	S210	Lei Liu et al	1	2	3		4b		[224]
S86	A. R. Kazemi et al.	1	2		4a	4b	5	[165]	S211	Yunxiang Liu et al	1	2	3		4b		[225]
S87	Y. Yang et al.	1	2	3	4a	4b		[114]	S213	Quoc-Huy Phan et al	1	2	3		4b		[226]
S88	Q. Yan et al.	1	2	3		4b		[25]	S214	Azami Hamed et al	1	2	3		4b		[236]
S89	J. -. De Boer et al.	1	2	3		4b	5	[132]	S215	Nadali Zarei	1	2	3		4b	5	[237]
S90	J. Reynolds et al.	1	2	3	4a	4b	5	[44]	S216	AboelmagdNoureldin et al	1	2	3		4b		[140]
S91	R. Imam et al.	1	2	3		4b		[96]	S217	Yu Jia et al	1	2	3		4b	5	[100]
S92	S. Li et al.	1	2	3		4b		[47]	S218	E. S. Abdolkarimi et al	1	2	3		4b		[131]
S93	Y. Su et al.	1	2	3	4a	4b		[49]	S220	Aly M.El-naggar	1	2	3	4a	4b		[93]
S94	Z. Ã–ZDEMÄ°R et al.	1	2	3		4b		[204]	S221	Yiming Quan et al	1	2	3		4b		[227]
S95	W. Ye et al.	1	2	3		4b		[205]	S222	Habarulema et al	1	2	3	4a	4b	5	[176]
S98	Y. Luo et al.	1	2	3	4a	4b	5	[162]	S223	John Bosco Habarulema et al	1	2	3		4b	5	[228]
S99	Y. Wang et al.	1	2	3	4	4b		[14]	S224	R. Sharaf et al	1	2	3		4b		[136]
S100	Q. Yan et al.	1	2	3		4b		[28]	S225	Christos Pikridas et al	1	2	3		4b		[113]
S101	L. Cong et al.	1	2	3		4b		[133]	S226	Pedro Benevides et al	1	2	3		4b		[62]
S102	L. He et al.	1	2	3		4b		[206]	S227	G. Panice et al	1	2	3	4a	4b		[126]
S103	J Mendez-Astudill et al.	1	2	3		4b		[50]	S228	Rui Sun et al	1	2	3	4a	4b		[80]
S104	M Kiani et al.	1	2	3	4a	4b		[51]	S229	Mosavi et al	1	2	3		4b		[81]
S105	M Kiani et al.	1	2	3	4a	4b		[52]	S231	Li Jing et al	1	2	3		4b	5	[187]
S106	Liu et al.	1	2	3	4a	4b		[101]	S232	Yimin Zhou et al	1	2	3		4b		[127]
S107	ES Fogarty et al.	1	2	3		4b		[207]	S233	Guangcai Wang et al	1	2	3		4b		[128]
S108	K Maschera et al.	1	2	3		4b		[185]	S234	Fangni Lei et al	1	2	3		4b		[229]
S110	M Łoś et al.	1	2	3		4b		[54]	S235	Zhengxie Zhang et al	1	2	3		4b		[108]
S111	Y Jia et al.	1	2	3		4b		[34]	S236	Li et al.	1	2	3		4b		[121]
S112	M Kiani et al.	1	2	3	4a	4b		[53]	S237	Wu et al	1	2	3		4b		[18]
S113	Alessandro Neri et al.	1	2	3		4b	5	[72]	S238	Savas et al	1	2	3	4a	4b	5	[177]
S114	Y Zhu et al.	1	2	3		4b		[29]	S239	Liu et al	1	2	3		4b	5	[230]
S115	Y Liu et al.	1	2	3		4b		[102]	S241	David et al	1	2	3		4b	5	[231]
S116	H Xu et al.	1	2	3		4b		[208]	S242	Huang et al	1	2	3		4b	5	[232]
S117	V Senyurek et al.	1	2	3		4b		[39]	S243	Yilmaz et al	1	2	3		4b		[188]
S118	Y Jia et al.	1	2	3		4b		[36]	S244	Habarulema et al	1	2	3		4b		[233]
S119	Q Yuan et al.	1	2	3		4b		[48]	S245	Sabzehee et al.	1	2	3		4b		[178]
S121	A Lwin et al.	1	2	3		4b		[37]	S246	Leandro et al	1	2	3		4b	5	[234]
S122	H Liu et al.	1	2	3		4b		[55]	S247	Wang et al	1	2	3		4b	5	[235]
S124	J Wang et al.	1	2	3	4a	4b		[31]	S248	Lyu et al	1	2	3		4b	5	[19]
S125	N Liu et al.	1	2	3		4b		[130]	S249	Shafiee et al	1	2	3		4b	5	[125]
S126	HU Kim et al.	1	2	3		4b		[56]									

TABLE IX
Strengths and Weaknesses of Mostly Used ML Techniques

Strengths	Weaknesses	Studies Ref.
DT and ensemble DTs 1. Decision trees can learn non-linear relationships and are fairly robust to outliers. 2. It can avoid overfitting by pruning or making use of ensembles. 3. Intuitive and easy to understand.	1. Unconstrained, individual trees are prone to overfitting as they can keep on branching until the training data is memorized.	[13, 16, 29, 63, 94–96, 124, 180, 201]
DL models 1. Perform very well on images, audio, and text data. 2. They can be updated easily with new datasets using batch propagation. 3. Their architectures (that is, the number of layers and the structure of the layers) can be adapted to fit many types of problems. 4. Capable of dealing with noisy data. 5. Hidden layers reduce the need for feature engineering. **LSTM (a special type of RNN)** 1. Easy to implement. 2. Scaleable with the dataset. 3. Perform well even with small data sets.	1. Require a very large amount of data (therefore, cannot be used as a general-purpose algorithm). 2. Computationally intensive to train. 3. Require much more experience to tune them (that is, hyperparameters tunning). 4. Weak explanatory ability. **LSTM (a special type of RNN)** 1. Outperformed by NN models that have been properly trained and tuned. 2. LSTMs take longer to train. 3. LSTMs require more memory to train.	NN models: [3, 12, 17, 18, 20, 21, 25, 27, 30, 38–41, 43–46, 56, 60, 62, 73, 77, 78, 81, 82, 86, 88, 92, 93, 103, 105, 109–113, 115, 118, 123, 125, 130, 132, 134, 136, 138–140, 144, 147, 148, 160, 163–165, 169–171, 173, 175, 176, 178, 184, 186, 188, 189, 195–197, 203, 210, 212, 213, 227, 232–234, 236, 237] and LSTM: [15, 56, 69, 74, 91, 97, 123, 130, 149, 167, 174, 217, 225]
SVM 1. Fairly robust against overfitting, especially in high-dimensional space. 2. Used to model non-linear decision boundaries with many kernels to choose from.	1. Trickier when tuning because picking the right kernel is very important in the process. 2. They also don't scale well to larger datasets.	[14, 16, 17, 19, 28, 33, 36, 37, 39, 68, 72, 86, 89, 90, 97–102, 108, 120, 121, 126, 133, 162, 168, 184, 192, 198, 199, 207, 208, 223, 238, 240]

CNN and their combinations have been used most frequently.

2) *RQ2*—The ML algorithms were used for classification, clustering, forecasting, and anomaly detection depending on the GNSS use case. Some of these GNSS use cases include signal acquisition, signal detection and classification, Earth observation, GNSS/INS integration, anomaly detection, and spoofing and jamming detection, etc.
3) *RQ3*—Some of the data used were simulated data gotten from different simulation tools and SDRs, while others were real data collected using GNSS receivers. The utilized datasets can be publicly available (for free) or private in nature (not shared by researchers; therefore, results on such datasets cannot be verified and such studies are not replicable).
4) *RQ4a and RQ4b*—Regarding ML performance, in general, ML model is more accurate than non-ML model, which has been supported by most studies. Regression model and other traditional GNSS models depending on the GNSS use case were compared with ML models in 50 out of 213 selected studies.
5) *RQ5*—Different ML techniques have different strengths and weaknesses and thus favorable to different GNSS applications. The strengths and weaknesses of the studies based on the implemented ML algorithms were extracted from the selected studies and presented in this review. This was done because the quality assessment process of the selected studies can help ensure that they are from studies with acceptable quality. The strength and weaknesses from a list comprising of the most implemented algorithm in the selected studies was also presented.
6) *RQ6*—Regarding validation, it has been shown from the selected studies that for the validation of the ML models, most studies made use of Holdout, *n*-fold cross-validation, and comparison with another algorithms. While for accuracy metric, most made use of RMSE, ROC, MSE, and StD. Furthermore,

TABLE X

Strengths and Weaknesses of the approaches used in the Selected Studies

ID	ML Technique Used	Strengths	Weaknesses	Ref.
S6	Least-squares support vector machine (LSSVM) technique	Unlike classical KF, it adaptively identifies the dynamic model bias, which is then used to compensate for the dynamic model.		[71]
S12	Support Vector Machine (SVM)		Classifier developed is applied only for static applications	[191]
S19	Convolutional Neural Network (CNN)	The proposed methods can be used in carrier phase-based kinematic positioning, including RTK applications.		[158]
S21	MLP, Autoencoder network	Autoencoder approach is very promising as it needs samples not affected by errors.		[159]
S25	Long-Short Term Memory (LSTM)		Needs to be elaborated to incorporate sensors with more features as input data and the strategy on how to balance the weight between sensor data.	[69]
S26	Decision tree	Machine learning helps in facilitating the work of analyzing big sets of GNSS data affected by amplitude scintillation		[95]
S27	Neural Network (NN)		Need to include online learning in the neural network or use unsupervised algorithms	[117]
S30	Support vector machine (SVM)		Classification will be more accurate if the complexity of the training layers is increased	[122]
S32	Convolutional Neural Network (CNN)	A novel methodology which predicts GNSS phase scintillations 1 hour in advance.		[195]
S33	C-Support Vector Machines (C-SVM)	Correlation analysis is a good approach for the selection of variables that serve as an input for the supervised machine learning approach.		[120]
S34	Neural Network (NN)		Applicability should be assessed if other techniques such as convolutional neural networks are used and the hardware requirements for analyzing large amounts of data.	[104]
S35	Gradient boosting decision tree (GBDT)	Removing NLOS based on the proposed method can improve the static positioning accuracy to some extent		[13]
S37	Recurrent neural network (RNN)	Anticipates proposed method can be applied in the field of multi-sensors integrated navigation system.		[135]
S38	Convolutional Neural Network (CNN)		The limitation of the proposed algorithm is that one trained estimator is bound to specific sensors. The neural network model should be retrained when used on a new navigation system.	[129]
S40	Convolutional Neural Network (CNN)		Proposed algorithm needs to be validated with the real signals	[181]
S42	Deep Neural Network (DNN)		The investigated NN model requires a multi-correlation scheme, thus involving an increased computational cost when compared to standard methods.	[161]
S53	Convolutional Neural Network (CNN)	The usage of filters in the convolution layer reduces the noise in the DDM.		[26]
S82	Neural Network (NN)		Further investigation on the relationship between the wind speed or the wind vector and the last hidden layer neurons can potentially provide a better understanding of the underlying physical meaning of the network	[43]
S86	Neural Network (NN)	Classification algorithm outperforms the original PD- ML detector and PSO-NN classifier, but it comes with more computation complexity		[165]
S89	Neural Network (NN)	NN-aided GNSS/MEMS integration provides more accurate position estimates than GNSS/MEMS without NN corrections.		[132]
S90	Artificial Neural Network (ANN)		The ANN methodology has difficulty to estimate unusual occurrences of very low or very high wind speed and the need for a large training set to obtain accurate retrievals over a time frame of several months or years.	[44]
S98	Support vector machine (SVM)	The proposed method does not require the radio telescope, and can achieve all-time, all-weather detection by processing large quantities of data at the same time and the detection results demonstrate whether multiple stations are affected by SRBs.		[162]
S133	Deep Neural Network (DNN)	SVM has low performance than the NN model while RNN performance is the best, but needs initial time and takes a long time to train and DNN has less performance than RNN but does not require initial time and is faster to train.		[211]
S138	Generalized Regression NN	It is purely a mathematical model with high accuracy, up to centimeter level. Including observation accuracy and the physical conditions of the environment may lead to a more accurate algorithm, capable of achieving higher accuracies, possibly up to the millimeter level.		[166]
S146	Long-Short Term Memory (LSTM)	Inclusion of selected features in the supervised LSTM algorithm and that LSTM networks are equipped with memory cell which holds information content in the input STEC data, gives superiority and an extra boost to the proposed method. Non-linearity and long-term prediction are additional advantages of the proposed LSTM method.		[167]
S148	GP regression	The approach has a good generalization capability even with a small set of training samples. Wider range of sampling results in better generalization capabilities.		[107]
S155	Support vector machine (SVM)		The model cannot accurately predict the ionospheric TEC in high years of solar activity	[168]
S162	Neural Network (NN)		The NN model does not have the ability to calibrate vTEC by itself, it relies on data provided by the calibration technique.	[173]
S163	Wavelet Neural Network (WNN)		The problem of optimal wavelet network adjustment remains and because of that wavelet function selection should always be based on practical experimentation and trial and error tests.	[83]
S170	Long-Short Term Memory (LSTM)	SL-LSTM method achieves a better long-term prediction accuracy and stability than the other three methods. The quality of satellite clock bias prediction is better than that of other three methods.		[174]
S187	Neural Network (NN)		The ANN consumes computer resources while training large dataset	[164]
S190	Neural Network (NN)	The proposed method is effect on an equatorial region		[103]
S191	Artificial Neural Network (ANN)	Installing an antenna with a non-trivial and confidential radiation map, the security of the GPS signal for a specific fixed receiver can be increased.		[20]
S192	Neural Network (NN)		The performances and complexity of both algorithms has been analyzed and those results are to be finalized to assess the cost of integration of those techniques inside a LEO GNSS receiver.	[147]
S196	Quantile Regression	The proposed model is well overbounding up to desired probability achieving better position accuracy, lower alarm rate, and tighter protection level.		[220]
S197	Bayesian Filter	Filtering has a greater impact on the results of the mobile positioning with significant movement compared to static positioning		[221]
S203	Deep Neural Network (DNN)	Using pseudorange residuals and LOS vectors from the initial position guess as inputs and NED position corrections as outputs to the DNN improves the numerical conditioning of the DNN and provides global applicability to the algorithm.		[76]
S207	Neural Network (NN)	The method does not require changes in the architecture of the GNSS receivers and can be deployed as a software service.		[78]
S215	Neural Network (NN) trained with PSO, NPSO, GA, and ICA		GPS GDOP approximation and classification are time-consuming and unreliable using existing approaches	[237]
S217	Support vector machine (SVM)		New phase scintillation detectors based on phase observations need to be developed	[100]
S222	Neural Network (NN)		The availability of historical data affects the NN model	[176]
S223	Feed Forward Neural Networks (FFNN)	NN model makes more accurate predictions on TEC than GPS-derived TEC due to the availability of data within the NN model from nearby stations.		[228]
S231	Ensemble learning algorithm (LS-Boost or Bagging)		The accuracy of the proposed algorithm is not good as SINS error does not have noticeable divergence in a short period of time	[187]
S238	K-means clustering		Implementation parameters of the algorithm must be well optimized.	[177]
S239	convLSTM	convLSTM-based architecture forecasts an entire regions' ionospheric irregularity occurrence and intensity values		[230]
S241	Neural Network (NN)	MSEs were very low for most of the months, hence accuracy is high		[231]
S242	Radial basis function (RBF) Neural Network (RBF-NN)	RBF network is a reliable and alternate tool for the ionospheric TEC forecast of single station		[232]
S246	Neural Network (NN)		The TEC values for each station based on the technique used is not an optimal approach as it depends on ambiguity term	[234]
S247	Wavelet Neural Network (WNN)		The architecture of WNN employed is not guaranteed to be the best and unique design due to the theoretical limitations inhering in ANN	[235]
S248	Support vector machine (SVM)	The proposed weight scheme is superior to the traditional weight scheme as it can better model the GNSS measurement NLOS error in urban environments.		[19]
S249	n Multi-layer NN	Spoofing detection using the algorithm after training is low-cost, easy to implement, and reliable		[125]

TABLE XI
Algorithms, GNSS Use Case, Data Type, and Validation Method

ID	Authors	Year	ML Technique	Study Application	Data type	Accuracy/Validation	Type	Ref.
S1	Simon et al.	1995	Neural Network (NN)	Satellite selection	Real	Not mentioned	Journal	[144]
S3	Machado et al.	2011	Artificial Neural Networks (ANN)	Earth monitoring	Real	Root-mean-squared (RMS) and standard-deviation (StD)	Conference	[189]
S4	Bhatt et al.	2012	Support Vector Machines (SVM)	GNSS navigation	Real	not mentioned	Conference	[68]
S5	Socharoentum et al.	2016	Logistic Regression (LR), SVM, Naïve Bayes (NB), and Decision Tree (DT)	NLOS Detection	Real	Validation data set	Conference	[180]
S6	Z. Zhou et al	2016	Least-squares SVM (LSSVM)	GNSS navigation	Real	k-fold cross-validation	Journal	[71]
S7	Jiao et al.	2016	SVM	Ionospheric scintillation	Real	Receiver operating characteristic (ROC) curves and confusion matrices and hold-out for validation.	Conference	[97]
S9	Favenza et al.	2017	DT	GNSS Scintillation	Real	Cross-validation, and F-score	Conference	[94]
S10	Y. Quan	2017	ANN, Convolutional Neural Network (CNN), Random Forest (RF)	Multipath Detection	Real and Simulated	Not mentioned	PhD thesis	[3]
S11	Yang et al.	2017	Deep Neural Network (DNN)	GNSS Interference	Real	Not mentioned	Conference	[190]
S12	L.-T. Hsu	2017	Recurrent Neural Network (RNN)	Multipath Detection	Real	Not mentioned	Conference	[191]
S14	Suzuki et al.	2017	SVM	Multipath Detection	Real	Using different numbers of correlation outputs	Conference	[192]
S15	Jiao et al.	2016	SVM	Ionospheric scintillation	Real	Five-fold cross-validation, receiver operating characteristic (ROC) curves and confusion matrices	Journal	[98]
S16	B. GUERMAH et al.	2018	DT, SVM and KNN	LOS/Multipath Signal Classifier	Real	Not mentioned	Conference	[16]
S18	Y. Liu et al.	2018	SVM	Ionospheric scintillation	Real	10-folds cross validation, and validation datasets	Conference	[89]
S19	Y. Quan et al.	2018	Convolutional Neural Network (CNN)	Multipath Detection	Real and Simulated	Simulated and Real GPS data and compared with existing multipath mitigation methods in position domain.	Journal	[158]
S20	P. Huang et al.	2018	PointNet and VoxelNet networks	Satellite selection	Real	Test data from 220 IGS stations.	Journal	[143]
S21	Gogliettino et al.	2019	Multi-Layer Perceptron (MLP), autoencoder network, LR	GNSS security	Simulated	ROC, and area under the curve (AUC)	Conference	[159]
S22	Zhidong et al	2019	NN	GNSS/INS integration	Real	Not mentioned	Conference	[193]
S23	Z. Liu et al.	2019	NN	GNSS/INS integration	Simulated	Validation test with the help of STM32.	Conference	[137]
S25	H.-U. Kim et al.	2019	LSTM	GNSS positioning	Real	Not mentioned	Journal	[69]
S26	N. Linty et al.	2019	DT	Ionospheric scintillation	Real	Not mentioned	Journal	[95]
S27	M. R. Manesh et al.	2019	NN	Detection of GPS Spoofing Attacks	Real	K-fold cross validation	Conference	[117]
S28	A. KURATOMI	2019	DT, SVM	GNSS Position Error Estimated	Real	Root mean square error (RMSE)	Msc Thesis	[63]
S29	Q. Liu et al.	2019	NLOS and multipath detecting network (NMDN)	Indoor Navigation	Real	Support vector machine (SVM)	Journal	[87]
S30	Ferre et al.	2019	SVM	Jammer Classification	Real	Validation dataset	Journal	[122]
S31	A. LOUIS	2019	NN	Evil waveforms (EWF) detction	Real	ROC curves	Journal	[194]
S32	K. Lamb et al.	2019	CNN	Ionospheric scintillation	Real	Not mentioned	Journal	[195]
S33	S. Semanjski et al.	2019	C-Support Vector Machines (C-SVM)	Detection of GNSS Signal Spoofing	Real and Simulated	Validation dataset	Conference	[120]
S34	R. Orus Perez	2019	NN	Ionospheric delay	Real	Not mentioned	Journal	[104]
S35	R. Sun et al.	2020	Gradient Boosting Decision Tree (GBDT), Traditional Decision Tree (DT), distance weighted KNN, adaptive network-based fuzzy inference system (ANFIS)	Signal classification	Real	RMSE value	Journal	[13]
S36	D. Brum et al.	2020	ANN	Earth monitoring	Real	Matthews Correlation Coefficient (MCC), and Mean square error (MSE)	Journal	[22]
S37	H. Dai et al.	2020	RNN, Extreme Learning Machine (ELM)	GNSS/INS integration	Real and Simulated	RMSE value	Journal	[135]
S38	Z. Zou et al.	2020	CNN	GNSS/INS integration	Real	Not mentioned	Conference	[129]
S39	Chang et al.	2020	Genetic Algorithm (GA), NN	GNSS integrity	Real	Averaged and the standard deviation	Conference	[82]
S40	E. Munin et al.	2020	CNN	Multipath Detection	Real	Accuracy percentage	Conference	[181]
S42	Li et al.	2020	DNN	GNSS signal correlation	Simulated	MSE	Conference	[161]
S43	Borhani-Darian et al.	2020	Multi-layer perceptron (MLP), CNN	GNSS spoofing attack	Simulated	ROC curves	Conference	[182]
S44	Borhani-Darian et al.	2020	MLP, CNN	GNSS Signal Acquisition	Real	ROC curves	Conference	[12]
S45	S. Tohidi et al.	2020	MLP trained by Particle Swarm Optimization (PSO)	Detection of GPS Spoofing Attacks	Real	Compared with results achieved via classification based Bayes rule.	Conference	[118]
S46	Munin et al.	2020	Deep CNN	Multipath Detection	Real and Simulated	ROC curves	Conference	[196]
S47	M. Alshaye et al.	2020	CNN	Earth monitoring	Simulated	MSE	Conference	[24]
S48	Yunxiang Liu et al.	2020	RF, SVM	GNSS abnormaly detection	Real	Validation dataset, and cross-validation	Conference	[183]
S49	L. Mallika I et al.	2020	Gaussian Process Regression (GPR)	Ionospheric delay	Real	Mean Absolute Error (MAE), MeanAbsolute Percentage Error (MAPE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and correlation coefficient.	Journal	[106]
S50	Suzuki et al.	2020	CNN	Multipath Detection	Real	Cross-validation	Conference	[197]
S51	M. O. Selbesoglu	2020	ANN	Tropospheric delay	Real	Comparison with the values estimated from Global Navigation Satellite System observations	Journal	[109]
S52	Y. Xia et al.	2020	RNN	Indoor Navigation	Real	Using new test sets.	Journal	[85]
S53	Q. Yan et al.	2020	CNN	Earth monitoring	Real	Reference SIC data	Journal	[26]
S54	Calvo-Palomino et al.	2020	LSTM	Detection of GNSS Signal Spoofing	Real	Not mentioned	Conference	[119]
S55	Haiyu et al.	2020	SVM	GNSS/INS integration	Real	ROC, and AUC	Conference	[198]
S56	S. Semanjski et al.	2020	Support Vector Machine classification (C-SVM), PCA	Detection of GNSS Signal Spoofing	Real and Simulated	Not mentioned	Journal	[238]
S57	S. Semanjski et al.	2020	C-SVM	Detection of GNSS Signal Spoofing	Real and Simulated	Not mentioned	Journal	[199]
S58	F. Dovis et al.	2020	K-means classes, SVM	Multi-path, interference and atmospheric limitations	Real	Not mentioned	Conference	[200]
S59	Y. Jia et al.	2019	RF	Earth monitoring	Simulated	Not mentioned	Conference	[32]
S60	E. I. Adegoke et al.	2019	DT	GNSS navigation	Real	Not mentioned	Conference	[201]
S61	Y. Jia; et al.	2021	RF, SVM, XGBoost, ANN	Earth monitoring	Real	Not mentioned	Journal	[33]
S62	Q. Yan et al.	2020	CNN, SVR	Earth monitoring	Real	TDS-1 measurements in 2017 and 2018 of thin sea ice with thickness less than 1 m.	Conference	[27]
S63	M. Asgarimehr; et al.	2020	NN	Earth monitoring	Real	Not mentioned	Journal	[40]
S65	L. Miotti et al.	2020	ANN	Tropospheric delay	Real	Saastamoinen model	Conference	[110]
S67	Y. Liu et al.	2019	NN	Earth monitoring	Real	Not mentioned	Conference	[41]
S68	T. Mortlock et al.	2021	Time delay neural network (TDNN)	LEO satellite	Real	Ground vehicle Doppler measurements extracted from two Orbcomm LEO satellite signals.	Conference	[146]
S69	L. Mengying et al.	2020	SVM	Ionospheric scintillation	Real	Not mentioned	Conference	[99]
S71	A. Lwin et al.	2020	Bayesian Regularization Neural Network (BRNN)	Earth monitoring	Real	Not mentioned	Conference	[35]
S73	S. J. Cho et al.	2019	RNN, SVM, LSTM	Multipath Detection	Real	Not mentioned	Conference	[184]
S74	J. Wang et al.	2019	Deep belief network(DBN)	Earth monitoring	Real	10-fold Cross Validation	Conference	[202]
S75	X. Chu et al.	2020	HMDL	Earth monitoring	Real	Validation dataset	Journal	[42]
S76	G. Zhang et al.	2021	Fully connected NN (FCNNs), LSTM	GNSS Navigation	Real	Validation dataset	Journal	[70]
S77	D. R. Kartchner et al.	2021	LSTM, CNN	GNSS security	Real	Validation accuracy	Conference	[123]
S79	R. Klus et al.	2021	NN	GNSS denied environments	Real	Not mentioned	Conference	[88]
S80	M. Y. Klimenko et al.	2021	NN	Multipath Detection	Real	Not mentioned	Conference	[203]
S82	Y. Liu et al.	2019	NN	Earth monitoring	Real and Simulated	Conventional wind speed retrieval method and other prevailing ML algorithms.	Journal	[43]
S84	A. Hu et al.	2018	ANN	Earth monitoring	Real	Using Constellation Observing System for Meteorology, Ionosphere, and Climate/FC-3 atmPhs (level 1b) data and compared with SVM.	Journal	[115]

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ID	Authors	Year	ML Technique	Study Application	Data type	Accuracy/Validation	Type	Ref.
S86	A. R. Kazemi et al.	2020	NN	GNSS Interference	Real	Maximum-Likelihood Power-Distortion (PD-ML) detector and Particle Swarm Optimization-Neural Network (PSO-NN).	Conference	[165]
S87	Y. Yang et al.	2017	BP neural network	tropospheric delay	Real	UNB3m and GPT2 models.	Conference	[114]
S88	Q. Yan et al.	2017	NN	Earth monitoring	Real	Mean error, MAE, Standard deviation, and correlation coefficient	Journal	[25]
S89	J. -. De Boer et al.	2009	NN	GNSS Navigation	Real	Mean absolute error (MAE)	Conference	[132]
S90	J. Reynolds et al.	2020	ANN	Earth monitoring	Real	Validation data set with global root mean square (RMS) difference (RMSD)	Journal	[44]
S91	R. Imam et al.	2020	DT	Ionospheric scintillation, multipath	Real	Validation dataset	Conference	[96]
S92	S. Li et al.	2019	RF	Earth monitoring	Real	10-fold cross-validation, and RMSE	Conference	[47]
S93	Y. Su et al.	2021	RF	Earth monitoring	Real	Validation dataset with cross-validation	Journal	[49]
S94	Z. Ã–ZDEMÃ°R et al.	2019	Logistic Regression	GNSS navigation	Real	Mean square error (MSE)	Conference	[204]
S95	W. Ye et al.	2020	Gaussian Process Regression	GNSS Navigation	Real	Validation dataset	Journal	[205]
S98	Y. Luo et al.	2020	SVM	GNSS Interference	Real	5-fold cross-validation	Conference	[162]
S99	Y. Wang et al.	2020	SVM	GNSS signal detection	Real	Using Spire's GNSS-R measurements with cross-validation	Conference	[14]
S100	Q. Yan et al.	2019	SVM	Earth monitoring	Real	Using Delay-Doppler maps (DDMs) datasets	Journal	[28]
S101	L. Cong et al.	2020	SVM	GNSS/INS integration	Real	Simulation using two 180-s GNSS outages, while the observation window size stays at 60 s.	Journal	[133]
S102	L. He et al.	2020	ELM	Satellite clock	Real	Accuracy percentage	Journal	[206]
S103	J Mendez-Astudill et al.	2021	ML regression, SVR	Earth monitoring	Real	Mean absolute error (MEA), the residual sum of squares (MSE), and the coefficient of determination R2	Journal	[50]
S104	M Kiani et al.	2020	MLP, Bayesian NN, radial basis function (RBF) functions, Gaussian processes, k-nearest neighbor, generalized regression neural network, classification and regression trees, and support vector regression.	Earth monitoring	Real	Traditional statistical method called Theta, Mean Absolute Scaled Error (MASE), Mean of Absolute Errors (MAE), and Root of Mean Squared Errors (RMSE)	Journal	[51]
S105	M Kiani et al.	2020	ML	Earth monitoring	Real	Theta - a traditional statistical method , StD and MAE values	Journal	[52]
S106	Liu et al.	2020	RBF-SVM	Ionospheric scintillation	Real	Compared with threshold method, the linear SVM, the threshold voting, and the logistic regression	Conference	[101]
S107	ES Fogarty et al.	2021	SVM	GNSS/ACCL integration	Real	Validation dataset	Journal	[207]
S108	K Maschera et al.	2021	Logistic Regression, SVM, RF, ANN in form of a Multilayer Perceptron (MLP)	GNSS Navigation	Real	Validation dataset	Conference	[185]
S110	M Łoś et al.	2020	RF	Earth monitoring	Real	5-fold cross-validation	Journal	[54]
S111	Y Jia et al.	2019	XGboost	Earth monitoring	Simulated	Using two GNSS-R ground-based campaigns with different soil conditions and compositions, which corresponds to the soil composition of the Simulated data set.	Journal	[34]
S112	M Kiani et al.	2020	KNN, SVR, MLP, BNN, GRNN, GP, CART	Earth monitoring	Real	RMSE, Mean Absolute Scaled Error (MASE), and Mean of Absolute Errors (MAE)	Journal	[53]
S113	Alessandro Neri et al.	2020	LR, Linear Discriminant Analysis (LDA), SVM, KNN, Classification and Regression Trees (CART), Gaussian Naive Bayes (NB)	GNSS navigation	Real	Not mentioned	Conference	[72]
S114	Y Zhu et al.	2020	DT, RF	Earth monitoring	Real	Validation data: Comparing with the sea ice edge (SIE) data from the Special Sensor Microwave Imager Sounder (SSMIS) data. Two sea ice datasets are used to evaluate the performance of the proposed sea ice monitoring approach. The sea ice edge (SIE) data provided by the Ocean and Sea Ice Satellite Application Facility (OSISAF) are used as the reference data.	Journal	[29]
S115	Y Liu et al.	2020	RBF-SVM	Ionospheric scintillation	Real	Validation datatset with cross-validation	Conference	[102]
S116	H Xu et al.	2020	SVM	NLOS Detection	Real	Mean error	Journal	[208]
S117	V Senyurek et al.	2020	ANN, RF, SVM	Earth monitoring	Real	5-fold, site-independent, and year-based cross-validation methods	Journal	[39]
S118	Y Jia et al.	2020	RF, SVM	Earth monitoring	Real	Using GNSS-R system and ground-truth rod sensor used to make measurements before and after rain in bare and smooth fields (Gruliasco/Agliano)	Journal	[36]
S119	Q Yuan et al.	2019	back-propagation neural network (BPNN), generalized regression neural network (GRNN), RF	Earth monitoring	Real	10-fold cross-validation method, Correlation coefficient (R) and the RMSE	Journal	[48]
S121	A Lwin et al.	2020	SVM	Earth monitoring	Real	Cross-validation with RMSE	Conference	[37]
S122	H Liu et al.	2021	Xgboost	Earth monitoring	Real	Validation dataset	Journal	[55]
S124	J Wang et al.	2020	DBN model: composed of a back propagation (BP) layer and several restricted Boltzmann machine (RBM) layers.	Earth monitoring	Real	Correlation coefficient (R), mean absolute error (MAE), root-mean-square error (RMSE), and 10-fold cross-validation	Journal	[31]
S125	N Liu et al.	2021	CNN-LSTM	GNSS/INS integration	Real	Not mentioned	Journal	[130]
S126	HU Kim et al.	2017	LSTM, ANN	Earth monitoring	Real	Validation dataset with RMSE values	Journal	[56]
S127	S Li et al.	2021	LSSVM	tropospheric delay	Real	RMSE value	Journal	[209]
S130	M Kaselimi et al.	2020	CNN	Ionospheric delay	Real	MAE, RMSE value	Conference	[210]
S131	K Kasantikul et al.	2018	ANN, particle filter	Earth monitoring	Real	RMSE value	Journal	[45]
S132	J Hu et al.	2018	BPNN	GNSS navigation	Real	Dual EKF design used to improve the position accuracy, and provide low-noise training and validation samples	Journal	[179]
S133	Dongchan et al.	2019	DNN	Multipath Detection	Real	Standard deviations (StD with TTFF	Conference	[211]
S134	V Otugo et al.	2019	ANN	Ionospheric scintillation	Real	Validation dataset, root-mean-square deviations (RMSDs), and RMSE	Journal	[92]
S136	X Zou et al.	2019	CNN	GNSS/INS integration	Real	Not mentioned	Journal	[212]
S137	O Eroglu et al.	2019	ANN	Earth monitoring	Real	Validation dataset	Journal	[38]
S138	M Kiani et al.	2020	generalized regression NN	GNSS Navigation	Real	Mean Absolute Percentage Error (sMAPE), Standard Deviation (StD), and Mean Absolute Errors (MAE)	Journal	[166]
S139	E Loli Piccolomini et al.	2019	LSTM	GNSS signal detection	Real	Validation dataw with Mean Squared Error (MSE) value and standard deviation (STD)	Journal	[15]
S140	M Moses et al.	2020	NN	Earth monitoring	Real	By comparing the ARITM predictions with ground-based GNSS TEC, the space-based F3/C ionospheric profiles TEC estimates and the existing GIMs. Also using RMSE and Mean Absolute Error (MAE)	Journal	[213]
S141	MR Veronez et al.	2011	ANN	GNSS Navigation	Real	Compared with the Brazilian Geoid Model (MAPGEO2004)	Journal	[73]
S142	Y Liang et al.	2019	BPNN	Earth monitoring	Real	Cross-validation	Journal	[57]
S143	Y Shi et al.	2021	GA-BP	Earth monitoring	Real	Pearson correlation coefficient R, RMSE, bias, and ubRMSE	Journal	[58]
S144	M Zeybek et al.	2014	Linear Regression	Earth monitoring	Real	Standard deviation (StD), and Mean values	Journal	[11]
S145	L Zhao et al.	2019	Regularized Softmax Regression	GNSS/INS integration	Real	RMSE value	Conference	[214]
S146	M Kaselimi et al.	2020	LSTM	Earth monitoring	Real	Mean absolute error (MAE), and RMSE	Journal	[167]
S147	S Miyazawa et al.	2020	LSTM	GNSS Navigation	Real	Using Real data the model with different parameter settings and based on categorical accuracy	Journal	[74]
S148	Shamshiri et al.	2020	GP regression	Tropospheric delay	Real	RMSE value	Journal	[107]
S149	Surisetty et al.	2021	SVR	Earth monitoring	Real	Compared with in-situ depth points. Also using Bias, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Normalized bias (MNB) and Difference Median (DM)	Journal	[59]
S150	Mutchakayala et al.	2020	Extreme Kernel–Based Learning Machine (KELM)	Earth monitoring	Real	With the error measurements like MAE, MAPE, and RMSE	Journal	[215]
S151	Wojtusiak et al.	2021	ML	GNSS Navigation	Real	10-fold cross-validation, and validation data	Journal	[75]
S152	Osah et al.	2021	DL	tropospheric delay	Real	Mean Bias (MB), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R2), Nash-Sutcliffe coefficient of Efficiency (NSE), and the fraction of prediction within a Factor of Two (FAC2)	Journal	[216]

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ID	Authors	Year	ML Technique	Study Application	Data type	Accuracy/Validation	Type	Ref.
S153	Salar et al.	2021	LSTM	Ionospheric TEC content	Real	Root mean square error (RMSE), and mean absolute error (MAE)	Journal	[217]
S155	Xia et al.	2021	SVM	Earth monitoring	Real	RMSE, and relative error (RE)	Journal	[168]
S156	Li et al.	2021	ANN	Earth monitoring	Real	RMSE value	Journal	[46]
S157	Mohammed et al.	2021	ANN	tropospheric delay	Real	Cross-validation, Mean Square Error (MSE) or Sum of Square Error (SSE), and RMSE	Journal	[111]
S158	Okoh et al.	2016	NN	Earth monitoring	Real	Validation dataset with RMSE	Journal	[169]
S159	Rafatnia et al.	2018	Recurrent wavelet neural network (RWNN)	GNSS/INS integration	Real	Mean value and standard deviation: Highly accurate Vitans navigation system is used to provide reference values for evaluatio	Journal	[172]
S160	Sahu et al.	2021	NN	Ionospheric TEC content	Real	Comparison of hourly values of NN TEC with GPS TEC using relative error.	Journal	[170]
S161	Sivavaraprasad et al.	2020	NN	Ionospheric TEC content	Real	RMSE value	Journal	[171]
S162	Ferreira et al.	2017	NN	Ionospheric TEC content	Real	Comparison with Global Ionospheric Maps provided by CODE is performed using RMSE.	Journal	[173]
S163	P. Pavlovčič Prešeren et al.	2013	Wavelet Neural Network (WNN)	GNSS ephemerides distribution and short-time prediction	Real	Minimum value of differences min; Maximum value of differences max; Mean value of differences; Normalized root mean square error (NRMSE): $NRMSE = RMSE/(max - min)$	Journal	[83]
S164	Rahimi et al.	2018	ANN	Earth monitoring	Real	Using six IGS stations. The collected ZTD products were used to compare and validate the accuracy of the estimated ZTD by GNSS analysis MIT (GAMIT)	Journal	[60]
S165	Kemal Tütüncü et al.	2021	ELM	GNSS/leveling geoid determination	Real	Checkpoints serving as a kind of validation	Journal	[239]
S166	R.E. Guinness et al.	2013	SVM, ANN, LR, BN, DT, NB, IBk, LWL and KStar	Situation/Context Awareness	Real	10-fold cross-validation	Journal	[86]
S167	N. Yamaga et al.	2019	NN	Earth monitoring	Real	Not mentioned	Journal	[160]
S168	Q. Yuan et al.	2019	ANN, RF	Earth monitoring	Real	10-fold cross-validation	Journal	[186]
S169	L. Li et al.	2020	GRNN	tropospheric delay	Real	A popular R-ratio is used as the validation method and a threshold value is set to 2.5	Journal	[218]
S170	B. Huang et al.	2021	LSTM	satellite clock	Real	Not mentioned	Journal	[174]
S171	M. Kim et al.	2016	NN	Ionospheric delay	Real	Not mentioned	Journal	[105]
S172	B. Zhang et al.	2021	GRNN	Earth monitoring	Real	10-fold cross-validation (CV)	Journal	[61]
S173	C. Herbert et al.	2021	Regression NN	Earth monitoring	Real	Validation dataset	Journal	[30]
S174	Taro Suzuki et al.	2021	SVM, NN	Multipath Detection	Real	Cross-validation	Journal	[17]
S175	Marco Mendonça et al.	2020	SVM	GNSS/INS integration	Real	Not mentioned	book-chapter	[240]
S179	Selbesoglu et al.	2019	ANN	tropospheric delay	Real	Cross validation	Journal	[112]
S180	Mohamad Orabi et al.	2020	NN	Multipath Detection	Simulated	RMSE value	Conference	[163]
S181	Yu Jiao et al.	2017	Linear SVM, medium Gaussian kernel SVM with a kernel scale of 9.1	Ionospheric scintillation	Real	5-fold cross-validation, and ROC curve	Conference	[90]
S183	Hany Ragabet et al.	2020	MLPNN	GNSS/INS integration	Real	RMSE value	Conference	[219]
S185	J. Rossouw van der Merwe et al.	2020	Logistic regression (LR), K-nearest neighbors (KNN), naive Bayes (NB), DT, SVM	GNSS spoofing attack	Real and Simulated	F1-score	Conference	[124]
S186	Yung-Cheng et al.	2006	NN	GNSS/INS/Odometer integration	Real	RMS value (degree)	Conference	[138]
S187	Hamad Yousif and Ahmed El-Rabbany	2008	NN	GNSS Navigation	Real	Corresponding precise rapid ephemeris before any improvement is applied	Conference	[164]
S188	Jianguo Jack Wang et al.	2007	NN	GNSS/INS integration	Real	Mean RMS	Conference	[139]
S190	T. Désert et al	2015	NN	Ionosphere modelling	Real	EGNOS	Conference	[103]
S191	Li He et al	2016	ANN	GNSS signal detection	Real	Not mentioned	Conference	[20]
S192	W. Vigneau et al.	2006	NN	LEO satellites	simulalted	Mean square error (MSE)	Conference	[147]
S194	Pere Ramos-Bosch et al.	2007	NN	LEO satellites	Real	3D RMS	Journal	[148]
S195	Chengquan Xu et al.	2008	NN	Earth monitoring	Real	Not mentioned	Conference	[175]
S196	Heekwon No et al	2021	Quantile Regression	Multipath Detection	Real	By an integrity assessment of the experimental data.	Conference	[220]
S197	Qiming Zhong et al	2021	Bayesian Filter	GNSS Navigation	Real	Not mentioned	Conference	[221]
S198	Chengjun Guo et al	2021	CNN	GNSS Interference	Simulated	Validation dataset	Conference	[21]
S199	Nesrine HARBAOUI et al	2021	DCNN	GNSS Navigation	Real	Maximum error, and RMSE	Conference	[222]
S200	Sharbel E. Kozhaya et al	2021	TDNN which are a type of Feed Forward Neural Network (FFNN), LSTM a type of Recurrent Neural Network (RNN)	GNSS Navigation	Real	RMSE value	Conference	[149]
S201	Adyasha Mohanty et al	2021	CNN	GNSS/INS integration	Real	RMSE value	Conference	[134]
S202	Kahn-Bao Wu et al	2021	SVM	Oscillator Anomaly detection	Real	Grid-search-based cross-validation	Conference	[223]
S203	Ashwin V. Kanhere et al	2021	DNN	GNSS Navigation	Real and Simulated	Comparison of the absolute localization error to a weighted least squares (WLS) baseline with positioning error	Conference	[76]
S204	Akpojoto Siemuri et al	2021	LR, BR, NN	GNSS Navigation	Real	Validation dataset	Conference	[77]
S207	Gianluca Caparra et al	2021	NN	GNSS Navigation	Real	Percentile, cumulative distribution function (CDF)	Conference	[78]
S208	Nesreen I. Ziedan	2021	Self-Organizing Map (SOM) neural network	GNSS Navigation	Simulated	RMS error	Conference	[79]
S209	Annabel R. Gomez et al	2021	Ridge Regression, LSTM, Classification Neural Network (CNN), Autoencoder Classification Neural Network (ACNN), LSTM Autoencoder Classification Neural Network (LACNN)	Ionospheric scintillation	Real	Validation dataset	Conference	[91]
S210	Lei Liu et al	2021	custom- designed loss function Lc (convLSTM-Lc)	Ionospheric scintillation	Real	Validation dataset	Conference	[224]
S211	Yunxiang Liu et al	2021	spatiotemporal deep learning (STDL) LSTM network	Ionospheric scintillation	Real	ROC curve, and AUC	Conference	[225]
S213	Quoc-Huy Phan et al	2013	SVR	Multipath Detection	Real	Standard deviations	Journal	[226]
S214	Azami Hamed et al	2013	NN (including Levenberg–Marquardt (LM), modified LM, and resilient BP (RBP), scaled conjugate gradient, one-step secant (OSS) and quasi-Newton methods), PCA	GNSS GDOP classification	Real	Classification rate	Journal	[236]
S215	Nadali Zarei	2014	PSO, NPSO, GA and ICA, to train an NN.	GNSS GDOP classification	Real	Classification rates	Journal	[237]
S216	Noureldin et al	2010	NN	GNSS/INS integration	Real	Simulation using 100s GPS outages with RMSE values	Journal	[140]
S217	Yu Jia et al	2017	SVM	Ionospheric scintillation	Real	A 25% hold-out validation is configured to evaluate the performance of the training with ROC curve	Journal	[100]
S218	E. S. Abdolkarimi et al	2018	ELM	GNSS/INS integration	Real	RMSE value	Journal	[131]
S220	Aly M.El-naggar	2013	ANN	Ionospheric scintillation	Real	Not mentioned	Journal	[93]
S221	Yiming Quan et al	2018	CNN	Multipath Detection	Simulated and Real	RMSE value	Journal	[227]
S222	Habarulema et al	2009	NN	Earth monitoring	Real	RMSE value	Journal	[176]

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ID	Authors	Year	ML Technique	Study Application	Data type	Accuracy/Validation	Type	Ref.
S223	John Bosco Habarulema et al	2009	FFNN	Earth monitoring	Real	RMSE value	Journal	[228]
S224	R. Sharaf et al	2005	RBF-ANN	GNSS/INS integration	Real	MSE value	Journal	[136]
S225	Christos Pikridas et al	2010	ANN	tropospheric delay	Real	RMSE value	Journal	[113]
S226	Pedro Benevides et al	2019	NN	Earth monitoring	Real	RMSE value	Journal	[62]
S227	G. Panice et al	2017	SVM	GNSS security	Real	False Positive Rate (FPR); True Positive Rate (TPR); and Accuracy	Conference	[126]
S228	Rui Sun et al	2020	GBDT	GNSS Navigation	Real	RMSE value	Journal	[80]
S229	Mosavi et al	2017	RBF-NN	GNSS Navigation	Real	Validation dataset, with RMSE	Journal	[81]
S231	Li Jing et al	2016	ensemble learning algorithm (LS-Boost or Bagging)	GNSS/INS integration	Real	Position error	Journal	[187]
S232	Yimin Zhou et al	2017	BPNN	GNSS/INS integration	Real	MSE value	Conference	[127]
S233	Guangcai Wang et al	2019	BPNN	GNSS/INS integration	Real	Mean value of absolute errors (MAE)	Journal	[128]
S234	Fangni Lei et al	2020	ML	Earth monitoring	Real	Correlation coefficient (R) and unbiased root-mean-square-difference (ubRMSD)	Conference	[229]
S235	Zhengxie Zhang et al	2019	SVM	Ionospheric delay	Real	RMSE value	Journal	[108]
S236	Li et al.	2016	Twin SVM	GNSS Interference	Simulated	Not mentioned	Journal	[121]
S237	Wu et al	2017	CNN	GNSS Interference	Real	Accuracy percentage	Journal	[**?**]
S238	Savas et al	2019	K-means clustering	Multipath Detection	Real and Simulated	Standard deviation	Conference	[177]
S239	Liu et al	2021	convLSTM	Ionospheric irregularities	Real	Not mentioned	Journal	[230]
S241	David et al	2016	Neural Network	Ionospheric Scintillation	Real	Validation dataset	Journal	[231]
S242	Huang et al	2014	RBF-NN	Ionospheric Scintillation	Real	Not mentioned	Journal	[232]
S243	Yilmaz et al	2009	NN	Earth monitoring	Real	Sum-squared error (SSE)	Journal	[188]
S244	Habarulema et al	2007	NN	Earth monitoring	Real	RMSE value	Journal	[233]
S245	Sabzehee et al.	2018	ANN	Earth monitoring	Real	RMSE, and R2 values	Journal	[178]
S246	Leandro et al	2007	NN	Earth monitoring	Real	Not mentioned	Journal	[234]
S247	Wang et al	2017	WNN	satellite clock	Simulated	Not mentioned	Journal	[235]
S248	Lyu et al	2020	SVM	GNSS Navigation	Real	Comparison with the built-in RTK solutions of a dual-frequency u-blox F9P, and multi-frequency Trimble BD982.	Journal	[19]
S249	Shafiee et al	2017	Multi-layer NN	GNSS security	Real and Simulated	K-fold cross-validation	Journal	[125]

regarding the type of data used for evaluating the model, the studies made use of either simulated data, real data or semisimulated data when evaluating the model.

In a multi-GNSS environment, due to the availability of large number of satellite signals and capable hardware, the issue of optimum geometry (i.e., dilution of precision, DOP) can be easily taken care of by use of multiple satellites giving the lowest DOP. However, error situations, such as multipath, can benefit from optimal selection of the satellites. ML plays a major role in this area of research, as this review indicates.

This review provides recommendations as well as guidelines for researchers and practitioners. For researchers, we recommend that they conduct more empirical studies making use of the rarely-used ML algorithms, keeping in mind the GNSS application context, in order to further strengthen the evidence about their performance. For future work, we encourage exploring the possibilities of using unapplied ML techniques to new or already studied GNSS use cases. Additionally, more studies should be performed using the combination of non-ML and ML algorithms to further strengthen the evidence about their performance when utilized in GNSS. Furthermore, it would be important to use the same data. Section III-D shows that there are plenty of different datasets used by different researchers. Therefore, we suggest the development of a common test bench to study the utilization of ML algorithm in GNSS.

Appendix A

See Table X.

Appendix B

See Table XI.

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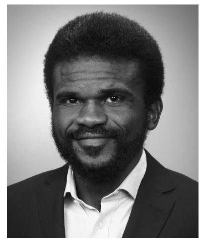

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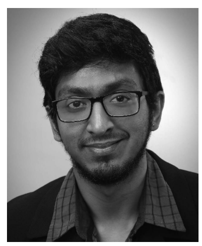

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