Engineering Science and Technology, an International Journal 44 (2023) 101455

HOSTED BY

ELSEVIER

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

A survey of applications of artificial intelligence and machine learning in future mobile networks-enabled systems

İbrahim Yazici[a,*], Ibraheem Shayea[a,*], Jafri Din[b]

[a] Electronics and Communication Engineering Department, Faculty of Electrical and Electronics Engineering, Istanbul Technical University (ITU), 34469 Istanbul, Turkey
[b] Wireless Communication Centre, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia

ARTICLE INFO

Article history:
Received 5 December 2022
Revised 22 April 2023
Accepted 29 May 2023
Available online 12 June 2023

Keywords:
Cyber security
Deep learning
Digital twin
Intelligent transportation systems
Reinforcement learning
Smart energy
Smart healthcare
Supervised learning
Unsupervised learning
Unmanned Aerial Vehicle (UAV)
5G
6G

ABSTRACT

Different fields have been thriving with the advents in mobile communication systems in recent years. These fields reap benefits of data collected by Internet of Things (IoT) in next generation (5G and 5BG) mobile networks. The IoT concept transforms different fields by providing large amount of data to be used in their operations. This is achieved by massively utilized sensors and mobile devices that acquire data from internet connected devices to keep track of physical systems. Hence, different use cases benefit from the data generated thanks to future mobile network systems. Intelligent Transportation Systems, Smart Energy, Digital Twins, Unmanned Aerial Vehicles (UAVs), Smart Health, Cyber Security are of significant use cases that big data plays an important role for them. Large amount of data entails more intelligent systems with respect to conventional methods, and it also entails highly reduced response time for use cases. Artificial intelligence and machine learning models are adept in satisfying the requirements of this big data situations for different use cases. In this sense, this paper provides a survey of machine learning and artificial intelligence applications for different use cases enabled by future mobile communication systems. An overview of machine learning types and artificial intelligence is presented to provide insights into the intelligent method concepts. Available studies are extensively summarized, and they are also grouped to provide a complete overview of the study. Discussions on the reviewed papers based on artificial intelligence and machine learning concepts are made, and some descriptive figures about the results of the discussions are also given in the paper. Finally, research challenges for artificial intelligence and machine learning applications in the use cases are introduced, future research directions and concluding remarks are presented accordingly.

Contents

* Corresponding authors.
E-mail addresses: iyazici@itu.edu.tr (İ. Yazici), shayea@itu.edu.tr (I. Shayea).

https://doi.org/10.1016/j.jestch.2023.101455
2215-0986/

1. Introduction

Machine learning (ML) is a sub-branch of Artificial Intelligence (AI), and it is a popular research area which has attracted significant attention. Although machine learning has many definitions throughout the literature, Arthur Samuel and Tom Mitchell, two prominent figures in the machine learning field, provided concise definitions of the term. According to Samuel [1], machine learning is where computers learn to perform defined tasks without being explicitly programmed to do so. Tom Mitchell [2] defined machine learning as a construction of computer programs that automatically improve with experience. He validated his definition with the following concept: "*A computer program is said to learn from experience **E** with respect to some classes of task **T** and performance measure **P**. Its performance at task **T**, as measured by **P**, improves with experience **E***" [2]. The common characteristic of these two definitions is computer learning. The distinction between machine learning methods is done based on this learning process, they are generally divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning and unsupervised learning differ in terms of the data used. Supervised learning uses labeled data for training its algorithms. A loss function is optimized by an optimizer to perform classification or regression tasks. Unsupervised learning uses unlabeled data in its training procedure and extracts hidden/latent patterns in the data used. To solve a problem through supervised learning, a designer must follow four basic steps: collect a viable training set, determine an input representation and structure of the learning function and algorithm, run the algorithm to fit the data, and optimize it using optimizers on a validation set, and evaluate the accuracy. Unsupervised learning, on the other hand, completes the learning process by looking for previously undetected patterns in an unlabeled dataset. Instead of using a feedback technique, it employs common-features identification based on the presence of similarities such as k-means clustering, hierarchical clustering, principal component analysis, kernel methods, independent component analysis, non-negative matrix factorization, and singular value decomposition. Unsupervised learning algorithms perform three main tasks: clustering/anomaly detection, dimensionality reduction, and association. Some examples of frequently used unsupervised learning algorithms include k-means clustering, hierarchical clustering, gaussian mixture models, association rules, principal component analysis, singular value decomposition, and autoencoders. In contrast, supervised learning performs two main tasks: regression and classification. In these tasks, the learning process is accomplished by mapping input examples with their associated outputs based on the input–output pairs. The tasks in supervised learning differ in the type of output produced. The outputs are real values for regression, and categories for classification. Artificial neural networks (ANNs), naïve Bayes (NB), support vector machine (SVM), random forest (RF), linear regression (LR), and logistic regression (LGR) are some examples of supervised learning algorithms.

Reinforcement learning differs from these learning types by its learning manner. Rather than using labeled and/or unlabeled data, it learns by interacting with an environment through a trial–error mechanism with the aim of maximizing cumulative expected rewards. The algorithms of reinforcement learning are modeled as Markov Decision Processes (MDP) for some situations, which are discrete-time stochastic control processes. Five basic terms in reinforcement learning are present: agent, state, environment, action, and reward. The agent receives an initial state of S_0 and takes action A_0 towards the environment based on that initial state. Next, the environment transitions into a new state S_1 and gives reward R_1 to the agent. The agent then maximizes the cumulative reward. Q-learning, SARSA, deep Q-learning, actor-critic (AC), deep deterministic policy gradients (DDPG), and trust region policy optimization (TRPO) are some examples of reinforcement algorithms used throughout the literature.

5G and 5BG, as future mobile network systems, will bring several advantages by their powerful capabilities with respect to previous network generations, i.e. 2G, 3G, and 4G. They will densely utilize heterogeneous networks to ensure seamless connectivity for massively connected devices, and novel technologies such as beamforming, massive multi–inputmultioutput (MIMO), Orthogonal frequency-division multiplexing (OFDM) technologies thereby providing high bandwidth and data rates, massive connectivity, broad coverage, and low latency/ultra-low latency. These future mobile network systems will enhance uses of different spectrums which 5G networks can use low and high band frequencies- these are sub 6 GHz and above 24.25 GHz. On the other hand, 6G networks will be able to use the frequency spectrums in the range from 95 GHz to 3 THz. These different spectrum uses will enhance different use case implementations of the future mobile network systems. They will in turn provide higher data rates and speed by enhancing reliability and network coverage with respect to the previous generations. In addition, low/ultra-low latency will be facilitated by the future mobile network systems. With the combination of these advancements of the future mobile network systems, enhanced mobile broadband (eMBB), massive machine type

TABLE 1
An overview of existing research on machine learning.

Paper	Year	Description
[13]	2019	• Machine learning and IoT in smart transportation systems were reviewed. Smart transportation was considered as a broad problem, and several sub-problems of ML deployment were highlighted. The reviewed studies were not restricted to journal papers. ML deployments in IoT for smart transportation systems and IoT smart transportation applications with/without ML were examined and categorized.
[14]	2020	• The paper focused on CNN applications in intelligent transportation systems. Intelligent transportation systems were assessed by dividing their problems into sub-problems. Comprehensive categorizations of the sub-problems were presented. The reviewed studies were not restricted to journal papers. The power of CNN deployment in intelligent transportation systems was showcased with respect to conventional algorithms.
[15]	2020	• A survey was conducted on machine learning applications in smart city-related areas such as intelligent transportation systems, cyber security, smart grids, and UAVs. The reviewed studies were not restricted to journal papers. Application areas and specific classifications were discussed. Future research directions regarding data issues, standardization of big data concept, and UAV-based recommendations were presented.
[16]	2020	• A survey of ML deployments in distributed smart grids was provided. Various applications of machine learning in the sub-problems of smart grids were reviewed. ML deployments were categorized and highlighted for each problem. The reviewed studies were not restricted to journal papers. Recommendations of ML deployments in smart grids were discussed for future research.
[17]	2021	• The paper focused on different problems of 5G and B5G network enabled systems rather than specific application fields. The reviewed studies were not restricted to journal papers. Learning type-related problem-specific classifications were presented.
[18]	2021	• A short review of smart transportation using ML and IoT was presented by summarizing several research regarding different problems in smart transportation systems. The reviewed studies were not restricted to journal papers.
[19]	2021	• Open data-based ML applications in smart city-related areas were reviewed. This included smart governance, smart economy, smart mobility, smart environment, smart people, and smart living. The reviewed studies were not restricted to journal papers. Inferences and comments on machine learning applications were made regarding smart city-related fields. A comprehensive taxonomy of the reviewed papers was provided. Supervised learning significance, its prevalence in applications, as well as deep learning in smart city-related problems were highlighted.
[20]	2021	• Wireless sensor network and IoT technology-based open research problems were examined. Papers on ML applications in the field of smart cities were examined. The reviewed studies were not restricted to journal papers. A comprehensive summary of ML techniques in WSN-IoT for smart city challenges was provided. Supervised learning was found to be the most deployed learning type in applications, followed by reinforcement learning.
[21]	2021	• A brief review was provided on machine learning applications in smart grids for solving specific problems. Only journal papers were included in the study.
[22]	2021	• A review was made on machine learning applications for various problems in IoT-integrated modern power systems. The paper provided a summary of the reviewed research. Only journal papers were included in the study.
[23]	2022	• A comprehensive survey was made on the deployment of ML-based methods for different security concerns in vehicular networks. The reviewed studies were not restricted to journal papers. Taxonomy-based security attacks in vehicular networks were examined. Several security challenges and requirements in vehicular networks were discussed. Future research directions for ML deployment in vehicular networks were highlighted.
This survey		• A comprehensive survey has been made on ML deployment in different fields using future mobile communication systems. The paper does not focus on specific application areas and reviews the deployment of ML algorithms throughout various fields. In the reviewed papers, ML applications are considered for different application fields such as intelligent transportation systems, smart energy, smart healthcare, UAVs, digital twins, and cyber security. These fields, although interrelated, have been separately reviewed due to the broad range of applications that do not fall under one category. Hence, this paper covers an extensive range of applications in related topics and makes a general review for machine learning deployments in different application fields. Only journal papers were included. A timeline of machine learning evolution has been presented to provide insight into artificial intelligence, machine learning, and machine learning types for deployments across various fields using 5G and B5G systems. A comprehensive summary of the reviewed papers has been accomplished. The time span of the reviewed papers is from 2015 until present. A detailed taxonomy for each paper is also provided. Discussions on learning types in relation with each application area and total applications have been accomplished. The current challenges from the aspect of different application fields have been analyzed. Recommendations and future research directions which may solve challenges and help in the large-scale deployment of ML algorithms in various fields have been presented and discussed.

communications (mMTC), and ultra-reliable and low-latency communications will be adopted across different fields. Since the future mobile network systems will provide benefits in terms of latency, speed, enhanced connectivity, and data rate and network capacity, data collected by IoT from various sources, smart devices, and communicating machines will gain importance. Different use cases such as cyber security, healthcare, unmanned aerial vehicle deployments, digital twins, and so forth will try to reap benefits that the future mobile networks provide.

Since the big data concept is enabled by IoT and smart devices in the future mobile communication systems, rapid digitalization has matured by means of this concept recently. This situation has provided numerous opportunities for deploying intelligent methods in various fields enabled by the future mobile network systems. Machine learning, which is an integral part of data science, has vast application fields since several machine learning algorithms can successfully accomplish clustering, classification, and prediction. Along with big data abundance, powerful hardware solutions such as Graphical Processing Units (GPUs), Tensor Processing Units (TPUs), Massively Parallel Processing (MPP), and the advent of algorithms (deep neural networks in particular) are major contributors for widespread applications of machine learning across various fields. These solutions have propelled machine learning applications across different domains with the recent advancements of future networks. Computer vision [3], natural language processing [4], predictive analysis in energy [5], image processing and analysis [6], telecommunication [7], robotics [8], recommender systems [9], healthcare [10], bioinformatics [11], and autonomous driving [12] are remarkable examples of commonly used ML application fields.

This paper highlights artificial intelligence and machine learning deployments in different fields enabled by future network systems. Table 1 provides an overview of the existing research studies on machine learning deployments enabled by future mobile communication systems.

Reviewed research papers have brought domain-independent advances for their scopes, and contributed to the current literature as well. In [13], problem specific review of machine learning applications with IoT use exploitation in one-specific domain is made. In [14], the focal point of the paper is to study CNN applications in one-specific domain, and its sub-problems. Authors of the paper provide detailed review of CNN's algorithmic perspectives on the domain. In [15], a brief summary of AI applications in some different smart city aspects is introduced to the literature. In [16], a review of AI applications in one-specific domain and its sub-problems are introduced to the literature. In [17], a review of ML types, and their applications for several specific problems in future mobile network systems are introduced to the literature. In [18], a review of ML application in one domain is made, and making intelligent systems in this domain through ML integration with IoT systems is discussed. In [19], the study tries to address some questions in ML applications in one-specific domain in relation to open data use in the domain. In [20], a review of ML applications with one of the leading technology, wireless sensor networks-IoT, in one specific domain is made by introducing learning types application analyses in the study. In [21], a review study for ML applications in one-specific domain and main findings of the reviewed papers are introduced to the literature. In [22], a review of ML techniques and applications with IoT systems in one-specific domain with comprehensive summaries is introduced to the literature. In [23], the study defines sub-problems in one specific domain in relation with communication systems, then reviews the papers for the problems by providing ML and implementational information such as accuracy, dataset information, etc. Besides, the paper reviews ML learning type applications for the domain as well.

In our paper, we gleaned papers that povide insight about AI/ML applications in different use-cases enabled by future mobile network systems. This paper brings about taxonomies of the gleaned papers in addition to brief summaries of them. Hence the study provides review study of the various use-cases in a comprehensive manner with respect to the compared studies. In the context of this paper, the learning types of ML are presented to provide some basic insights into readers in advance, and different machine learning application fields in relation to mobile communication networks are then highlighted. Challenges and future research directions of machine learning applications in future mobile communication networks are also pointed out to provide an outlook for future studies and applications.

This paper is organized as follows: In Section II, we provide an overview of ML, its core concepts, its evolution throughout years, and the types of machine learning, which are supervised, unsupervised, and reinforcement learning, through an extensive analysis. In Section III, we summarize studies on machine learning applications in relevant fields in detail, and categorize them. In Section IV, we discuss the current challenges on machine learning deployments in different fields enabled by future mobile communications networks. In Section V, we highlight future research directions on the research topic by providing an outlook for further studies and applications. Finally, in Section VI, we conclude the paper.

2. Evolution of AI and machine learning

This section presents the evolution of ML in relation to AI. Artificial General Intelligence (AGI), or general-purpose AI, is the superset of AI. These terms are related to several integral components of intelligence which generally belong to humans, such as learning, reasoning, problem solving, and perception. In AI research, two approaches have been competing with each other throughout the years to imitate intelligence: connectionist and symbolist. The connectionist approach models cognition processes according to human brain's operating mechanism and its interconnected neurons. The symbolist approach models cognition processes without considering brain structure or neural connections, and instead uses semantics and symbols in the modeling.

AGI claims that an intelligent agent can understand and learn any intellectual task on par with humans. Reaching this level is a controversial issue for researchers of different fields. The controversy roots back to fundamental approaches in intelligence and cognition; i.e., the connectionists and the symbolists, as mentioned earlier. AI has the ability to perform the tasks of intelligent beings by simulating human intelligence in machines, such as in computers or robots. While the capability of AGI is comparable to humans, such capability is limited for AI. For instance, AI systems excel at performing assigned tasks, which is untrue for unassigned tasks. In some fields, AGI achieves higher than human-level performance, such as DeepMind's algorithm for AlphaGo. This type of achievement is also expanding. The proliferation of such achievements may be a sign of the shift from AI to AGI. These accomplishments are due to several powerful machine learning algorithms, a subset of AI, with different learning types. Evolution of AI is seen in Fig. 1.

In 1943, Walter Pitts (a logician) and Warren McCulloch (a neuroscientist) created the first mathematical model of a neural network, providing a significant piece of a puzzle. Published in their seminal work "A Logical Calculus of Ideas Immanent in Nervous

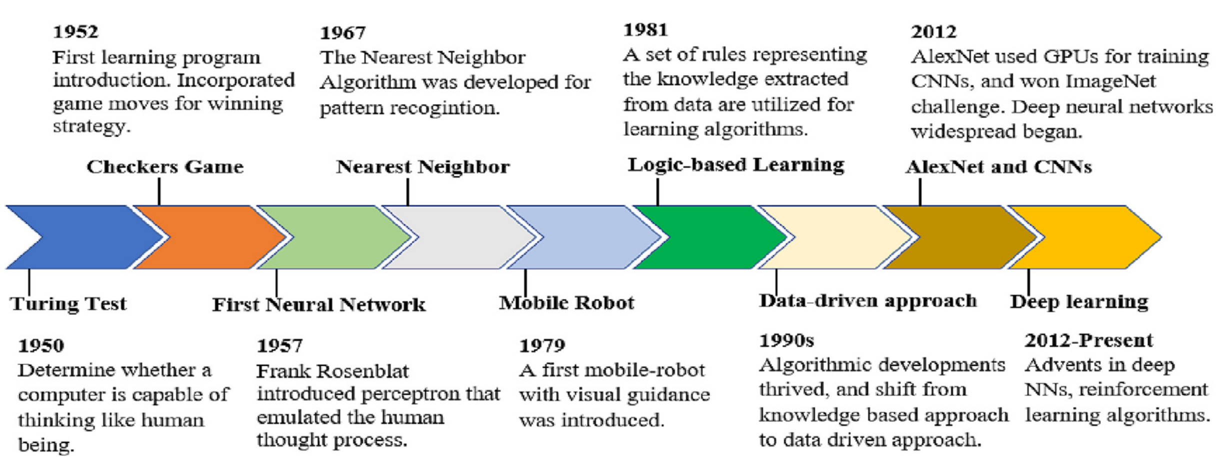

Fig. 1. Timeline of machine learning evolution.

Activity" [24], a combination of mathematics and algorithms were proposed to mimic the human thinking process. The first concept of ML came from human brain model with a vast number of neuron cells connected to each other; a type of connectionist approach. This model was proposed by Donald Hebb in 1949 which clarified activations and communications of neurons [25]. In terms of ANN, the model was described as the relationship between nodes, and the nodes of individuals that are changing. The relation is powerful if two nodes are simultaneously activated, otherwise it is poor. The term 'weight' was used to illustrate the relations between nodes in this model.

In 1950, Turing proposed such a machine, even hinting at genetic algorithms in his paper "Computing Machinery and Intelligence". In the paper, he crafted what was dubbed as the Turing Test, which he called the Imitation Game, to determine whether a computer is able to "think". The test required a machine to conduct a conversation with a human via text. If the human was convinced after five minutes that they were talking to another human, the machine would have passed the test [26].

The origin of machine learning concept was initiated in 1950. Alan Turing developed the Turing Test to test whether a machine may perform cognition tasks similar to a human [27]. Turing suggested that a machine might produce similar basic human behaviors within the framework of pre-determined and specified testing rules. The original test consisted of three main components which were separated from each other. The first component, isolated from the other two components, was a computer-based system. The other components consisted of two people and a machine. One person asked the questions, while the other person and the computer-based system answered them. The person asking the questions must determine whether the answering entity was the other person or the machine. The person answering the questions may only respond using a keyboard, and s/he must provide normal answers to the questions. Since the machine was answering the same questions as the person, it tried to convince the questioner that it was human through its answers in the test [26]. This test was repeated several times. If the questioner was unable to distinguish between the person answering and the machine, and was convinced by the machine that it was human after the tests, the machine algorithm was then regarded as having AI. After the Turing Test, remarkable developments were made in the 1980 s and 1990 s. Programmers created an ANN prototype that resembled a human brain in various aspects. The ANN model included layers of synthetic neurons that were linked together. Unfortunately, research could not further progress since computing devices were limited, and those present did not have much capability to manage larger synthetic neuron clusters.

In the 1950 s, Arthur Samuel introduced a checkers-playing program [1]. He established an alpha–beta pruning due to the memory size of the computer used. The scoring function was applied in Samuel's design. This function calculated the chances of winning for each side. The following step was determined by the minimax algorithm. Samuel improved his program through rote learning so that it could memorize all possible positions by combining them with values of reward functions. In 1952, Samuel was the first person who introduced the term 'machine learning (ML)' to the world.

In 1957, Rosenblatt discovered the idea of the perceptron [28]. The perceptron was the combined results of learning taken from the contributions of both Samuel and Hebb. The perceptron was a machine used for image recognition tasks. The first model was called 'Mark 1 perceptron'. The perceptron seemed to be a promising solution, however, it failed to recognize numerous patterns. It was mostly good at so called "AND" and "OR" problems. This was not the case for "XOR" problems since "XOR" was much more complicated for it. Hence, it did not yield promising results.

In the 1960 s, an important discovery was made regarding the multilayer invention. However, this discovery did not stop the abandonment of the connectionist approach for intelligence research [29]. It did facilitate research advancements for neural networks. Adding two or more hidden layers to a neural network led to enhanced performance by boosting the learning ability of the network. These layers have the ability to determine more complex patterns which, in turn, led to the creation of feed forward neural networks and backpropagation algorithms. These innovations significantly revolutionized machine learning field.

In 1967, Marcello Pelillo invented the "nearest neighbor rule". The introduction of this algorithm led to the creation of the basic pattern recognition. The idea behind the algorithm was to use mapping routes that had been applied to find the optimal route for traveling salespeople [30].

The backpropagation algorithm was later invented in the 1970 s [31]. The algorithm got neural networks to modify layers according to derivations of forwarded activation values. Its workflow began with an error calculation that was a result of the output vs true value. This error was consecutively distributed backwards through layers from the output layer into the input layer within the network. In 1979, a general-purpose robot with visual guidance was introduced.

In the late 1970 s and early 1980 s, ML and AI took separate paths since AI researchers began focusing on logical knowledge-based approaches instead of algorithms in their research. Studies on neural networks were also abandoned. ML research shifted from AI-based approaches to methods used in probability theory and statistics.

In 1985, Rumelhart et al. [32] re-discovered the backpropagation algorithm that revolutionized and revived the neural network research. In 1990, boosting algorithms were released to improve ML by reducing bias in supervised learning and transforming weak algorithm learners to strong ones; weak classifiers can produce a final strong one. Boosting algorithms employ a training process of turning weak classifiers into one strong classifier. A weighting process then takes place to evaluate the accuracy of the weak classifiers. The weights are re-weighted iteratively throughout the learning process of boosting. Several boosting algorithms are available throughout the literature such as AdaBoost, Light Gradient Boost, Gradient Boost, and Logit Boost. These algorithms differ from each other simply by how the training dataset is weighed.

In 1997, Schmidhuber and Hochreiter [33] introduced a neural network model that could handle tasks which required memory events that may have occurred thousands of times, such as speech. This type of memory was called 'Long Short-term Memory' (LSTM). It was a remarkable solution for the vanishing gradient problem which had been an enduring problem for recurrent neural networks before the introduction of LSTM. This model consisted of several gating mechanisms that store relevant information. The relevant information was conveyed by passing through these gates in successive layers. These gating mechanisms diminished the effect of the vanishing gradient during neural network performance. Although the model was applied in earlier times when it was first introduced, its widespread application was delayed due to insufficient amounts of data and powerful hardware requirements for model training.

In the late 1980 s, convolutional neural network emerged as another neural network type. The filter-type kernels in a model learnt weights of a neural network, which was contrary to conventional convolution operations in signal processing. The first Convolutional Neural Network (CNN) was designed by LeCun et al. [34] for hand-written digit recognition tasks. This type of neural network suffered from the same problems as LSTM.

Developments in machine learning algorithms continued throughout the years. Their achievements have grown in line with new developments. In 1997, Garry Kasparov lost in a game of chess by IBM's supercomputer. This illustrated the extent of development of the machine learning concept. With time, another IBM supercomputer defeated numerous masters of chess in special events with the help of comprehensive algorithms. These facts proved that artificial intelligence was comparable with human-level performance. Progress has been steadily increasing in the machine learning field.

By 2012, machine learning has become widespread and increasing with the application of deep neural networks. Since training deep networks was computationally expensive and required significant amounts of data to achieve better performance, CNN and LSTM utilizations were extremely limited. It was only after the introduction of AlexNet, which applied deep neural networks with powerful hardware of its time, that problem of computational burdensome was alleviated. AlexNet architecture based on CNNs was proposed by Alex Krizhevsky et al. in 2011 [35]. It was a contestant in the ImageNet large scale visual recognition competition, and ranked first in the challenge with a 25.8% error rate, the lowest error rate in that time.

A new computational paradigm was later introduced with AlexNet for deep neural networks, known as Graphical Processing Units (GPUs). GPUs can significantly reduce the computation time from several weeks to a few days. This is a significant breakthrough for machine learning and artificial intelligence. These deep neural networks are data hungry, requiring massive amounts of data for achieving higher performance as compared to other machine learning algorithms. Powerful hardware solutions are also needed for computations. The emergence of hardware solutions combined with the surge in big data and several algorithmic developments in deep neural networks have all accelerated spread of deep learning algorithms.

Since 2012, after the success of AlexNet, several architectural developments of deep neural networks have been introduced throughout the literature such as VGG, Inception, ResNet, NASNet, RCNN, Transformers, etc. The use of deep neural networks in reinforcement learning has further increased applications of reinforcement learning by transforming them into deep reinforcement learning. Deep neural networks have become extremely important for machine learning, recently superseding conventional machine learning algorithms in numerous applications.

In 2015, Google DeepMind achieved a significant breakthrough in artificial intelligence by introducing the AlphaGo algorithm. This algorithm defeated human competitors in the game Go. In recent years, several novel developments in reinforcement learning have been accomplished, achieving beyond human-level performance in some tasks with high success, particularly in games. Fig. 1 presents a timeline of the milestones in machine learning evolution throughout the years.

With these rapid developments in artificial intelligence, which are mostly due to deep neural networks from the algorithmic aspect, numerous application fields can now reap benefits of machine learning such as natural language processing [4], autonomous driving [12], speech translation [36], machine translation [37], computer vision [3], robotics [8], energy predictive analytics [38], etc. These developments have enabled high-tech companies to thrive such as Google, Facebook, Twitter, Tesla, etc. For instance, Google uses machine learning algorithms in its recommender systems to customize ads for relevant users. This is also the case for Facebook's Meta and Amazon. Google also uses machine learning algorithms for its Google Assistant which performs speech recognition. YouTube and Twitter gained several benefits of machine learning algorithms with highly effective recommender systems as well. Further developments in machine learning applications are ongoing with Tesla producing autonomous cars and companies adopting numerous industrial robots.

Due to deep neural networks' easy implementation, and their widespread uses across different application fields, artificial intelligence research have reached to a new stage, thereby transforming all industries. This transformation combined with additional developments and the big data concept enabled by IoT in future network era are expected to exponentially grow in the near future. Hence, this paper provides an overview of machine learning deployments across various fields in the future network era.

It needs to introduce main learning categories to provide insight on the learning types as well as their deployments. The main objective of machine learning is to enhance the performance of a particular set of tasks.

This is accomplished by creating a model that helps determine patterns using learning algorithms under certain conditions, as mentioned in previous sections. To accomplish this objective, machine learning enables computers to make decisions without being

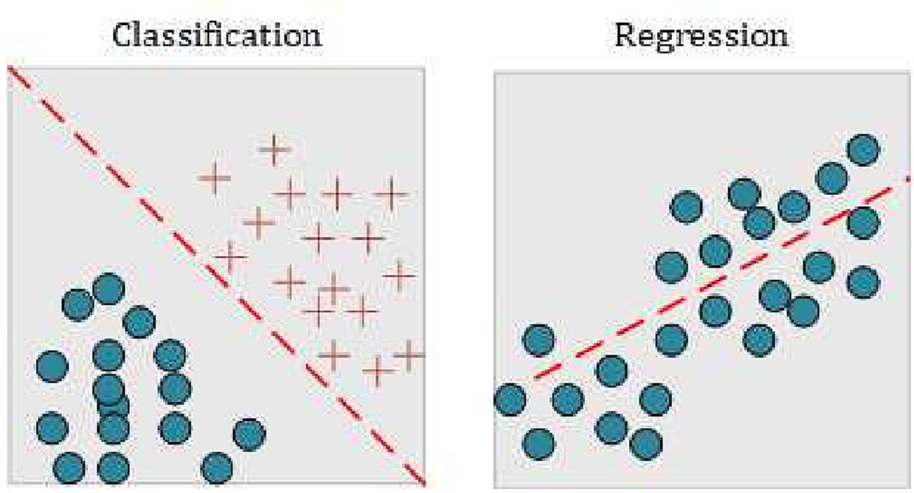

Fig. 2. (a) Classification and (b) regression.

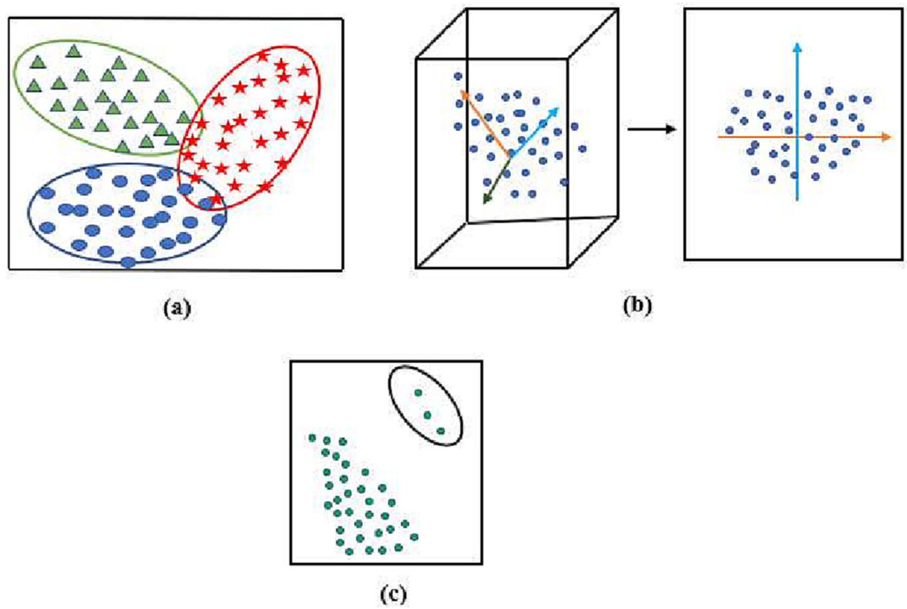

Fig. 3. (a) Clustering, (b) dimension reduction, and (c) anomaly detection.

explicitly programmed. This is conducted by analyzing and performing several tasks (such as prediction, classification, grouping, etc.) for a set of attributes that represent measurable features of a process or an observed event. A machine learning approach consists of two main stages during the learning process: training stage, which includes a validation stage, and inference stage. During the training stage, the machine learning method is applied to train a model built with its algorithmic setups. A training dataset is used to feed the model. In the inference stage, estimated output for each new input is obtained through test data using the trained model. The following subsections introduce supervised, unsupervised, and reinforcement learning, which are the three main types of machine learning.

2.1. Supervised learning

Supervised learning is a task-driven learning technique that requires a supervisor to train a machine learning model to perform classification and regression tasks. In supervised learning, a labeled training dataset, which consists of inputs and known outputs, is fed into the machine learning model. Through a supervisor, parameters of the machine learning model are learned, and the model is trained to produce a mapping between inputs and outputs. Throughout iterations in the training stage, the model, that best represents the mapping, is created. The trained model can then be used to produce expected output when a new input is fed into it.

In Fig. 2(a), distinction between different classes is performed by classification. In Fig. 2(b), a line fitting for input data is achieved by regression. Both regression and classification tasks attempt to form a relationship, either linear or non-linear, between input and output data by extracting meaningful features from the input dataset to map them to the output dataset. In their mappings, regression models produce real-valued output such as age, price, salary,

etc., while classification models produce binary or multi-class label outputs such as male or female, true or false, and spam or not spam. Hence, supervised learning algorithms can easily be turned into classification from regression, and vice versa by tuning their output producing mechanisms. For instance, linear regression can be turned into logistic regression, and decision tree regression can be turned into decision tree classification.

2.2. Unsupervised learning

Unsupervised learning is a task-driven learning type that discovers hidden patterns and structures in unlabeled data. It determines the similarities between a set of unlabeled input data by clustering sample data into different groups based on the similarities between them. Contrary to supervised learning, unsupervised learning has no output associated with its inputs and no supervisors. Therefore, an unsupervised model must accurately learn outputs based on the unlabeled input data. It uses previously learned features to recognize a class of new input data when it is presented to the model. However, performance is generally subjective and domain-specific in unsupervised learning when compared to supervised learning. Unsupervised learning problems are of three types: clustering, dimensionality reduction, and anomaly detection. Fig. 3 presents an illustration of unsupervised learning algorithms. Clustering is organizing a collection of instances that are not previously classified in any way. These instances, in turn, do not have a class attribute associated with them, and grouping is performed according to some similarity metrics. Thus, the membership of instances for clusters proposed by a few procedures is computed by a similarity measure, then instances are assigned to their associated clusters according to the similarity measure used. A clustering example is displayed in Fig. 3(a). The concept of similarity can be expressed in different ways according to the study purpose, the assumptions specific to the application field, and the domain knowledge of the handled problem. One problem of clustering methods is that the interpretation of obtained clusters is difficult in some cases, which entails specific domain knowledge in advance. Detailed information on clustering in unsupervised learning can be found in [39]. Prominent algorithms for the clustering method include the k-means clustering, Gaussian mixture models, and density-based spatial clustering of applications with noise (DBSCAN).

Dimensionality reduction projects a dataset onto a lower-dimensional space with a low information loss to reduce data complexity and enhance the interpretability of the data used. It creates

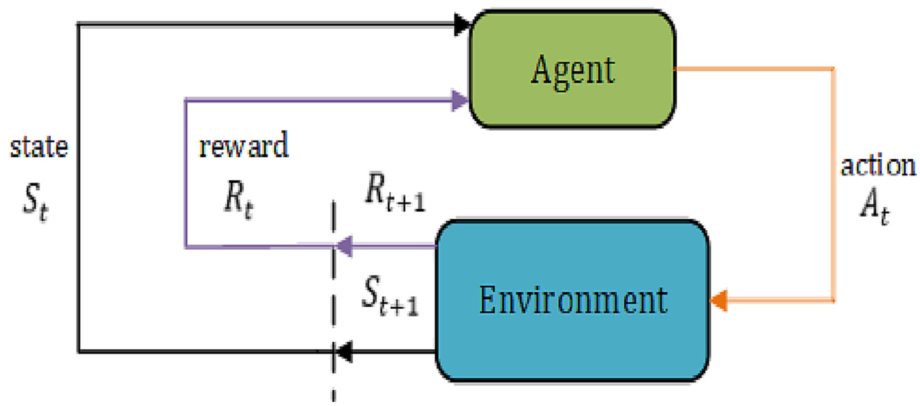

Fig. 4. The reinforcement learning framework.

a subset from the dataset by selecting the most useful feature to train, and has a lower prediction error than the full model. The general flaw of most existing dimension reduction techniques is that they do not produce a function that can be applied to new points whose relationship with the training dataset is unknown, from multiple inputs to outputs. Hence, several methods used for dimension reduction presume existence of a significant distance measure in the input space [40]. Principal component analysis (PCA) and principal axis factoring (PAF) algorithms are important examples of dimensionality reduction methods.

Anomaly detection algorithms try to identify rare events or observations in a dataset that distinctively differ from most of data in the dataset. They do not fit to normal patterns in the dataset. Anomaly detection algorithms assume that the number of normal instances is substantially greater than the number of anomalies, and that the anomalies are qualitatively different from normal instances [41]. Hence, their aim is to capture available anomalies in a dataset by powerful algorithms. Even they are similar to clustering methods in some respect, they differ in nature. Isolation Forest model, DBSCAN, local outlier factor (LOF), and neural network autoencoders are the frequently used anomaly detection algorithms.

2.3. Reinforcement learning

Reinforcement learning (RL) is a framework in which an agent or a controller optimizes its behavior by interacting with its environment. RL is a learning from the mapping of states to actions in order to maximize cumulative reward by using a scalar reward or a reinforcement signal. Contrary to most machine learning algorithms, a learner is not informed of what action to take in advance. Instead, it is expected to discover which actions will provide the highest reward in reinforcement learning by experimenting through trial and error. Actions are RL's most distinctive features compared to other algorithms. They include trial and error investigation and delayed reward computations [42]. A typically enhanced learning algorithm consists of four integral components: policy, reward function, value function, and environment. Fig. 4 presents the reinforcement learning system.

Policies are responsible for mapping states to actions taken by the agent. *The reward function* evaluates the current states and gives penalties or rewards according to the result of the action. *Value function,* which has two types *(state-value and action-value),* evaluates expected reward from the future state of the agent in the long run. The *environment* is a task or simulation where the agent performs maximization of cumulative reward via the trial–error mechanism.

In an RL algorithm, an agent interacts with its environment, senses its current state and the state of the environment, and constantly learns and collects information to perform certain actions. Thus, it perceives the exact state of the environment at every step of time, and takes an action that pushes the environment to move into a new state. A reward-punishment system is present depending on the agent's action selection and its result. At this point, if the action is good, it will get a reward. If the action is bad, it will get a penalty. While this feedback is less informative than supervised learning where the right actions are given, it is more informative with respect to unsupervised learning. This algorithm allows the agent to discover correct actions merely from the trial and error of its own actions without any explicit feedback on its performance.

At each step $\boldsymbol{t}$, the agent monitors state $\boldsymbol{S_t}$ and chooses an action $\boldsymbol{A_t}$ from action space A. Next, it receives a scalar reward $\boldsymbol{r_t}$ that indicates the quality of the action chosen, and moves to the next $\boldsymbol{S_{t+1}}$, this is the new state. The RL algorithm takes this combination of experiences $(\boldsymbol{S_t}, \boldsymbol{A_t}, \boldsymbol{R_{t+1}}, \boldsymbol{S_{t+1}})$, and learns to map them from states to a measure of the long-term value of being in this state, known as the optimum value function. The learning process of an RL agent has been highlighted in Fig. 4.

In the RL context, there is a long-term problem called trade-off between exploration and exploitation in the action selection. According to this trade-off, an agent must decide whether it is better to randomly explore which outcome will result in taking another action (exploration) in the environment, or preserve the existing knowledge and maximize the rewards by selecting dictated actions [43]. Deep Q-learning, deep double Q-learning, trust region policy optimization (TRPO), and deep deterministic policy gradient (DDPG) are some of the most popular RL algorithms used in numerous applications.

3. Applications of AI and machine learning in future networks-enabled systems

Future networks will enable immense simultaneous connections and widespread network in high mobility situations and extremely dense areas [44]. Due to the exponential growth of data acquired from numerous wireless enabled devices (such as smartphones, drones, connected vehicles, wearables, and virtual reality devices that boost IoT technology), communication traffic will therefore increase. Future networks are expected to bring higher data rates, lower latency, and massive simultaneous connections in future communication systems [45,46]. However, these novel network systems will encounter challenges alongside the advantages they bring to both business and daily life. New technologies enabled by future network systems will have require machine learning applications due to the requirements of more intelligent methods and the enormous amounts of data collected. Recently, highly efficient and accurate real-time decision-making enabled by intelligent methods, especially deep learning methods, have

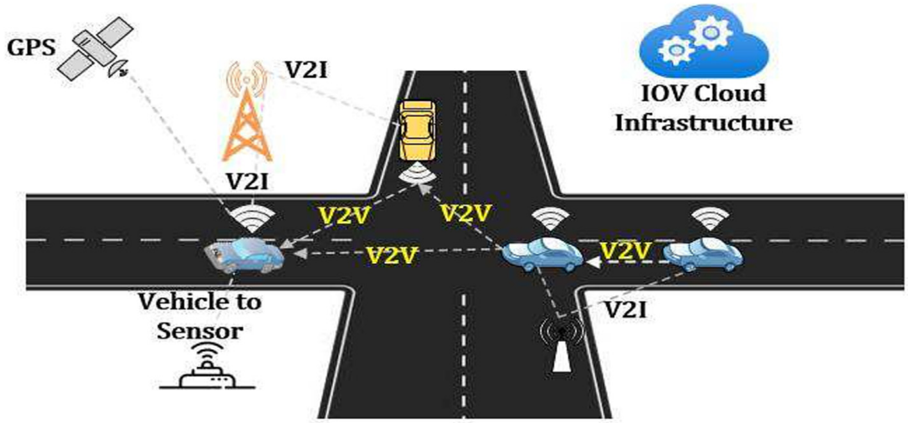

Fig. 5. An intelligent transportation system.

been increasing throughout various fields along with the IoT concept in the future networks' era. Hence, an extensive literature review and research categorization are presented in the following subsections.

3.1. Intelligent transportation systems

It is expected that intelligent transportation systems will be a hot topic with the introduction of future network communication systems. Autonomous driving, vehicle detection, intrusion and collision prevention systems, and communication between vehicles and network infrastructures will require transportation systems to be more intelligent. This subsection presents the use cases of intelligent transportation systems throughout the literature. Fig. 5 presents an illustration of an intelligent transportation system. Several use cases in relation to intelligent transportation systems and future mobile communication systems have been introduced into the literature in recent times.

A case study based on IoT big database for solving transportation network planning was accomplished in [47]. The problem was divided into several parts using deep belief networks (DBNs) model. K-means clustering algorithm was then used for clustering according to the Geographical Information System data. The DBN model classified all real time IoT data, and selected the k initial points for clustering centers. The aim was to determine an optimal dynamic transportation network with the lowest total cost in the deployment of these models. Authors tested different cluster numbers to analyze their effects in terms of computational efficiency. They found an optimal solution with the use of their model. According to their results, the study contributes to city traffic planning and generates economic benefits. The study enables the rapid construction of a smart city network based on the IoT dataset [47].

In [48], the problem of detecting parking lot occupancy was managed using specifically designed CNN in smart cameras. CNNs was developed for the sole purpose of detecting certain objects. Smart cameras could process obtained images and convey the results to a remote server. Smart cameras built using Raspberry Pi 2 model B were used in experiments instead of ground sensors due to two reasons: low cost per parking space and versatility. The cameras also had additional capabilities such as tracking, logging, and recognition, making them much more adaptable. The study employed CNNs to PKLot (an existing dataset in the literature) and CNRPark-EXT (a newly introduced dataset). The newly introduced dataset was used for various settings in the experiments, such as obstructed point of views, illumination, and weather conditions, to contribute to the generalizability of the deep learning method used [48]. The applied datasets exhibited the efficiency of the proposed CNN architecture in managing the parking lot occupancy task within the context of intelligent transportation systems. In the application stage, periodically captured images of parking lot segments for each parking space were detected by the smart cameras' software. The occupancy status was then identified by the CNN model. The CNN model was deployed to function on embedded systems such as smart cameras.

In [49], automatic detection of street elements (such as traffic lights, street crossing, and roundabouts) was examined to create street maps. Authors of the paper presented a novel algorithm to obtain road infrastructural elements using GPS traces from drive conditions. GPS data from mobile devices included speed and acceleration data. An outlier detection algorithm was initially applied to spot abnormal driving patterns were automatically analyzed, and relevant features were extracted. These features were then classified as different road elements, such as traffic lights, crossroads, urban roundabouts, etc. Since these road elements might vary and generate outliers in the pattern of speed and acceleration similar to nearby locations for the same drive, the proposed method would spot and filter outliers in advance for detected driving points due to random traffic conditions. After the outlier detection pre-filtered candidate points, a classifier algorithm (deep belief network) was used to determine the types of road elements. The authors employed a classifier to distinguish between samples in a set of classes. An autoencoder-based similarity method was used to achieve the objective. A final classifier based on k-nearest neighbor (KNN) and support vector machine (SVM) algorithms were applied, achieving high performance in terms of precision and recall. To enhance the performance of the proposed algorithm in real-time scenarios, a variation of the proposed architecture with a similarity measure that included null classes for road elements was also introduced. This variation used auto-encoders with a similarity measure based on Pearson's correlation coefficient. Two datasets, with one from the literature, were used that they presented real time conditions to validate the performance of the proposed method. DBN and the final classifier layer evaluated whether observed differences in the acceleration and speed patterns of the outlier locations were well classified. DBN was first trained, and class dependent features were then extracted. These features were used as input for the final classifier. Performance evaluation of the proposed method, in terms of recall and precision metrics for the classification task, was successfully accomplished [49].

In [50], the traffic flow prediction for planned work zones of significant importance was examined for intelligent transportation systems. Several applications (such as ramp metering and hard shoulder running) were implemented at work zones. These applications tremendously benefited from short-term traffic flow forecasts. The dynamic variation of demand and capacity due to work zones affected traffic flow forecasting. Authors of the paper used data collected from two different types of roadways in St. Louis. Detectors on road segments provided the data, while the Missouri Department of Transportation database supplied extensive information on road segments. The acquired data were used for long and short-term traffic flow prediction tasks. Intervals of 24-hrs, 1, 15, 30, 45, and 60 min were provided since multiple time period predictions would enable a wider range of applications in intelligent transportation system management. The authors applied regression tree, random forest (RF), and neural networks for long-term predictions. To compare, these algorithms were also employed for short-term predictions. Performance outcomes were compared in terms of the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) metrics. Variable importance for each prediction was also presented in the paper. From the outcomes, the authors discussed the important features of each type of traffic prediction for effective transportation management [50].

In [51], predicting the traffic flow was the main goal in this research. Traffic data were acquired from several sources of sensors such as radars, cameras, and mobile Global Positioning System (GPS). As traffic steadily increased, predicting the traffic flow would be crucial and more data driven. Intelligent methods were needed to manage the problem since previous solutions would be inadequate. The stacked autoencoder model was trained in a layer-wise manner to learn features of the data used. In this method, spatial and temporal correlations were considered, and traffic flow prediction was accomplished by the Stacked Autoencoder (SAE). SAE method was first used for extracting traffic flow features, and a logistic regression layer at the end of SAE was then utilized for prediction. The method was deployed using real data which were collected from the Caltrans Performance Measurement System (PeMS) database obtained from numerous individual detectors implemented statewide throughout the freeways of California. 15, 30, 45, and 60-minute intervals of traffic flow predictions were conducted. SAE was compared to neural network, the random walk method, SVM, and radial basis function NN in terms of MAE, MRE, and RMSE [51].

In [52], a novel framework named Branch Convolution Neural Network was proposed to increase the test-time performance of traffic sign recognition. Germany's traffic sign recognition dataset was utilized. The branching method in earlier CNN layers was examined. This method was similar to deep networks since it gave solutions to several problems, such as shortcut in ResNet and Highway Net. The framework speed, which was the main aim of the model, was accomplished in this manner. The proposed method nearly produced results similar to existing methods for the same tasks. The optimum branch strategy doubled traffic sign recognition, and only decreased accuracy by 1%. When considering real-time deployment conditions, the framework can provide speed with a marginal loss in accuracy [52].

With Intelligent Transportation Systems (ITS), the combination of autonomous and manual vehicles may cause safety risks. These risks must be efficiently managed to ensure safer systems. In [53], a solution for traffic safety was proposed using the deep learning-based method for different vehicle types. The approach performed well in recognizing the intention for lane changes, with enhanced real-time intention recognition during various traffic situations. Intention recognition was accomplished using deep learning based on LSTM. Dataset used in the experiments was obtained from a driving simulator, a smart eye pro tracker system, and traffic cameras. Design scenario attempted to simulate road situations by including highway segments with real conditions. The scheme of the proposed model was compared with other LSTMs and one machine learning model in terms of recognition accuracy and RMSE metrics. According to the results, the proposed method outperformed other techniques, improving accuracy and efficiency of lane-changing recognition [53].

In [54], CNN method was employed for traffic sign recognition and data detection in Germany. Weighted multi-CNN was the proposed approach in this study. Authors of the paper used preprocessing to transform RGB colored dataset into HSV and grayscale-colored spaces. Data augmentation, which is a significant generalization technique, was applied to increase the generalizability of the deep learning model used. The application was deployed by using different CNN scenarios. Performance was compared in terms of F1-score and Matthews Correlation Coefficient (MCC). Combined model of CNN produced the most promising results based on the performance metrics. According to the performance results, the proposed classifier exceeded the frame rate of 10 fps. The classifier performed well when used for traffic datasets of other countries. For the scalability of the proposed model, the public traffic datasets of 3 European countries (Belgium, Sweden, and Croatia) were used for applications. For the stability of the classifier, the proposed model was evaluated on the Challenging Unreal and Real Environments for Traffic Sign Recognition (CURE-TSE) dataset, which consisted of traffic sign images in 12 challenge types and 5 levels. The method was compared with existing techniques throughout the literature. According to the classification accuracies obtained, the proposed method yielded promising results for sign detection and recognition as well as for several notable CNN architectures: MobileNet, SqueezeNet, GoogleNet, ResNet50, and VGG-16 [54].

In [55], the aim was to develop automatic vehicle detection and recognition. The authors employed a dataset of vehicle images collected by traffic surveillance cameras during the day for 1 week from the local police department. Feature extraction and building classifiers with Haar-like features and AdaBoost algorithms were utilized for spotting vehicle location over the input image. The Gabor wavelet transform and the local binary pattern operator were used to extract multi-scale and multi-orientation vehicle features. Next, PCA was employed to reduce the dimension of images. Nearest neighbor algorithm was then implemented for the final classification [55].

In [56], fine-grained recognition of vehicles was examined for intelligent transportation systems. Applied approach was based on 3D bounding boxes built around vehicles. CNN was used for the fine-grained recognition of vehicles in traffic surveillance applications. The paper employed 116 k images of vehicles from different viewpoints which were collected from various surveillance cameras. Data was obtained from surveillance cameras mounted on nearby streets for tracking passing vehicles in Brno, Czech Republic. The data were further enhanced with additional processes. Authors conducted several experiments, confirming that the results did improve with the use of CNN. The applied method outperformed the state-of-the-art methods in the task of fine-grained recognition of vehicles. The architecture yielded promising results compared to other CNN methods [56].

In [57], CNN method was used for detecting vehicles and classification. The method was deployed using the multi-task cascade model. Vehicles were first detected in the image, followed by image classification. Two different CNNs were used for these tasks. Apart from the detection task, vehicle type classification for ITS management was also accomplished. The employed methods outperformed in their tasks due to data enhancement operations, which might be included in future ITS management applications. The modified CNN and data enhancement techniques boosted its performance in classification and detection. Real-world data was also used to verify the practicality of the cascade model in the study [57].

In [58], real-time vehicle classification was accomplished by CNN and AdaBoost. High prediction accuracy of the utilized model along with low storage cost have enabled its utilization for vehicle classification in real-time. In the utilized methodology, CNN was used as a feature extractor, exhibiting high accuracy and low storage cost. SVM was combined with AdaBoost, serving as the weak classifier of AdaBoost. The assembly process was designed by SVM and AdaBoost hybridization. Two datasets were integrated and used for method deployment, one regarding cars which exists in the database and one that includes images taken in real-time. According to the obtained results, the novel methodology outperformed several state-of-the-art CNNs during its tasks [58].

In [59], a multitask deep convolutional neural network was used for detecting structural cues in visual signals. CNN performed two types of tasks: classification and regression. Lane marks were first detected by a classifier. If the detection was positive, the orientation and location of the lane mark with the region of interest (ROI) would be estimated by the regressor part, which was efficient in managing large ROIs since it presented sophisticated target prediction results. The detection accuracy increased due to the large regions captured, which contained richer contextual information for the given input. The RNN layers applied with CNN enabled the memory for data structures. This feature was used for identifying global targets from local cues without the need for structural knowledge. To summarize, multi-task CNN detected the target and its geometric attributes with respect to the ROI. RNN used the extracted memory for determining whether a lane was present over a sequence of images. The proposed method as well as other deep learning-based methods were applied to a real-world traffic data. The methods were tested using an existing dataset known as the Caltech dataset. In the experiments, CNN, RNN-based proposed model, and SVM were compared for lane detection performance. The RNN-based lane detection model surpassed the other methods in terms of the Received Operating Curve (ROC) performance [59].

In [60], large-scale speed predictions of transportation networks were accomplished. CNN was applied for traffic feature extraction and network-wide traffic speed prediction. Data collected by GPS location sensors was used in the application of two real-world transportation networks: the second ring road and northeast transportation network in Beijing. Different horizons and look-back strategies were applied for the speed prediction task, and the proposed method was compared to several machine learning algorithms such as ordinary least squares, KNN, ANN, RF, SAE, RNN, and LSTM. As per results obtained in the paper, CNN method outperformed the other methods. However, due to its model capacity, training time of the proposed method was a computational burden with respect to the machine learning methods used. This problem may be solved with the use of highly efficient hardware [60].

In [61], traffic light recognition using deep learning was conducted since it is crucial in autonomous driving and intelligent transportation systems. A novel real-time method was recommended for this task. In the experiments, previously proposed original CaffeNet model was modified to perform in real-time conditions. To achieve robust experiment results, different scenarios for used dataset were considered to compare various algorithms. Performance evaluation of the methods was accomplished using precision and recall metrics with and without ROI. According to the obtained results, inclusion of ROI in the model proved its efficiency. With the ultimate goal of deploying the model for real-time application and achieving high accuracy, the proposed approach was compared with the YOLO algorithm. It outperformed YOLO, efficiently detecting traffic lights under the conditions of low exposure and dark frames. The performance of the proposed method in terms of accuracy and robustness was enhanced by incorporating temporal trajectory tracking. Speed of the algorithm increased using a prior detection mask which performed with high efficiency in real-time tasks. Integration of the algorithm in autonomous vehicles and its robust performance were proven in real-time conditions [61].

In [62], a novel method was used for a pedestrian detection system based on deep learning and the adaptation of a CNN to tasks at-hand. For real-time application, a lightweight version of the proposed algorithm was set on modern hardware to prove efficiency of the method used. This hardware can be adopted for car prototypes since it functions as a computational brain in the intelligent transportation system. Intelligent transportation systems enabled by 5G communication systems will demand similar hardware. The experiments were conducted using the Caltech Pedestrian Dataset which is challenging yet the most used dataset in the literature for pedestrian detection algorithms. The AlexNet and GoogleNet algorithms with region proposals were deployed, and comparisons of the algorithms were made in terms of the miss rate and false positives per image metric. As per results obtained in the paper, AlexNet LDCF yielded the best results with nearly the same ratio as GoogleNet in terms of the miss rate with 0.1 false positives per image. One of the main contributions of the paper is the lightweight version of the proposed algorithm's deployment to a real-time modern hardware which will be embedded in future smart cars of intelligent transportation systems. The proposed algorithm has achieved promising results for the future deployment of AI in intelligent transportation systems [62].

In [63], the authors recommended a novel model called Scale-Aware Fast R-CNN. The model was based on VGG-19 and possessed a unified architecture that incorporated both large-size and small-size sub-networks. The combination of extracted features enabled the model to detect large and small-sized pedestrian instances. After conducting extensive experiments, the SAF R-CNN surpassed several challenging benchmarks for detecting small-sized pedestrian instances. The model appears to be promising for future real-time deployments [63].

A decentralized framework for collision avoidance in autonomous driving was proposed in [64]. A modified version of deep deterministic policy gradients Co-DDPG was used to train autonomous vehicles. The authors designed a robust and efficient framework to provide optimal autonomous driving solutions for driving condition requirements in several 5G enabled systems. A dynamic mobile network, vehicular ad-hoc network, and the algorithm for establishing vehicular network during autonomous driving were created and used for communication between participating agents within the vehicular ad-hoc network. Extensive experiments using TORCS showed that the created framework was highly efficient for autonomous driving. The authors compared the algorithm with the Partially Observable Markov Decision Process (POMDP) and evaluated the performance of the algorithms in terms of three prominent metrics in autonomous driving: collisions, reward, and system latency. According to results obtained in the paper, the proposed algorithm outperformed the other frameworks. The result is promising for 5G mobile communication systems that it may enable further enhancements of intelligent transportation systems [64].

Internet of vehicles (IoV) is an emerging subset of IoT. In the active safety system for ITSs, wireless communication, vehicular sensing, and GPS localization are driving forces of the IoV concept. With IoVs, intelligent transportation management, intelligent vehicular control, and dynamic delivery of intelligent information are merged into a single network. In [65], a decision-making system that avoided rear-end collisions was proposed for IoVs. It

Table 2
Research on intelligent transportation systems.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
	[47]	2020	Transportation network planning	UL	Classification and clustering	DBN + k-means
	[48]	2017	Parking lot occupancy detection	SL	Classification	CNN
	[49]	2018	Traffic element detection	UL&SL	Classification and clustering	A novel outlier algorithm + DBN
	[50]	2015	Traffic flow prediction	SL	Regression	Regression Tree, DNN, RF, Non-parametric regression
	[51]	2015	Traffic flow prediction	UL&SL	Dimension reduction and regression	Stacked AE
	[52]	2017	Traffic sign recognition	SL	Classification	CNN
	[53]	2021	Intention recognition in traffic	SL	Regression	LSTM
	[54]	2018	Traffic sign recognition	SL	Classification	CNN
	[55]	2017	Vehicle detection and recognition	UL&SL	Dimension reduction and classification	AdaBoost + CNN + PCA
Intelligent Transportation Systems	[56]	2019	Vehicle detection	SL	Classification	CNN
	[57]	2017	Vehicle detection and classification	SL	Classification	CNN
	[56]	2018	Vehicle classification	SL	Classification	CNN + AdaBoost
	[59]	2017	Structural prediction and lane detection	SL	Classification and regression	CNN + LSTM
	[60]	2017	Traffic network prediction	SL	Regression	CNN
	[61]	2019	Traffic light recognition	SL	Classification	CNN
	[62]	2016	Pedestrian detection	SL	Classification	CNN
	[63]	2018	Pedestrian detection	SL	Classification	CNN
	[64]	2020	Autonomous vehicle collision avoidance	RL	RL	DDPG
	[65]	2018	Rear-end collision prediction	SL	Regression	CNN
	[66]	2018	Obstacle detection	SL	Classification	DSA + KNN
	[67]	2019	V2V communication	RL	RL	DQN
	[68]	2019	Intrusion detection for connected vehicles	UL&SL	Dimension reduction and classification	DT + DBN

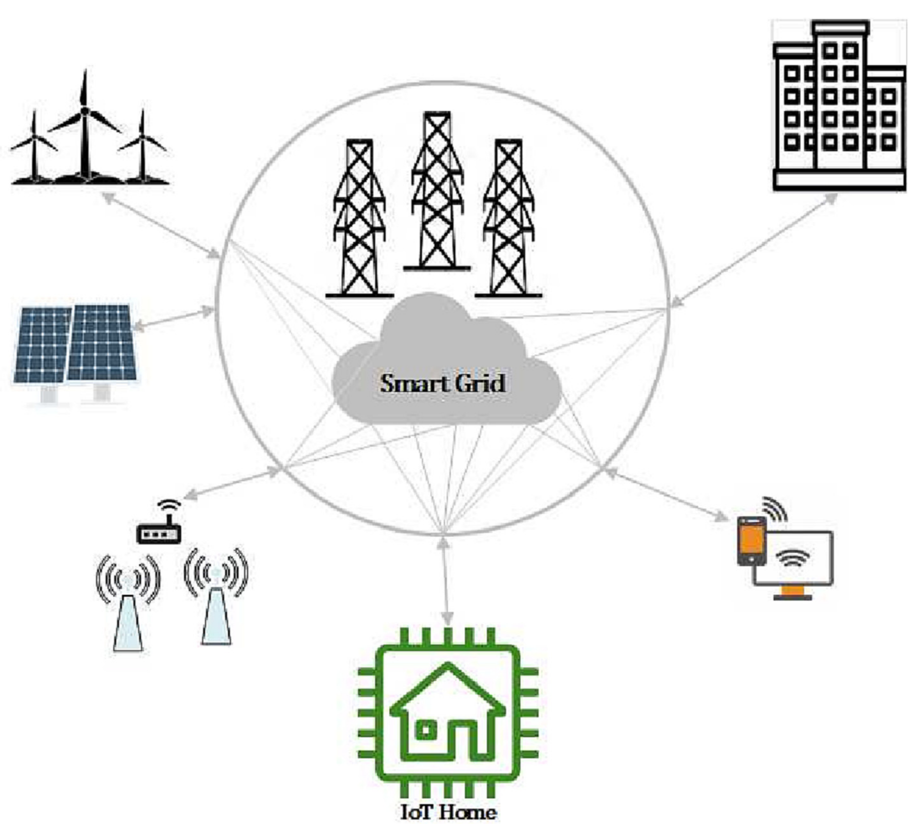

Fig. 6. A smart grid system.

was based on genetic algorithm, and optimized using deep neural networks. Decision-making system modeled the impact factors of collisions in IoVs. It predicted probability of rear-end collisions by regarding several influential factors. The proposed algorithm was compared with traditional backpropagation neural networks during simulation experiments. It achieved more accurate results with respect to conventional kinematic equation-based collision probability calculations. The study may provide information on benefits of autonomous driving in a distributed environment using intelligent transportation systems enabled with 5G mobile communication systems [65].

In [66], a stereovision-based method to detect obstacles in intelligent transportation systems was proposed by combining deep stacked auto-encoder (DSAE) and KNN algorithms. The proposed approach consisted of two stages. In the first stage, DSAE performed feature extraction and dimensionality reduction. In the second stage, the study's obstacle detection problem was treated as an anomaly detection, and KNN was used as a binary classifier. The authors employed three publicly available datasets taken from cameras, road sensors, lidars, and radars to their proposed method: the Malaga stereovision urban dataset, the Daimler urban segmentation dataset, and the Bahnof dataset. The proposed method was also compared with deep belief network-based clustering schemes. The results of the three deployments were compared in terms of recall, sensitivity, and area under curve (AUC). The applications of the proposed method integrated with real-time conditions will enhance intelligent transportation system management by providing efficient obstacle detection in urban areas [66].

Vehicle to vehicle (V2V) communications with ultra-low latency and high reliability are significant for safety requirements. In [67], a novel decentralized resource allocation model for V2V communications was proposed. The model was based on deep reinforcement learning and could be deployed for both unicast and broadcast scenarios. It provided an autonomous decision-making agent that determined the optimal sub-band and transmission power level without the need for global information. In experiments conducted, simulation setup for the Manhattan case detailed in 3GPP TR 36.885 was used, containing a total of 9 blocks with both line-of-sight (LOS) and non-line-of-sight (NLOS) channels. The proposed model jointly optimized scheduling and channel selection unlike previous works which separately managed these tasks. The two tasks were compared to assess performance of the methods, yielding different results. The model performed better than the compared methods in terms of V2I capacity and V2V latency. The model significantly increased V2V success rate and V2I capacity [67].

In [68], an automated and secure continuous cloud framework for smart connected vehicles was proposed. This approach detected intrusions from security attacks. DBN was used for data dimension reduction, while DT was applied for classifying attacks. The proposed approach exhibited high performance in the overall accuracy, detection rate, false positive, and false negative rates during deployment [68].

Table 2 summarizes available research studies on intelligent transportation systems.

3.2. Smart energy

One field that benefits from smart systems and IoT is likely to be smart energy field. With the introduction of next generation networks and extensive data from IoT systems, this field will further mature through intelligent applications. Specifically, assistance from artificial intelligence in next generation networks is expected to provide more secure, stable, real-time or near real-time effective management, control, and operation for smart energy systems. Artificial intelligence may also support smart grids and micro grids. Home energy management systems have grown in recent times, as seen throughout the literature. This subsection discusses smart energy use cases. Fig. 6 presents an example of the smart energy system.

Smart grid utilization facilitates digital and intelligent technology enabled by IoT systems. It provides more reliable power distribution systems as well as economic benefits. Therefore, smart energy community management was examined in [69]. Energy system management in a local energy pool based on real-time demand/supply ratio was accomplished by introducing a reinforcement approach combined with fuzzy logic. The energy trading process was modeled using fuzzy reinforcement learning (Q-learning) to enable stakeholders in the P2P trading system and the management of household energy storage systems. Real data collected by smart meters, British electricity retail price, and solar data (for a solar photovoltaic system) were applied for various scenarios. As per results of the paper, the proposed approach contributed to energy system management and reduced the decision-making period in used scenarios [69].

In [70], several deep RL methods were deployed to provide better energy management for a microgrid system consisting of a wind turbine generator, a set of thermostatically controlled loads, price-responsive loads, an energy storage system, and a connection to the main grid. The proposed approach coordinated between different flexible sources. Two enhancements for the A3C and PPO methods were applied, and they outperformed the other algorithms used in the paper. The algorithms were compared using a realistic microgrid simulation for various scenarios. In the paper, data consisting accurate electricity price and renewable energy production in Finland were used [70].

Since smart grids require advanced communication technology, management and scheduling problems do emerge. The real-time scheduling of operational household appliances was accomplished by applying reinforcement learning in [71]. Q-learning learnt reward that scheduled the operational time of household appliances in the next state and simultaneously ensured minimum energy consumption. RL agents attached to each appliance of a smart home shared memory synchronization and coordination. The actions of an agent are shared by other agents, establishing communication and coordination between all agents. Obtained results were compared with other scheduling algorithms. The utilized approach efficiently reduced energy consumption and effectively lowered the dissatisfaction level of home users [71].

In [72] a reinforcement learning approach was applied to control cooling setpoint and loads of smart buildings to provide energy flexibility. Automated and intelligent control of smart energy systems can be accomplished in future smart and sustainable electrical grids. The data used were a commercial building model from the United States Department of Energy, and it mostly consisted of commercial building stock in the USA. The robustness and scalability of soft actor-critic-based controller over heterogeneous building stock was investigated by running the model under different climatic conditions. According to obtained results in the paper, the deployed model was promising one for EnergyPlus-based high-fidelity environments for establishing building energy flexibility in the control policy [72].

Deploying agent(s) to different environments is useful for large scale applications in future smart grids. In [73], a deep reinforcement learning approach based on deep Q-learning was proposed for home energy management and system control. The proposed approach was deployed for a real-case study in Ireland. According to results of the paper, the approach contributed in saving energy, optimizing PV self-consumption of load shifting, and providing significant ease for user preferences. In terms of energy efficiency, the approach performed better than compared algorithm for the same task. It also significantly reduced renewable energy consumption as compared to the other algorithm. The proposed approach helped in load shifting and energy grid balance in smart systems [73].

In [74], a deep learning approach based on iterative residual blocks of deep neural networks for a short-term residential load forecasting was deployed using spatio-temporal correlation patterns in the load data of appliances. Dataset used in the experiments consisted of recorded consumption data of appliances for residential users. Experiments with real world measurements were conducted to evaluate the performance of the proposed approach. It was then compared with several machine learning algorithms in terms of RMSE, MAE, and MAPE. As per obtained results in the paper, the proposed approach surpassed the other algorithms [74].

In [75], a deep learning-based energy management system was examined for the microgrid system. The system had three components: a forecasting system, an optimizer, and an optimized EV charging station. Deep learning was used for the forecasting system. The aim was to minimize import of power from the main grid, thereby sustaining and increasing self-sufficiency. A real-case dataset from PV panels installed in Wroclaw University of Science and Technology was used for applying the methods in the paper. The study is the starting point for addressing the proposal to construct electric vehicle charge stations with modern energy management systems in the smart grid concept [75].

In [76], a scheduling framework for energy management in buildings was proposed using a deep learning method combined with discrete wavelet transformation. With the application of the proposed framework, monitoring and controlling different aspects of energy systems could be possible in smart grids. The combination of forecasting based on deep learning, energy storage, and scheduling significantly contributed in curbing energy import from the grid, further saving electricity cost as well. The proposed approach was deployed in a real-case problem using a dataset belonging to several residential buildings in the province of British Columbia, Canada. LSTM-DWT was used to conduct forecasting task. A scheduling algorithm was employed to schedule energy demands with the aim of minimizing electricity imports from the grid, thereby reducing energy costs. The LSTM-DWT method was compared with the LSTM method in terms of RMSE, MSE, MAPE, and R-squared metrics under different forecasting tasks including wind speed, solar supply, and energy demands. According to results presented in the paper, the implemented forecasting and scheduling framework managed to significantly achieved sustainable energy supply, renewable energy reliance, and cost-saving energy efficiency based on evaluations and financial analysis [76].

A multi-agent reinforcement learning approach was employed for managing the energy of residential buildings in [77]. Q-learning was also applied for this issue, and scheduling the operation of various components and demands in a multicarrier residential energy system was accomplished using the proposed MARL. Two experiments were conducted using energy management systems. One was the deterministic scenario, while the other one was the stochastic. According to results, the MARL approach achieved low consumer cost with respect to conventional optimization-based energy management programs [77].

Attaining optimal adaptive real-time decisions is of extreme importance in energy management systems [78]. In [78], ANN and MARL-based approaches were deployed using Q-learning for home energy management. The deployed ANN conducted a steady price prediction. After predicting future prices, MARL then ensured the optimum and decentralized decision-making mechanism for various home appliances in the energy management system. Data for price and energy were obtained from the Pennsylvania-Jersey-Maryland (PJM) electricity market data. Different scenarios were considered for the performance evaluations of the proposed approach in the energy management scheme. It was discovered that the proposed approach helped reduce cost for users in the system when compared to the benchmark method with no demand response [78].

Energy cost minimization for smart homes was examined in [79]. The aim was to design an optimal energy management scheme that scheduled different energy systems within a smart home using the DDPG algorithm. Real-world traces consisting of different values were obtained from the Pecan Street database, which is one of the largest real-world open databases for home energy consumption. Extensive experiments demonstrated the superiority of the applied algorithm [79].

The energy supply chain is a crucial issue in the development of smart grids since it maintains stability in energy distribution systems. Behavior and energy predictions at the customer level are crucial since they will affect the entire system. In [80], with the aim of increasing the prediction accuracy of energy consumption, two stochastic models for time series prediction were deployed: the Factored Restricted Conditional Boltzman Machine (FCRBM) and the Restricted Conditional Boltzman Machine (RCBM). Dataset consisted of electric power consumption obtained from an individual residential customer, and performance of the two models was compared with several machine learning methods such as ANN, SVM, RNN, and RCBM (in terms of RMSE and R-squared). According to obtained results in the paper, FCRBM outperformed all other methods [80].

In [81], an ANN-based method for demand side management was deployed with real-time optimization of power system management. The paper proposed a data classifier generated by digital meters through the deployment of ANN to classify the load curve patterns. This classification achieved the most suitable demand side management policy for each type of consumer ranked throughout the network. The dataset used in the experiments consisted of 2000 random consumers using low voltage from residential, commercial, and industrial areas. This dataset was obtained from a local energy distribution company. The proposed approach produced satisfactory results in the classification of load curve patterns for efficient demand side management in intelligent network environments [81].

In [82], smart appliance scheduling for optimizing an energy management system was examined using the hybrid ANN-GA. The deployed hybrid method successfully reduced energy demands during peak periods, maximized renewable source usage, and simultaneously minimized reliance on energy grids. The hybrid ANN method was utilized as a forecasting engine to capture operating patterns of appliances, and also to predict energy consumption and generation of renewable energy. The ANN-based prediction engine was combined with a GA-based optimization method to determine the level of energy grid usage, and one generated dataset and one real-case dataset were used for the implementations. The real-case dataset was collected from eco-friendly houses at the Little White Alice holiday resort in Cornwall (UK), further demonstrating the approach's reduction in energy grid usage [82]. The approach is promising for smart buildings since the authors are in the process of delivering commercial implementation of the proposed system, which will be applied through smartphones.

In [83], a real-time dynamic energy management system was proposed using deep reinforcement learning to enable the achievement of optimal scheduling decisions. PPO used long-term historical energy consumption data and renewable energy generation. It incorporated learned features from the data by updating neural network to learn optimal policies. Energy management systems provided stable operations by scheduling devices used, which helped consumers within distributed networks. Predicted wind turbine, photovoltaic output, load consumption, and reduced price were the foundations of decision-making in scheduling. Data were acquired from several sources (NERL measurement, Instrumentation Data Center, and California ISO) to conduct the experiments. The method was also deployed in real-time to demonstrate its efficiency in online decision-making. It was then compared to deep deterministic policy gradient (DDPG), DDN, and conventional stochastic programming. The results revealed that the proposed approach outperformed the compared methods [83]. Its efficiency in online decision-making and applicability in real-time problems make it a potential solution for smart energy systems in the future network era.

Lifelong control issues of an isolated grid were examined in [84]. Modeling of progressive and abrupt changes over the life span of microgrids was proposed in this paper. The modeling approach was implemented to model an off-grid microgrid for rural areas. The changes in the grid throughout its lifetime was incorporated in the modelling process, and the proposed approach applied an instance of Dyna, and used PPO for policy optimization. Training of the model was performed with distributional loss, the model was compared with a rule-based policy and a model predictive controller, which served as benchmarks. Performance evaluations were conducted using a real-case off-grid microgrid. The real-case data contained data from a micro-grid system of a village in Bolivia which has photovoltaic panels, battery storage, and a diesel generator. According to results obtained in the paper, the proposed model efficiently performed in the lifelong control of the off-grid microgrid for rural electricity management [84]. Hence, its potential deployment in large microgrids is promising.

In [85], an approach was developed to conduct demand-side management for households by producing a decision-making system that enabled an efficient battery management scheme. It successfully reduced the electricity cost of consumers, and further postponed investments for grid expansion when the electricity tariff of the day was very high due to higher loading period. The approach was based on an efficient recurrent neural network type, NARXNET. Validation was performed by configuring MDMS with different consumption and solar power scenarios for a set of households located at Sao Paulo city. Results proved efficiency of the decision-making system in managing battery usage, thus providing lower electricity bills [85].

Energy management system of multiple smart homes using a novel federated reinforcement learning approach was proposed in [86]. In this approach, a hierarchically distributed model with different agents was used for the energy system. The agents interacted with each other to optimally schedule the energy systems of several smart homes. A2C was implemented as reinforcement learning method in the paper. A private dataset was applied for the implementation of the proposed approach. Obtained results were promising since efficient management of scheduling energy systems for multiple smart homes was accomplished within considerable time [86]. The proposed approach can be beneficial for smart homes.

In [87], a noncooperative stochastic game perspective was used to model interactions between households and power grid. With the aim of searching for Nash equilibrium in game theory, a distributed deep reinforcement learning method was proposed in the paper. A real-case dataset from Pecan Street Inc. was used for implementing the proposed approach. A deterministic policy gradient-based method, known as the distributed power consumption schedule, was used to solve the problem. Performance comparisons between the proposed method and both centralized DDPG and distributed DDPG were accomplished for various household scenarios [87]. As per results obtained in the paper, faster real-time control with respect to model-based method enabled the approach to become a promising alternative for intelligent algorithm deployment in smart grids.

A deep RL approach based on DQN for demand-side management was proposed in [88]. The approach was compared with mixed integer linear programming for load peak reduction, and two case studies for residential demand response in smart grids were used for implementing the proposed approach. The first case minimized energy utility bill, while the second further reduced the energy utility bill by simultaneously lowering peak and cost. DQN was used as the reinforcement learning method. The proposed approach using DQN outperformed previously applied mixed integer linear programing (MILP) methods in the two experiments [88]. Obtained results in the paper demonstrate the potential of the proposed approach for smart grid deployment.

In [89], a task scheduling-based demand-side management was examined for integrated home energy management system. A deep reinforcement learning was utilized for the task scheduling-based demand-side management. DDPG model was compared with A3C (asynchronous advantage actor-critic), DQN, full local execution, and full SHOP methods. For real-case deployment, a dataset consisting of load, day-ahead, and real-time prices for ISO New England Control Area was employed. The task scheduling problem was formulated as an MDP to maximize reward of residential users, incorporating energy cost, execution time, shop server fee, and penalty of demand side management. Extensive comparisons revealed that the utilized method outperformed all other methods in the task scheduling problem for smart grids [89].

In [90], virtual power plants were deployed to efficiently manage and improve the stability of power systems using several distributed generation units since such work usually required elaborate planning. Due to several characteristics in distributed generation systems, timeliness and reliable communication between generations and load sides will need reliable economic dispatch from virtual power plants. In this paper, DRL algorithm was proposed to achieve optional online economic dispatch using virtual power plants. Offloading computation and communication loads to network edge was considered for satisfying near-real time communication and computation, successfully achieving economic dispatch in VPPs. A3C was used as reinforcement learning algorithm, and it was later compared with DPG method in terms of average cumulative cost. The proposed approach was also compared to DPG and DDPG regarding computational time requirement. The proposed approach outperformed all other methods as per results presented [90].

In [91], reinforcement learning was applied with edge-cloud integrated solutions for demand response management of smart grids, and RL agent of the proposed approach learned optimal control policy on the cloud infrastructure. The learnt policy was then distributed to edge devices for policy execution in the demand response management. A3C and Ape-X methods were used in the proposed approach. Utilized dataset consisted of data collected from a smart device in a real building. A utility company, building, and cloud service provider were synergistically connected. According to the implementation results, the proposed approach could be streamlined for real-time RL control execution and controller training in an end-to-end manner with minimal human intervention. Results of the proposed approach further highlighted the financial feasibility of the RL controller for smart building types [91]. This method is promising for cost-efficient, large-scale deployments in smart buildings.

In [92], a new approach was implemented based on reinforcement learning and blockchain to create a secure demand-response management scheme with the aim of reducing energy consumption and cost. Q-learning was used to determine optimal price decisions for reducing energy consumption. Q-secure demand-response management approach was then applied to handle data security, incorporating off-chain storage. U.S. dataset obtained from the Pecan Street database was utilized since it contained multivariate data from New York where day-ahead energy prices were obtained from PJM's Data Miner. According to re-

Table 3
Research on smart energy.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
	[69]	2019	Smart energy grid management	RL	RL	Q-learning
	[70]	2021	Micro energy grid management	RL	RL	A3C, PPO
	[71]	2020	Smart home energy scheduling	RL	RL	Q-learning
	[72]	2021	Smart building energy management	RL	RL	SAC
	[73]	2021	Smart home energy management	RL	RL	DQN
	[74]	2020	Short-term residential load forecasting	SL	Regression	DNN
	[75]	2020	Microgrid energy management	SL	Regression	LSTM-AE
	[76]	2021	Smart building energy scheduling	SL	Regression	LSTM
	[77]	2021	Residential buildings energy management	RL	RL	Q-learning
	[78]	2019	Demand response for home energy management	SL & RL	Regression & RL	Q-learning
	[79]	2020	Smart home energy scheduling	RL	RL	DDPG
	[80]	2016	Energy consumption prediction	SL	Regression	FCRBM
	[81]	2015	Demand side management	SL	Classification	ANN
	[82]	2016	Smart home appliance scheduling	SL	Regression	ANN
	[83]	2022	Microgrid energy scheduling	RL	RL	PPO
	[84]	2021	Off-grid microgrid control	RL	RL	Dyna-PPO
	[85]	2018	Demand side management	SL	Regression	NARXNET
	[86]	2022	Multiple smart homes energy scheduling	RL	RL	A2C
	[87]	2021	Load scheduling in residential smart grids	RL	RL	DPG-based algorithm
	[88]	2020	Residential demand side energy management	RL	RL	DQN
Smart Energy	[89]	2021	Demand side energy management in smart homes	RL	RL	DDPG
	[90]	2020	Dispatching of virtual power plant	RL	RL	A3C
	[91]	2021	Demand response management based on an edge-cloud	RL	RL	A3C, Ape-X
	[92]	2022	Demand response management in smart grid system	RL	RL	Q-learning
	[93]	2021	Control in smart home energy management	RL	RL	AC-based method
	[94]	2021	Electric vehicle smart charging strategy scheduling	RL	RL	DQN
	[95]	2019	Prediction in microgrid management	SL	Regression	LSTM
	[96]	2019	Secure computation offloading in Fog-Cloud-IoT	RL	RL	Q-learning

sults of the paper, the approach remarkably reduced both energy consumption and cost as well as data storage [92]. This success is promising since it may address large network bandwidth and latency issues in terms of energy data security during real-time access in the future network era.

In [93], optimal energy control and management approach to reduce energy consumption cost for smart home systems was proposed using actor-critic learning. An existing dataset in the literature was utilized in the study. The proposed approach was compared with two Q-learning variants and the baseline. The results revealed the superiority of the proposed approach in the optimal energy control for smart home systems [93].

In [94], reinforcement learning approach was used to coordinate charging in smart charging systems by considering baseload present in power grids. The approach could coordinate charging schedules of any sized fleet of electric vehicles, and it was flexible and fully scalable to an arbitrary number of participating electric vehicles. The approach managed to reduce the grid impact of electric vehicle charging from a charging provider. The proposed approach provided a centralized smart charging coordination system for a scalable EV fleet with a single agent. DQN was also used in this study. The proposed approach was applied in 250 households and 50 commuter electric vehicles, with each possessing a 30 kWh battery [94]. Obtained results proved that the proposed approach could be applied in real-time applications and uncertain environments for optimizing charging systems in a reasonable and efficient manner.

Virtual Power Plants (VPPs) provide a cloud-based distributed power plant environment by incorporating different distributed energy resources that enhance power generation management. VPPs are important for maintaining system stability in smart grids, providing flexibility in an energy network and enhancing trading and forecasting in the system. Thus, they will be vital in smart grid management.

In [95], LSTM method was used as the machine learning algorithm. The proposed approach conducted cooperative learning of LSTMs in a distributed environment, which is a significant development in the context of smart grids. LSTM was applied for predicting each plant. To enhance accuracy of predictions, information was shared between the agents in the environment, which established cooperation between agents. The proposed approach was known as the distributed average consensus LSTM model since it created distributed cooperative learning without using a coordinator between agents. It was deployed in a photovoltaic plant located near Denver, Colorado in the US. Relevant data was acquired from the Measurement and Instrumentation Data Center database for deployment of the proposed approach. Three different LSTM models were applied and compared in terms of RMSE metric. According obtained results in the paper, the proposed LSTM variant, the distributed average consensus LSTM, performed well as compared to L-LSTM. Its performance was similar to C-LSTM but with an improvement in long-term forecasts [95].

In [96], a hybrid method consisting of particle swarm optimization (PSO), neuro-fuzzy system, and reinforcement learning was deployed for a secure computation offloading scheme in the Fog-Cloud-IoT environment by using synergistical effect of the used methods. The proposed method made contributions to offloading latency, and minimized energy consumption simultaneously. PSO method conducted optimal node selection for offloading IoT workload while Q-learning achieved suitable cloud selection at the fog level. The neuro-fuzzy model was used to isolate IoT nodes that could congest the network by sending invalid data. The proposed method was implemented in a Fog-Cloud-IoT network, including one smart gateway, 5–10 IoT mobile devices, one hybrid cloud server, and five fog nodes. The proposed method was compared against other methods, and the comparisons were made in terms of throughput, delay, energy consumption, utilization rate, and response time. According to results obtained in the paper, the proposed method securely and effectively balanced trade-off between latency and energy consumption [96].

Table 3 presents summarized papers regarding smart energy.

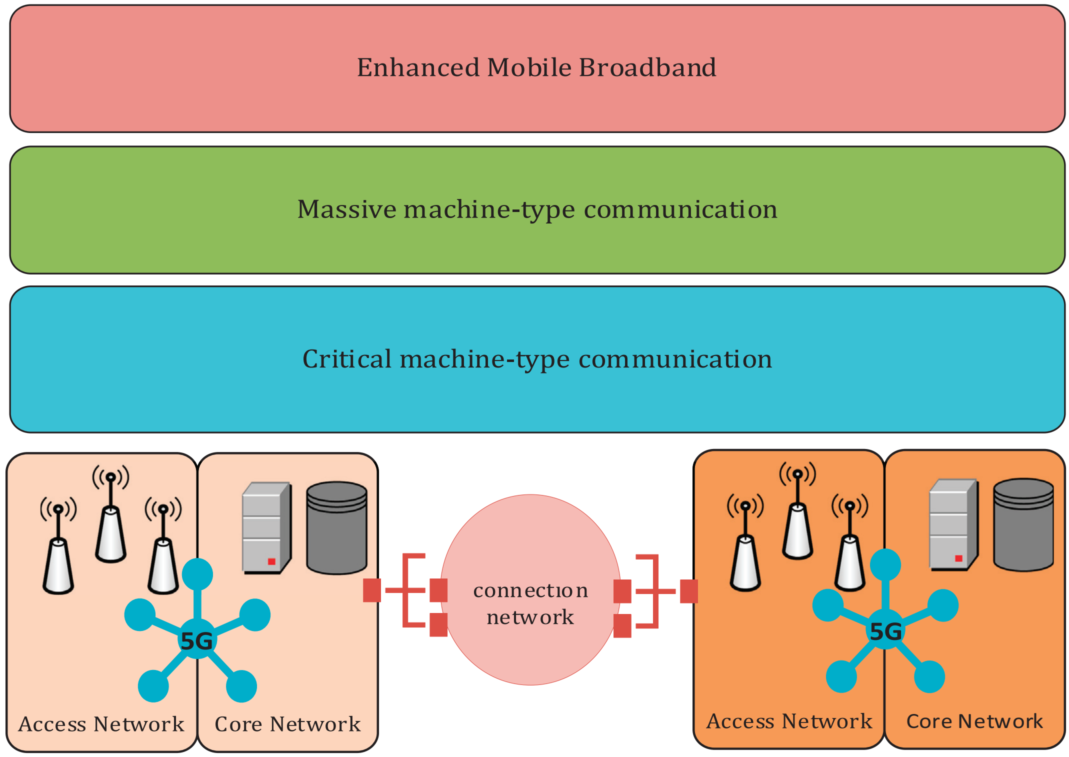

Fig. 7. Cyber security system.

3.3. Cyber security

Cyber security issues are significant problems in recent intelligence-assisted systems. With the advancement of IoT and blockchain technologies enabled by future mobile communication systems, managing cyber-physical systems will have landmark importance since they can move between physical and cyber systems with intensive intelligence assistance. However, security issues in these cyber-physical systems are growing. It is crucial to maintain system stability and secure operations. Numerous problems have currently emerged in cyber-physical systems, such as data integrity attacks, anomaly detection, system authentication, and intrusion detection, and etc. Studies are still ongoing to address these problems, and this subsection briefly discusses relevant research papers on cyber security. Fig. 7 presents an illustrative example of a cyber security system.

Smart grid systems provide reliable and robust operations for power grids as well as remote control with advanced information and communication control. However, the real-time monitoring of such systems is extremely important for secure management. False data injection attacks may harm cyber-security in control and operation of power grids since smarter grids are more vulnerable to cyber-attacks.

In [97], an AI-based method was proposed to spot false data injection (FDI) attacks, eradicating them by singling out malicious meters in a power grid system. A previously proposed approach for attack detection was used in combination with ANN and ELM. In this mechanism, after successful detection of an attack by Kullback-Leibler (KL) divergence-based method, AI-based load estimator detected the attacked meters using ANN and ELM. Preventive measures were then taken to maintain system stability. A real case NY ISO data were used to simulate the capability of attack and meter detections in real time. According to results obtained in the paper, ANN exhibited superior performance, however, ELM's computational time was shorter. For large-scale smart grid deployments, applied methods may require some trade-off between accuracy and computation time complexity [97].

The crucial role of state estimation in monitoring and managing smart grids is obvious to maintain grid system stability. Data integrity attacks may pose risks to power grids. In [98], deep Q-network detection-based approach was proposed to defend against data integrity attacks in alternating current power systems. The proposed approach was compared with other reinforcement algorithms, and successfully outperformed them in terms of detection accuracy and speed. Three evaluation metrics were defined and used in performance comparisons which they are delay-alarm error rates, false-alarm error rates, and detect-failure rates. Two attack models were designed for evaluations: continuous attack model and discontinuous attack model. Experiments were conducted using IEEE 9, 14, and 30-bus systems. With computational time complexity, the algorithm was found to require further enhancements for more efficient functionality in real-time systems [98].

In [99], a novel 5G-oriented cyber defense architecture based on deep learning method was proposed to effectively detect cyber threats in 5G mobile networks. A well-known botnet dataset (the CTU dataset) was utilized, consisting of 13 scenarios with several infected computers and seven botnet families. It was employed to prove the efficiency of a neural network model for the anomaly detection system that consisted of two sub-systems: anomaly symptom detection (ASD) and network anomaly detection (NAD). LSTM network was applied in the implementation of NAD. DBN and SAE models were used in ASD to perform symptoms detection. Local anomalous traffic conditions occurred in a short time period, and all gathered symptoms were fed to NAD with a merged form. LSTM recognized temporal patterns of cyberattacks. Classification performances were evaluated in terms of precision, recall, and the F1 score. According to results obtained in the paper, the proposed approach proved its self-adaptability in the anomaly detection system which had large volumes of network flow gathered in real time from user equipment of 5G subscribers. The paper demonstrated capability of the proposed approach to self-adapt in managing traffic fluctuations [99]. According to conducted experiments, the approach is suitable for evaluating traffic in a real 5G scenario, which is promising for future network systems.

In [100], LSTM-based autoencoders were used for anomaly detections in smart grids. Simple autoencoder, variational autoencoder, and attention autoencoder were used for this problem. The experiments utilized two datasets containing a large volume of the daily usage patterns of different appliances from real customers. The first dataset was acquired from the State Grid Corporation of Chine (SGCC), while the second was from the Irish Smart Energy Trial (ISET). The proposed approaches were compared with several machine learning methods using different metrics. Results obtained showed that deep learning-based attention autoencoder model exhibited notable improvements in false alarm rate and anomaly detection in smart grids [100].

In [101], cyber-attacks and anomalous behavior identification in different levels of a power grid system was proposed using deep learning. The IEEE 9-bus system was used in the study, and Nonlinear autoregressive (NAR) neural network was applied to capture underlying behaviors of the power grid system and to detect any cyber-attacks. As per results obtained in the paper, the proposed approach can successfully detect cyber-attacks in power systems, making it suitable for the new 5G era [101].

In [102], hybrid authentication, data privacy, preservation approach based on machine learning, and a cryptographic parameter-based encryption and decryption algorithm were proposed. The approach assured authentication of legitimate IoMT-based-cyber-physical system with encrypted data transmission through wireless communication channels. The proposed approach performed impressively in security features. RF model was utilized as machine learning method, and a real dataset was utilized to recognize smart phone users during ML implementation. The proposed approach produced encouraging results in efficiency and resilience against several security threats, thereby enhancing security analysis, computation cost, computation time, storage memory, authentication latency, and parameters [102].

To efficiently detect attacks, various smart home security attacks and quality of features used in detection algorithms were examined with the deployment of several machine learning algorithms [103]. Due to IoT devices' vulnerability to several attacks, an intrusion detection and prevention system (IDPS) for smart homes was analyzed in this paper. Effective intrusion prevention mechanisms and a software-defined networking (SDN)-based architecture of IDPS were used in smart home networks. Several ML methods were applied to analyze the impact of features. A realistic smart home testbed containing commercially available IoT devices was the first dataset used. The second was a dataset available in the literature, known as NSL-KDD. Machine learning algorithms used included DT, KNN, RF, bagging, AdaBoost, and voting classifiers. Performance of the algorithms using various attack detections with different features were compared in terms of detection rate. ML and SDN-based intrusion detection and prevention systems provided a solution for cyber-attacks targeting smart home security and privacy. The proposed approach can be a guideline for future projects interested in building datasets that include ML-based intrusion detection systems in IoT networks. Other than using the ML method, it was found that the applied feature set is also an important factor for detection accuracy [103].

Different cyber security attacks can be encountered in IoT systems. A novel lightweight random neural network-based prediction model was proposed for IoT-based data in [104]. With the proposed method, a new machine learning-based scheme to detect cyber-attacks for industrial IoT was presented by random neural network, and the proposed method was deployed for an open-source dataset named DS2OS. Comparisons were conducted with several machine learning methods in terms of accuracy, precision, recall, and F1 score. Real-time deployment of the proposed attack detection method was accomplished on a single-board computer using Raspberry Pi 4B with Intel Neural Compute Stick 2. Results indicated that the proposed approach was easy to implement at the edge for IoT attack detection and can be beneficial in future smart system applications [104].

In [105], mobile edge computing (MEC) and physical-layer security for emerging cyber-physical systems were combined, and a security problem was solved by deep reinforcement learning (DRL) and convex optimization (CO) algorithm, accordingly the algorithm was dubbed as DRCO. A secure mobile edge computing in which some eavesdroppers attacked a network that threatened task offloading was studied to ensure an efficient and secure MEC. In the paper, finding a proper solution for offloading ratio was performed by DRL, and allocating transmission power and computational capability was done by CO. In addition, offloading strategy making was performed by DQN, and the convex optimization was used for transmission power and computational capability allocation after the DQN determined a specific offloading ratio for the convex optimization. The proposed algorithm was compared against two different algorithms for MEC.

In [106], an intelligent reflecting surface-assisted mobile edge computing network was studied as a cyber-security problem in physical-layer in a network. The aim in the paper was to secure data transmission rate for ensuring physical-layer security. DDPG was used for optimizing system performance, and it tried to learn and perform resource allocation and task offloading decisions for MEC network in order to optimize cost of latency and energy consumption. Impacts of different resource schemes oftentimes existed in MEC network and different resource allocation schemes were considered in applications in the paper. The authors compared different resource allocation schemes, and they found out one version, devised criterion, had superior performance over the other schemes and robust enough for performing well with different conditions of MEC networks.

In [107], an AI-based trust and privacy preserving system (ATPS) for vehicle management in VANETs was proposed. Authors of the paper considered privacy-preserving as a wholistic approach in terms of data trustworthy, data availability, protection performance in the VANETs, and proposed a novel method called ATPS. With the ATPS system, they aimed to protect privacy of data providers with data availability at the same time, and maximize the original data trustworthy. ATPS used Wasserstain Generative Adversarial Networks as AI tool, and trajectory privacy protection for vehicular data provider was performed by WGAN and differential privacy. As per obtained results, the ATPS method significantly improved data quality, reduced malicious vehicle participants along with vehicle privacy protection and data availability ensuring.

Global air connectivity is obtained through UAV use, but some technical problems such as wireless communication deployment and channel modeling in this communication system will still remain as obstacles. UAV-assisted communication in agriculture system was intended in [108]. In an agriculture deployment, safe operation of agricultural information systems and data security of smart agriculture were aimed through UAV-assisted communication systems use in the paper. Agricultural IoT intrusion detection system based on machine learning was implemented through deep reinforcement learning for UAV localization and trajectory planning, and hybrid CNN + LSTM for intrusion detection system. Authors of the paper used KDD-CUP99 data set in their experiments. Different parameters for performance evaluation of different UAV wireless network deployments were experimented by comparing DDQN, k-means, random static deployment, and global

Table 4
Research on cyber-security.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
Cyber Security	[97]	2018	Cyber-attack detection	SL	Classification	ANN + ELM
	[98]	2019	Data integrity attack defending	RL	RL	DQN
	[99]	2018	Anomaly detection	SL	Classification	DBN + SAE + LSTM
	[100]	2021	Anomaly detection of electricity cyber attacks	SL	Classification	LSTM-based AEs
	[101]	2019	Cyber-attack detection	SL	Regression	NARNET
	[102]	2022	Authentication of cyber-physical systems-mIoT case	SL	Classification	RF
	[103]	2022	Intrusion detection and prevention in smart homes	SL	Classification	DT, KNN, RF, Bagging, AdaBoost, Voting
	[104]	2020	Attack detection in smart homes	SL	Classification	Random NN
	[105]	2022	A secure MEC for emerging cyber-physical systems	RL	RL	DQN
	[106]	2022	An intelligent reflecting surface-assisted MEC	RL	RL	DDPG
	[107]	2022	Privacy protection in VANETs	SL	Classification	GAN
	[108]	2023	Agricultural information security and intrusion detection	SL&RL	RL & Classification	DDQN, CNN + LSTM
	[109]	2023	Secrecy energy efficiency maximization for picocells	RL	RL	Dueling double DQN
	[110]	2023	An IoT intrusion detection model for metaverse security	SL	Classification	GAN + DAE + RF
	[111]	2023	Securing edge computing vulnerability	RL	RL	Q-learning

position information-learning algorithms, and the global position information-learning algorithm outperformed the compared algorithms in most of wireless network scenarios as per given results in the paper. Then, with the setting of the proposed wireless network system, CNN, CNN + LSTM, and one generic algorithm were compared, and hybrid CNN-LSTM method outperformed the other methods. From obtained results, LSTM introduction into CNN significantly contributed to performance of the intrusion detection system.

In [109], a multi-agent cooperative deep reinforcement learning-based approach was proposed for secrecy efficiency maximization for picocells in a 5G heterogenous network. Beamforming vectors of picocells, channel allocation, and power control were jointly optimized with the aim of boosting average secrecy rate with reduced power consumption consideration in the paper. In the problem setting, a two-tier HetNet that had a sub-6 GHz macro-cell and multiple mm-Wave picocells were considered. In eavesdroppers' medium in realistic-time varying channels, the average secrecy energy-efficiency of the picocells were maximized through the multi-agent DRL approach. The proposed approach, dueling double deep Q-learning, was compared against Q-learning-based and deep Q-learning-based multi-agent reinforcement learning secrecy energy-efficiency approaches, joint beamforming-based secrecy energy-efficiency, and one-time pad-based encrypted data transmission approaches. Secrecy rate analyses of the approaches were performed along with algorithmic analyses. As per obtained results, the proposed approach outperformed the compared approaches in terms of the average secrecy energy-efficiency performance of picocell users.

A software defined network IoT intrusion detection model for a metaverse security was considered in [110]. A novel method combining deep auto-encoder, generative adversarial network, and random forest was proposed for the intrusion detection problem. The deep auto-encoder performed data feature extraction and representation while the generative adversarial network made imbalance processing for data and data optimization. Random forest model finally performed classification. A public-available data set, InSDN, was used for experiments in the paper. Four different models, which they were CNN, LSTM, CNN + LSTM and the proposed model, were compared for both binary classification and multiple classification for the detection system. The methods were compared in terms of accuracy, recall, and precision metrics. As per obtained results in the paper, the proposed method outperformed the compared methods.

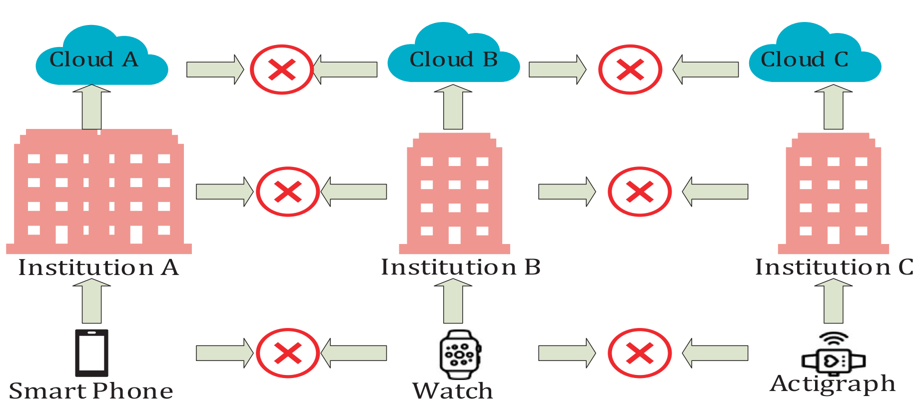

Fig. 8. Smart healthcare framework based on cloud.

In [111], a security framework for edge computing vulnerabilities in smart cities through genetic algorithm-based reinforcement learning combined with a distributed authorization algorithm was developed. A secure framework modeling was done by the authorization algorithm called secure trust-aware philosopher privacy and authentication to mitigate privacy breaches in networks, then genetic algorithm-based reinforcement learning approach was used for optimizing the search, and detecting anomalies in the networks along with finding shortest route during the RL agent's learning process. The RL method was compared against existing methods for anomaly detection frameworks in the literature. As per results obtained in the paper, the proposed approach outperformed the compared approaches in terms of F1-measure, precision, and sensitivity.

Table 4 presents a list of summarized papers on cyber security.

3.4. Smart health

The next generation network systems will contribute to enabling remote and real-time smart healthcare services. Data collected from different sources in future network-enabled systems (such as medical IoT, wearable devices, and smart health sensors) are steadily increasing, thereby playing a crucial role in enhancing smart healthcare. Fog computing, cloud servers, short and long-range wireless communications, portable processing units, IoTs, and blockchain further assist in the expansion of smart healthcare. These systems combined with machine learning methods synergistically contribute to the efficient diagnosis and treatment of diseases, providing more reliable and secure management for smart healthcare operations. Healthcare can also be personalized with the assistance of next generation network systems. It is expected that remote robotic surgeries will be more likely a common concept in the near future with the assistance of u-RLLC in future network systems. Smart healthcare assisted by next generation networks will expand remote healthcare services, and positively contribute to daily life by benefitting the disabled, the elderly sections, etc.

With the vast applications on healthcare enabled by the future networks, innovations will be more possible in this field. This subsection presents smart healthcare and machine learning applications in the existing literature. Fig. 8 presents a smart healthcare framework based on cloud.

A novel blockchain-based secured information management system as well as data and predictive analytics modules were designed in [112]. Real-case data consisting of healthcare appointment scheduling from a veterinary clinic at Jeju National University, South Korea were used for deployment of the proposed module. Machine learning methods were applied for two different cases. In the first case, several DNNs and SVR were compared in terms of RMSE, MAE, and R-squared metric for veterinary patient appointments. In the second case, LSTM was compared with different schemes for veterinary patient appointments. The proposed module contributed to overall performance in throughput and minimization of latency of the permissioned blockchain system [112]. As per obtained results in the paper, the proposed module has potential for smart healthcare implementation in 5G-enabled systems.

Multi-sensor-based framework for human activity recognition was conducted in [113]. Several deep learning methods, simple recurrent units, and GRU in the hybrid form were used for the framework. A mobile health dataset consisting of recorded body motions and vital signs of SHIMMER2 wearable sensors was used for deploying the proposed framework. It was compared the deep simple recurrent unit in terms of precision, recall, F1-score, and sensitivity metrics. The proposed framework outperformed compared method [113].

A voice pathology detection system was proposed in [114]. Deep learning-based mobile healthcare framework was utilized for the proposed approach. The aim was to improve accuracy of smart healthcare systems through deep learning. Audio captured by mobile smart sensors were processed, and predictions were made by the proposed approach. Two real audio datasets were used, and VGG-16, CaffeNet models, and several other conventional methods were compared in terms of accuracy, sensitivity, and precision through the datasets. The proposed approach based on CaffeNet outperformed all other methods [114].

In [115], a novel technique for smart healthcare systems was proposed to overcome several problems such as data availability in isolated island, privacy security breaching, etc. The approach was a federated transfer learning framework for wearable healthcare. This approach addressed the mentioned problems using data aggregation through federated learning. It made relatively customized models using transfer learning. The proposed framework was deployed for two datasets: wearable activity recognition data and real Parkinson data collected by smart phones. The framework was compared with KNN, SVM, RF, and without federated learning in terms of accuracy and F1 score, outperformed all other methods [115]. The proposed approach is promising for smart healthcare systems since it tackles several issues from the aspect of data management in healthcare systems. This will enable personalized and flexible healthcare solutions in smart healthcare systems integrated with IoMT technologies in the 5G era.

In [116], physical activity recognition was accomplished using CNNs. Data obtained from a multi-sensor system was fed to a deep learning model as it was encoded to an activity image. CNN was then used to extract multiscale spatio-temporal correlations from the image. In the method used, handcrafted and extracted features using deep learning were merged to be processed by a multiclass SVM. Authors implemented the method for three different real-life datasets available throughout the literature, and they compared the proposed method with several other methods that had used the same datasets in terms of accuracy. The proposed approach achieved outstanding performance in most of the comparisons [116]. IoMT-enabled computer-aided diagnosis has valuable and important in smart healthcare. It enables remote communication between medical experts and patients. One area where IoMT enabled CAD system can help would be cancer detection. In [117], brain tumor classification based on transfer learning integrated classifiers was performed using brain MRI images. An automated brain tumor classification was proposed to classify different brain tumor types. Authors of the paper deployed GoogleNet for feature extraction, then used several classifiers for the extracted features. Brain MRI images of patients were collected from Nanfang Hospital in Ghuangzhou, China and the general hospital of Tian-jin Medical University. Performance evaluation of the propose method was conducted using different classifiers and compared in terms of precision, recall, and specificity. The method produced the highest results for brain tumor classification [117]. Hence, the proposed method can potentially be applied to other IoMT-enabled computer aided diagnosis systems for smart healthcare.

IoT based real-time data acquisition systems will significantly contribute to smart healthcare systems. Machine learning algorithms will be beneficial since they can handle enormous amounts of data. During Covid-19 era, several machine learning techniques were considered for Covid-19 detection through speech and voice analyses. In [118], an efficient machine learning model for speech and voice analyses of Covid-19 patients was proposed, and later embedded in mobile health systems to enhance smart healthcare. The proposed approach used a dataset from a crowd-sourced database released by the Indian Institute of Science, Bangalore. Several machine learning algorithms were compared with the dataset in terms of accuracy, F1-score, specificity, precision, recall, and AUC metrics. SVM outperformed all other methods in terms of accuracy [118].

5G-enabled cloud computing and edge computing do provide low-latency and high-performance computing in 5G communication systems. Real-time output and data forgery detection in such systems are extremely important. In [119], a smart healthcare system was proposed for detecting forgeries of medical images using cloud and edge computing. The novel image forgery detection model consisted of noise-pattern extraction, a multi-resolution regression filter realizer, and two classifiers. Wiener-filter-based noise reduction technique was used for the noise-pattern extraction, while SVM-ELM was used as the binary classifier. Three datasets were utilized to implement the model. The first two were publicly available image datasets, CASIA 1 and CASIA 2, that contained both authentic and forged images. The third dataset consisted of real mammography images obtained from a healthcare database. The method was compared with several methods in terms of classification accuracy, and hybrid SVM-ELM outperformed all other methods. Another key aspect of the study was that the bandwidth consumption in bits per second, with and without edge computing, was also examined. The proposed model did not require much bandwidth as per obtained results [119]. It can therefore be implemented in other smart healthcare applications of future networks-enabled systems.

In [120], a fog-centric wireless, real-time smart wearable and IoT-based framework for smart healthcare and fitness analysis in a smart gym medium was proposed. The framework supported athletes, trainers, and physicians by providing several physical signs that alerted them in case of an emergency health situation. The fog-centric model in the framework achieved real-time response using a smart healthcare mobile application. The framework consisted of three layers: the IoT sensor network layer, fog node and services layer, as well as a cloud storage and analytics layer. Real-time data collection from IoT sensors were performed in the fog node layer. The same node also classified data and alerted athletes and trainers in case of any developing health risks. It further conveyed processed data to the cloud infrastructure for storage and analysis. The cloud storage and analytics layer processed data and created reports for athletes, trainers, and physicians. Four data sets were collected from smart gym devices supported by mobile applications during framework deployment. LSTM was used for classification task. Different scenarios were considered using the dataset. The proposed method achieved higher performance as compared to other methods. Performance comparisons were conducted in terms of precision, recall, and F1-score. In this framework, fog computing predicted health emergencies on the network edge in real time rather than using cloud, further contributing to smart healthcare operations [120]. The framework has potential in 5G enabled smart healthcare systems.

In [121], a safe architecture based on the Android system was proposed for acquiring patient data, and a reliable cloud-based system was used for storing data. A predictive model was also applied for cardiovascular disease classification. The main objective of this paper was to form a secure Android-based application for smart healthcare system which protected sensitive patient data. This would enable better designs of smart healthcare application on any device. A predictive model for cardiovascular disease was deployed for this smart healthcare system. Data included clinical health records and physiological signals collected from wearable sensor nodes. The proposed predictive method and the hybrid form of SVM and DT were compared with SVM, DT, KNN, and naive Bayes using the CVD dataset acquired from the proposed secure cloud-based storage model. Comparisons were made in terms of accuracy, sensitivity, and specificity. According to the metrics, the proposed method outperformed all other methods in most deployed tasks. Obtained results revealed that the proposed method can be employed in 5G-enabled smart healthcare systems [121].

A smart healthcare system that provided efficient, scalable, reliable, and secure AI-enabled IoT with low latency edge computing-based smart healthcare system was proposed in [122]. The collected health-related data were initially processed and analyzed at edge nodes, then stored and shared at the edge data centers. Scheduling patients and providing resources in real time were achieved by the edge nodes and edge controller in the system. Different sensors were used for computing several vital parameters of the utilized data. Various sensors were connected to Raspberry Pi and Arduino Yun boards. The collected data were stored in an edge node, and three edge nodes were used for representing hospitals. A neural network method was utilized to monitor transmission latency for evaluating system performance in real-world scenarios. Obtained results revealed that computing, optimization, and transmission latency were adequate in the deployed system [122].

Use of big data enabled by IoT is growing in healthcare applications. Unfortunately, big data also creates problems for databases and cloud systems since system performance degradations tend to emerge. Fog and edge computing are novel solutions that bridge the gap between users and resources, providing low latency and energy efficiency in data processing as compared to conventional types of data storage. In [123], a new framework based on ensemble deep learning in edge computing devices was proposed for automatic heart disease analysis. This framework was called HealthFog. It performed as a fog service using IoT devices, and processed heart patient data in real time by identifying the severity of the disease. The framework was tested using real-case data with

Table 5
Research on smart healthcare.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
	[112]	2021	Predictive analytics	SL	Regression	LSTM
	[113]	2019	Human activity recognition	SL	Classification	GRU
	[114]	2018	Voice pathology detection	SL	Classification	CNN
	[115]	2020	Activity recognition	SL	Classification	CNN
	[116]	2021	Physical activity recognition	SL	Classification	CNN + SVM
	[117]	2022	Brain tumor classification	SL	Classification	CNN
	[118]	2021	Detection of Covid-19 presence through voice and speech analysis	SL	Classification	SVM, AdaBoost, Naive Bayes, Bagging
	[119]	2018	Medical image forgery detection	SL	Classification	SVM + ELM
Smart Health	[120]	2021	Fog-centric IoT-based smart healthcare design	SL	Classification	LSTM
	[121]	2020	Cardiovascular disease detection	SL	Classification	SVM + DT
	[122]	2021	Healthcare monitoring system deployment	SL	Regression	ANN
	[123]	2020	Automatic diagnosis of heart diseases in IoT-Fog environment	SL	Classification	DNN

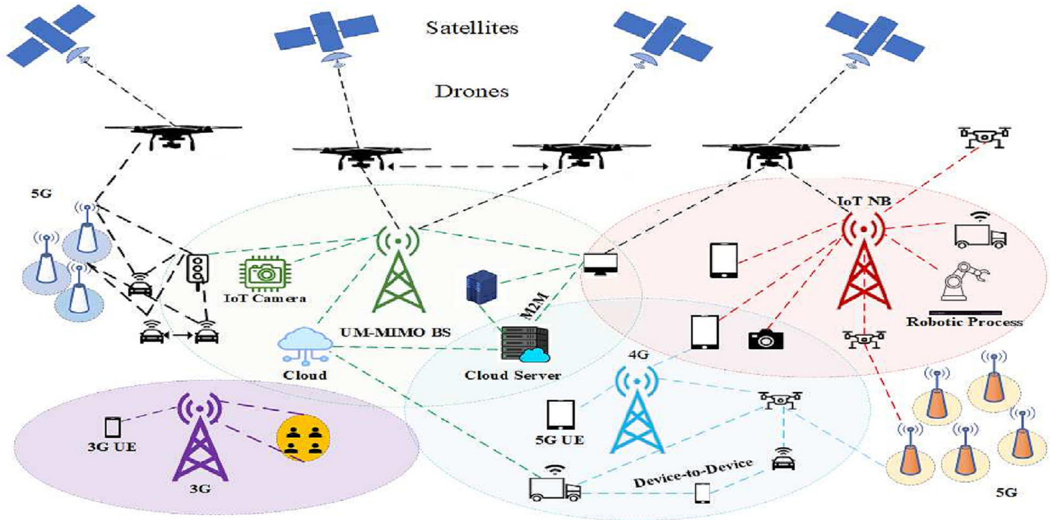

Fig. 9. UAV-assisted communication system.

different scenarios by applying deep neural networks based on the ensemble method. It achieved better results in the analysis of diverse fog computation scenarios and for different user requirements, exhibiting the best quality of service and prediction accuracy [123].

Table 5 presents studies on smart healthcare.

3.5. UAVs

UAVs are one of the disruptive technologies found in various fields. They provide a wide range of services such as cellular network assistance for both ordinary and emergency situations which maximize coverage area of the network. They also conduct inspection and detection tasks, serve as flying base stations to become a communication platform, network resource allocation, etc. UAVs will intensely contribute to quality of service and reliability in future generation networks. In 5G and B5G systems, network reliability and resource allocation will require much more consistent, flexible, and rapid solutions. These requirements can easily be met by UAVs since they provide reliable transmission efficiency, large coverage, and high flexibility when combined with intelligent methods in upcoming network generations. The use of the UAVs in 5G and B5G systems will likely be more apparent in the near future due to the potential benefits they offer. This subsection highlights use cases of UAVs. Fig. 9 further presents an exemplary UAV-assisted communication system.

In [124], an autonomous vision-based power line inspection approach was proposed using unmanned aerial vehicles and deep learning. A multi-stage component detection (MSCD) pipeline based on a multi-box detector was employed with deep residual networks, and data were collected from sensors. The data from the cameras mounted on UAVs were fed to the proposed approach, and augmented to perform better tasks. The approach exhibited significant improvements in autonomous inspection [124]. The proposed approach is promising for fully automated UAV inspections, and for directly operating on GPUs of UAVs.

In [125], an automated deep learning-based approach was developed to support manual detection of damaged wind turbines. Two real datasets acquired from wind turbines were used for applying the proposed method. With different data augmentation strategies, Fast R-CNN methods were compared with several existing CNN backbones. As per results obtained in the paper, the automated damage detection system was more cost efficient than manual inspection systems. The results were promising for partially automated inspection and analysis processes for damage detection since it minimized cost and human intervention [125].

In [126], a multi-layer perceptron and LSTM were applied to detect the position of UAVs. The aim was to maximize the overall system performance and user throughput that would subsequently enhance network performance for users. To evaluate system performance, a hybrid MLP-LSTM was deployed for classification and regression tasks, and k-means was used with MLP-LSTM to automatically cluster classes.

Class and grid-based data were gathered from several mobile users and UAVs. The data consisted of real-time data recordings from the National Taipei University of Technology, Taiwan. The method used was compared with SVM, MLP, and LSTM under different scenarios for assessing the positioning accuracy of UAVs. According to obtained results, the used method successfully achieved both tasks of classification and regression-based positioning [126].

UAV applications are more widespread and expected to grow in the near future. The connectivity of UAVs will thus be a crucial issue. Several challenges may emerge when establishing reliable wireless connectivity with secure operations, such as mobility management, handovers, cyber-physical attacks, and authentication issues. Therefore, ANN-based solutions were proposed to take advantage of wireless system resources of UAVs and ensure secure operations in real-time [127]. In [127], issues regarding UAV-based delivery systems, UAV-based real-time multimedia streaming networks, and UAV-enabled intelligent transportation systems were considered for potential deployment. A deep RL approach based on Echo State Network (ESN) was used to optimize the trajectories of multiple UAVs online. By performing this optimization, a reduction in latency and interference was possible for multiple cellular-connected UAVs. The proposed approach produced promising results. The next issue was user content request, which was also successfully managed. Based on a user's context information (such as gender, job, and age), the ESN-based algorithm determines the distribution of user content requests. As per these distributions, UAVs could determine the content to be stored at the UAV cache, thereby conveying the content to relevant users without backhauling.

A real-case study was considered in this paper, and the proposed approach was deployed for this real case study, exhibiting satisfactory performance. For the issue of security and authentication, LSTM-based deep RL method was applied. The proposed approach was compared with two baselines, and outperformed the compared baselines both in terms of vulnerability to cyber-attacks [127].

In [128], an interference-aware path planning for a cellular-connected UAV network was considered. In this scheme, the ultimate goal was to achieve a trade-off between energy efficiency maximization and both wireless latency and interference for each UAV in the network through ground network minimization. A novel multi-agent deep RL approach integrated with ESN was proposed for interference management. The study provided interference-aware path planning of cellular-connected UAVs based on deep ESN. A novel multi-agent reinforcement learning approach with ESN cells enabled numerous UAVs to optimize their trajectories online in cellular-connected UAV networks. The proposed approach required UAVs to jointly and autonomously learn their own path in a dynamic non-cooperative game condition. The approach was deployed for a system containing 15 BSs. The 800 m $\times$ 800 m square area was divided into 40 m $\times$ 40 m grids, and its performance was compared with the shortest path baselines for various scenarios. The proposed approach contributed to a trade-off between wireless latency, energy efficiency, and interference for the ground network [128].

In [129], a DRL-based intelligent solution was proposed to detect the best position for multiple drone small cells in an emergency scenario. The aim was to maximize the total coverage area for users under the constraints that drones may be hindered by backhauling and limited radio access network restrictions. Q-learning, that was the integral part of the intelligent solution proposed, was used as the machine learning approach in the paper to identify the best position for multiple drone small cells in an emergency scenario by performing maximization the total coverage area for the users under the mentioned constraints for the drones. In addition to maximizing the total coverage area, Q-learning could identify the best position of each drone small cell in the environment by minimizing the outage of users in radio access network as well. An urban scenario published in an earlier work was modified and adopted for deploying the proposed approach. A previously functional network that was completely destroyed due to a natural disaster was considered for the case setting, and the proposed approach was compared with various other methods. It outperformed all other methods in terms of identifying the best position for multiple drone small cells according to some metrics. The results showcases the importance of mobile BSs, which are suitable for dynamic environments in future cellular networks [129].

In [130], UAVs serving as aerial base stations were proposed to enable coverage and performance enhancements in communication networks for different real-world cases. Achieving certain communication coverage in a group of UAVs is a challenging task. A novel method was suggested to enhance DRL for controlling a group of UAVs using a highly efficient model. The method controlled connectivity and coverage, learnt and adapted in a dynamic environment. A simulation scenario consisting of numerous UAVs flying horizontally was accomplished to provide communication coverage for ground users in a particular location. The specified region was divided into K cells. Each UAV knew its own location within the setting. A point-of-interest (PoI) was defined at the center of each cell which was covered by at least one UAV for a reasonable amount of time. A DDPG-based energy-efficient control for coverage and connectivity method was used as the DRL approach, and it was then compared with two commonly used baseline methods (random forest and greedy algorithm) in simulation experiments. As per obtained results, the utilized method outperformed the compared methods in terms of average coverage score, average energy consumption, energy efficiency, and the fairness index [130].

In [131], a trajectory design framework of multiple UAVs was proposed. User mobility information was utilized with ESN and multi-agent Q-learning. Joint trajectory design and power control were used for maximizing the instantaneous sum transmit rate to simultaneously meet satisfaction rate and user coverage requirements. The proposed framework consisted of three-step deployment. First, a multi-agent Q-learning based placement algorithm was used to identify the initial deployment of UAVs. Second, user mobility was predicted using an ESN. Finally, the multi-agent Q-learning was used for trajectory acquisition and power control of UAVs. The proposed framework applied to a real dataset consisting of user mobility information collected from Twitter. As per obtained results, the proposed framework could potentially support the UAV wireless network by maintaining high quality user experience in mobility management [131].

In [132], a user association approach was proposed using a dual-UAV-enabled wireless network with D2D connections. The approach conducted user association optimization by maximizing the sum rate of UAV-served users and the total number of D2D-connected users. A learning-based clustering algorithm and an optimization approach were used for this method. In the first phase, users served by UAVs were regarded as cluster centers. In the second phase, the learning-based clustering algorithm determined user clusters via D2D connections. This method was implemented for an existing problem in the literature. According to results obtained, the approach achieved good results with low complexity due to the algorithms applied in the paper [132].

In [133], a novel framework was proposed for rapid UAV identification using encrypted Wi-Fi traffic. In the proposed framework, features were extracted by only using the packet size and inter-arrival time of encrypted Wi-Fi traffic. Detection of UAVs and identification of their operation modes were then accomplished. This framework was deployed in a real-world Wi-Fi data traffic with eight types of consumer UAVs, and the dataset was created using a computer embedded system-assisted wireless network interface card. Detecting the type of UAV was achieved using the logistic regression-based learning algorithm, while identifying their operation mode was accomplished using multi-class classification methods, SVM, and RF. The proposed detection system was tested using a dataset that contained the presence of non-UAV data traffic. Linear discriminant analysis (LDA) method was employed to detect UAVs [133]. As per results obtained, the proposed framework may be used in other cyber-physical/IoT systems for different wireless communication systems.

A machine learning-based recruitment scheme collecting massive data with the collaboration of vehicles and UAVs in the IoT network was proposed in [134]. A genetic algorithm was used for vehicular collector selection to collect massive data from sensors. The aim was to maximize the coverage ratio and minimize employment cost. A novel DRL-based route policy was employed to plan the collection routes of UAVs with limited energy. DRL-R method combined two data collection schemes: the first was a vehicular collector that operated with larger coverage ratio within limited costs using a genetic algorithm, the second was the UAV collection process where data were collected from remaining static devices. The main aim was to minimize flying routes of UAVs while meeting data collection coverage criteria within an acceptable range. The A3C method served as the machine learning method, and the proposed technique was compared with other existing methods found in the literature. A trajectory dataset of vehicles in Beijing was utilized for deploying the proposed scheme. As per results obtained, the length of the data collection path was significantly reduced. Moreover, the coverage ratio of data collection further increased as compared to other methods (U5). Hence, the proposed scheme was suitable for application in smart 6G-based IoT systems [134].

In [135], an approach to enhance fairness in network resource allocation among vehicles was proposed by identifying UAVs on-demand as flying communication infrastructures. A DRL method was applied for determining the position of UAVs by considering their communication, flying range, and energy constraints. This would increase the efficiency and fairness of network resource allocation. A simulated scenario including a real-world dataset was used for the experiments, and an existing bus tracing dataset in Rio was incorporated for the experimental settings. The proposed approach applied the dynamic UAV placement method using real-world vehicle mobility traces. Different DRL algorithms, DDPG, PPO, and temporal difference (TD)-3 were compared with the proposed approach, and the comparisons revealed that SAC used in the proposed approach outperformed all other methods. For UAV positioning, the results revealed that the proposed approach did improve network resource allocation according to the targeted fairness objective [135]. This method can be a promising solution for network resource allocation in future network systems.

In [136], a deep RL-based collaborative computation offloading and resource allocation approach were proposed for an aerial-to-ground network service for emergency cases. A central network controller trained observations, then fed the trained data to a multi-UAV cluster network. In this approach, each UAV cluster head acted as an agent while autonomously allocating resources to eIoT devices in a decentralized manner. The agents performed computation offloading in the defined setting with the aim of minimizing task execution delay and energy consumption. Efficient solutions were also achieved by learning in a dynamic aerial-to-ground network. This technique applied DDPG as the machine learning method, and, in the experiments, the simulation settings incorporated the deployment of the proposed approach with parameter configurations of previous studies. The DRL method determined optimal computation offloading policy for the eIoT devices and allocated resources as observed in mIoT network. The DDPG was compared with greedy-based, DQN-based, and A3C-based methods in terms of convergence, time-delay performance, energy consumption performance, and UCH resource consumption. According results obtained, the proposed approach outperformed all other methods [136].

In upcoming network generations with high mobility environments, the tasks of predicting dynamic traffic and channel conditions while scheduling time division duplex (TDD) configurations in real time will be crucial. In [137], a channel model was considered for a heterogenous network with high mobility. A deep learning method for feature extraction and a deep reinforcement learning-based model were employed for allocating online radio resources using an intelligent time division duplex configuration algorithm. In this approach, DBN was used for feature extraction and the Q-learning-based RL algorithm was applied for adaptively changing the time division duplex up/down-link ratio. A simulation model was created using users' traffic demand patterns from the existing literature. DQN was compared to both the conventional model and the Q-learning-based algorithm in terms of packet loss rate and network throughput. Results of the paper revealed that DQN outperformed all other methods. According to the results, the proposed approach dynamically changed the TDD configuration to optimize up/down-link radio resource allocation with low overhead. The network performance revealed a significant enhancement in the packet loss rate and the network throughput [137].

In [138], a reinforcement learning-based task scheduling approach was proposed for UAVs. The proposed approach achieved automatic and dynamic adjustments of the UAV task strategy by using the calculation of task performance efficiency. It was able to coordinate UAV movements and achieve real-time networking of UAV clusters using a decentralized networking protocol. A simulated scenario was considered for implementing the approach. A deep reinforcement learning method based on deep strategy gradient descent approach with actor-critic constraints was employed for optimizing the value functions to schedule UAVs [138].

In [139], a virtual network function (VNF) was developed to achieve better resource utilization. Machine learning was employed for predicting the resource requirements as per the network traffic load. SVR and Kernel Ridge Regression (KRR) served as the machine learning algorithms. Three existing datasets were used as benchmarks, and KRR outperformed SVR in the benchmark study. As per results obtained, the machine learning algorithm helped in the dynamic allocation of resources to VNFs according to their requirements. Through the deployment, excessive and insufficient resource allocation were prevented, thereby reducing wastage of unused resources and preventing service quality decline. The proposed approach may enable URLLC enhancement for B5G networks [139].

Assisting ultra-dense networks with flying base stations will be a significant task during emergency situations. In [140], a communication resource allocation scheme was proposed for UAV-assisted UDN systems to improve the quality of user experience. DQN method was applied in the resource allocation scheme to maximize energy efficiency of ultra-dense network systems. A simulated case study and its parameters were in line with 5G specifications, as set by 3GPP standards and existing studies. The applied DQN approach was compared with several methods in terms of energy efficiency and computation time by considering the number of BSs and the minimum transmission power. As per obtained results, the applied DQN efficiently performed the resource allocation task to maximize the system's energy efficiency [140].

In [141], MEC was used for UAV-assisted communication in maritime environment to provide powerful computation capabilities in terms of latency aspect and resource limitations. Deep reinforcement learning was used to provide minimum latency for both computation and communication in the environment of UAV swarm MEC network, and it found the required number of virtual machines in the network. In the paper, DQN and DDPG methods were used for trajectory optimization of top-UAV in the MEC network, and configuration of virtual machines in the network. Performance of the used two deep RL algorithms were compared against some baseline algorithms in terms of total average latency, and obtained results showed that they outperformed the baseline algorithms. The DDPG algorithm performed better than the DQN in reducing the total average latency for the joint optimization, i.e. trajectory finding for top-UAV in the network and configuration of number of VMs in the network.

In [142], UAVs were used as edge clouds for large-scale distributed user equipment to provide reliable and stable network. Due to the UAVs constrained computation and energy characteristics, a collaborative MEC system including multiple UAVs and multiple edge clouds was studied. A cooperative multi-agent deep reinforcement learning model was performed with the aim of minimizing energy consumptions and sum of execution delays by regarding trajectory design, communication resource allocation and computation task allocation. Authors carried out simulations with different settings such as mobile UEs, and fixed UEs, and different UAV numbers in their simulations, and they compared the proposed method MATD3 with different MADDPG, MATD3 scenarios (fixed power and fixed height ones) and random scenario. According to obtained results, MADT3 method produced better results than the compared ones.

In [143], UAV placement method assisted by ANN use for enhancing an integrated UAV-D2D non-orthogonal multiple access cooperative network system was proposed. UAV placement scheme in the network through the ANN was considered, and the proposed method was compared for different network scenarios against two unsupervised learning methods, k-means and k-

Table 6
Research on UAVs.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
UAV	[124]	2018	Intelligent monitoring and inspection	SL	Classification-Object Detection	CNN
	[125]	2019	Intelligent monitoring and inspection	SL	Classification-Object Detection	Fast R-CNN
	[126]	2019	Throughput maximization in wireless communication	UL & SL	Classification, regression, and clustering	LSTM + MLP + k-means
	[127]	2018	UAV-based delivery systems, UAV real-time multimedia streaming networks, and UAV intelligent transportation systems	SL & RL	Regression and RL	ESN + LSTM based proposed deep RL algorithms
	[128]	2019	Interference management	RL	RL	ESN based novel multi-agent RL algorithm
	[129]	2018	Base station positioning for emergency cellular network	RL	RL	Q-learning
	[130]	2018	Energy-efficient UAV control for effective and fair communication coverage	RL	RL	DDPG
	[131]	2019	Trajectory design and power control for multi-UAV assisted wireless networks	SL & RL	Regression and RL	ESN + Q-learning
	[132]	2019	User association for dual UAV-enabled wireless networks	UL	Clustering	A clustering-based method
	[133]	2020	UAV detection and operation mode identification in encrypted wireless network	SL	Classification	RL, SVR, RF, LDA
	[134]	2021	Recruitment scheme for massive data collections in 6G IoT networks	RL	RL	A3C
	[135]	2021	Fair 5G bandwidth allocation in vehicular communication by UAV harnessing	RL	RL	DDPG, PPO, SAC, TD3
	[136]	2021	Collaborative offloading computation and resource allocation in multiple UAV-assisted IoT networks	RL	RL	DDPG
	[137]	2020	Resource allocation in high mobility 5G HetNets	SL & RL	Regression based autoencoding and RL	DBN + DQN
	[138]	2019	UAV cluster task scheduling	RL	RL	An AC-based model
	[139]	2022	5G assisted drone networks for dynamic resource sharing	SL	Regression	SVR, KRR
	[140]	2021	Resource allocation for UAV-assisted ultra-dense networks	RL	RL	DQN
	[141]	2022	UAV-assisted maritime communication with MEC	RL	RL	DQN and DDPG
	[142]	2022	UAV-assisted edge cloud for large scale sparely-distributed user equipment	RL	RL	TD3
	[143]	2023	UAV placement for integrated UAV communication	SL	Regression	ANN
	[144]	2023	Location optimization for UAV-base stations in the presence of mobile endpoints	RL	RL	Actor-Critic
	[145]	2023	Resource slice embedding for UAV-assisted edge computing	SL	Regression	LSTM

medoids. In the comparisons, non-orthogonal multi access device-to-device cooperative, non-orthogonal multi access, and orthogonal multi access schemes considering sum rate and spectral efficiency were the scenarios in the paper. As per results obtained in the paper, the proposed method in the UAV-supported device-to-device non-orthogonal-cooperative network would provide more high-quality and reliable communication for terrestrial users with respect to non-orthogonal multi access and orthogonal multi access schemes.

UAV uses as a support to ground base stations is of important issue in future mobile network systems. UAVs as they offer base station tasks for the future networks will provide cost-effective internet connection to more users as well as they can be used in emergency cases when ground base stations in the network fails. However, locating UAVs in a highly dynamic user environment creates an optimization problem for UAV-base station deployment. In [144], a continuous actor-critic deep reinforcement learning approach was used to solve this problem for optimally locating the UAV-base stations in the presence of mobile endpoints. Authors of the paper brought about novelty to the literature by introducing continuous action space rather than discrete one for the problem setting, thereby enabling use of continuous actor-critic algorithm. In addition, they designed a new reward function for the proposed RL approach that enabled the RL agent to receive both positive and negative rewards, thereby keeping the UAV-base stations inside boundaries of area of interest while simultaneously aiming to maximize sum data rates of users in a cellular network. Firstly, the proposed approach was compared against random movement, q-learning, deep q-learning, and Gauss–Markov methods, and obtained results showcased that the approach outperformed the other ones in terms of packet loss of endpoints, transmission delays, and data rate. Apart from these comparisons, the proposed approach was compared against two RL approaches in terms of algorithmic performance, and, as a result, it surpassed the compared approaches in this comparison as well. As future research direction, inclusion of energy limitation of UAV-base stations to the current problem will be considered that will turn the current problem into a joint optimization problem which simultaneously minimizes the energy consumption and maximizes data rate. In addition, 6G inter-cell interference inclusion to the problem might be another important future research direction to extend the research problem.

Mobile edge computing assists in alleviating pressure of core networks in the future mobile network systems. Edge servers' mobility and flexibility are improved through combined use of UAVs and the mobile edge computing. Managing and allocating resources for massive number of devices is a kind of hard issues to tackle. Energy limitation of UAVs also makes them less stable than fixed edge server. Hence, resource slicing may be one of the promising solutions in these constrained problem settings for UAV-assisted mobile edge computing. In [145], a survivable resource slice embedding algorithm was proposed through network

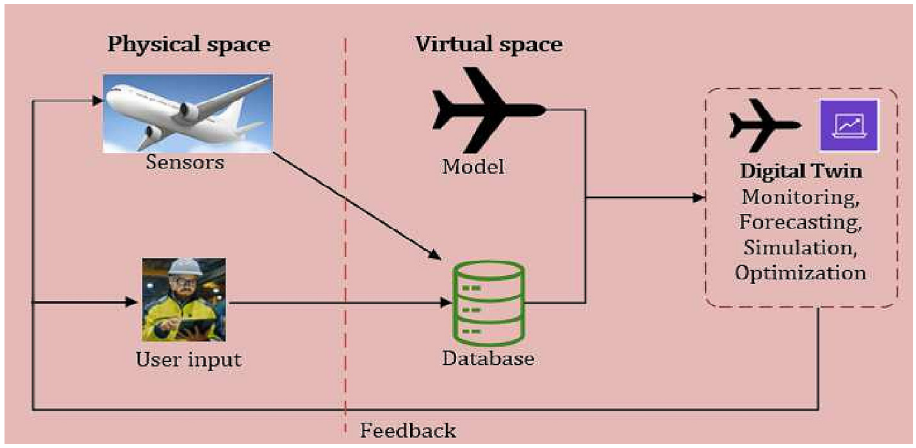

Fig. 10. A flight digital twin system.

slicing for UAV-assisted edge computing assisted by LSTM. The LSTM was used for forecasting workloads of resource slice, then resource slice algorithm for the UAVs was framed based on the forecast results. In case of the UAV failure in the edge computing system, a resource slice re-embedding algorithm was used to compensate the resource slice failure with minimum response time. A dataset was provided by a mobile operator in Ireland, including uplink and downlink transmission rates, access time, and mobile status of users. A real-world testbed was used to assess the proposed method's effectiveness by comparing it against two benchmark algorithms. As per results obtained in the paper, the proposed algorithm outperformed two existing algorithms, general network slice design algorithm and global resource capacity based survivable virtual network, in the system performance in terms of slice recovery ratio and consumption, and request acceptance ratio.

Table 6 presents available research on UAVs.

3.6. Digital twin

The main objective of a digital twin is to represent a virtual environment of an object or a system by integrating cyber space and physical space. For this objective, a replica of a physical system/object is created, and then updated by real-time data stream. It supports decision-making by using simulations and machine learning methods. Digital twin and simulations are similar, yet they differ in several aspects. Unlike simulations, a digital twin uses real-time data. A digital twin can also conduct multiple processes by running numerous simulations simultaneously. However, a simulation typically performs one particular process. 5G and B5G-enabled smart sensors, reliable communication of physical systems, low latency, and real-time system monitoring are the key driving forces that increase digital twin applications. For current and future applications, digital twin is a promising solution to easily manage physically large systems, manufacturing projects, and power systems with abundant data, and digital twin applications have recently spanned several fields. This subsection presents the digital twin use cases with machine learning applications, as reviewed from the literature. Fig. 10 displays an example of a digital twin application.

An intelligent context-aware healthcare system using the digital twin framework was proposed in [146]. The framework contained an ECG classifier utilizing machine learning in the diagnosis of heart disease. In the framework, IoT wearable sensors first acquired data, then conveyed that data in real time as the body metrics of patients. These sensors monitored health status and early detection of abnormalities. The utilized machine learning algorithms included CNN, MLP, logistic regression, LSTM, and SVR. The algorithms were used to sense the electrodes of ECG rhythms obtained from different patient data in real time. Performance metrics for the algorithms are precision, recall, and the F1-score. As per obtained results, digital twin (DT) in smart healthcare systems significantly enhanced healthcare processes. It promoted health and life expectancy and further reduces healthcare costs by providing novel solutions to healthcare problems. The inclusion of machine learning to the framework for ECG classification has proven that such intelligent systems are valuable for smart healthcare, and will significantly contribute to future healthcare systems [146].

In [147], a framework based on 5G next generation radio access network with cloud-based digital twins was proposed for monitoring wind turbines and constructing a prediction model for wind speed and generated power. A deep learning approach, temporal convolutional neural network (TCNN), and a conventional regression model (KNN) were used for predictions. The TCNN predicted the wind speed while KNN predicted the generated power based on the TCN results.

The proposed approach applied to a dataset belonging to a wind farm in Yalova, Turkey. The wind speed generation performance was evaluated in terms of MAE and RMSE for each quartile prediction period. Next, the power prediction performance of the proposed approach was compared with DT regression, RF, and SVR in terms of MAE. According to results obtained, the proposed approach outperformed all other methods [147]. The approach is encouraging for remote real-time monitoring of wind farms using digital twins as well as the real-time predictive modeling of wind turbines.

In [148], authors focused on digital twin enhancements for better similarity with reality. A system identification perspective was considered in this digital twin application. The hybrid form of RNNs was used for predicting between measured velocities and outcomes of the model used in ship motion prediction. With the application of digital twin, a maneuvering model was proposed with real-world ferry operation data. The model improved predictions in the ship's surge, velocities of sway, and yaw. The dataset used in the paper was collected from several sensors and provided by Scandlines for the ferry M/F Berlin. To model ship navigation, the hybrid maneuvering model was used along with different RNNs to predict the speed of a ferry with different operating conditions. Obtained results revealed that the model did improve predictions [148].

In [149], a digital twin framework was proposed for stochastic non-linear multi-degrees of freedom dynamical systems. The proposed framework consisted of four modules: a nominal model, a data collection module, an algorithm for real-time update, and a future state prediction module. Real-time update and predictions were performed by modeling approach that used physics-based and data driven modules. This enabled the digital twin to generalize and predict future states. The modeling used Gaussian process regression as the machine learning method. The proposed framework was deployed using two datasets: the 2-(DOF) system and the 7-(DOF) system. The proposed digital twin calculated time-evolution of parameters of the DOF systems. According to obtained results, the proposed DT performed well by achieving high accuracy rates, which was useful for other realistic systems [149].

In [150], a digital twin with a physics-based approach was proposed to investigate several damage scenarios. In this approach, a machine learning classifier was used to simplify real-time engineering of decision-making for physical twins. An emulated data constructed a synthetic dataset by considering real-time scenarios, and several machine learning algorithms were tested under various scenarios to analyze real-time conditions using the digital twin. Quadratic discriminant, SVM, linear discriminant analysis, KNN, bagged tress, decision tree, and ensemble boosted trees were compared in terms of accuracy metrics for performance evaluations. SVM with the Gaussian kernel method outperformed all other compared methods [150]. The results indicate that deploying digital twin is useful for a large range of applications.

A digital twin approach in the environmental science field was proposed in [151]. A process-based model generating data were aggregated for lowering resolution of time horizon to mimic real situations. A machine learning model was applied by using the process-based model inputs. ML models were used for predicting pasture nitrogen response rates, and their reliability was analyzed by evaluating their predictive and generalization capacity. The proposed approach was deployed using a dataset generated by APSIM as a reasonable estimator of pasture growth in New Zealand. The RF algorithm was used as the machine learning algorithm in this approach, and the study outcomes highlighted the practicality of developing operational digital twins for limited data scenarios [151].

The tasks of analyzing and predicting risk probability rate of an oil pipeline system were accomplished by a digital twin in [152]. Dirichlet process clustering and canopy clustering were used in the prognostic analysis for grouping the rise and fall of pressure of the system. The SVM algorithm was deployed to extract features of data obtained from multiple oil substation integration platforms, which enabled real-time control action in the pipeline system via wireless data communication. Data from an integrated IoT model in the system were used for implementing utilized approach to gauge the risks and conduct the prognostic analysis [152]. The utilized approach is promising for virtual intelligent automated control systems since it predicts the risk rate in the oil industry by providing real-time transmission lines via wireless networks in remote locations.

In [153], a digital twin framework was proposed for dynamical systems that evolved into two distinct operational time scales. The framework consisted of two modules: a physics-based nominal model to process data and predict responses, and a data-driven machine learning model for the system parameters to evolve in time. Gaussian Process and Markov Chain Monte Carlo methods were used in the data-driven model. The model was deployed for three different cases, and it considered different scenarios of data collected by IoT. According to obtained results in the paper, the proposed framework performed well in predicting system parameters that evolved in time. This is beneficial for future deployments of the framework in multi-timescale dynamical systems [153].

In [154], a digital framework for a petrochemical industrial IoT was proposed. A machine learning approach was also deployed to enable the digital twin model to accomplish production control optimization. The proposed digital twin approach integrated machine learning and real-time industrial big data in training and optimizing digital twin models. The dataset was collected from an industrial IoT, a production line in a petrochemical factory in China, to deploy the proposed framework. Different machine learning algorithms were used in the paper: RF, AdaBoost, XGBoost, Gradient boosting, decision tree, Light GBM, and ANN. The methods were compared in terms of different metrics such as MAR (model accuracy ratio), RMSE, and VIR (variance interpretation ratio). Light GBM performed extremely well in the predictions. The proposed digital twin framework based on industrial IoT and machine learning successfully optimized petrochemical production control. The paper further provided time series data processing methods in digital twin modeling, such as frequency unification and lag identification [154]. The proposed approach is promising for other production control optimization cases using digital twin.

In [155], a deep transfer learning digital twin-based fault diagnosis framework was proposed for machinery. The digital twin modeled a physical system in the paper. The framework trained a novel sparse de-noising autoencoder, which was then used as a transfer learning model for predicting machine fault diagnosis by considering different working conditions and characteristics of the machinery system. The proposed approach was deployed for diagnosing triplex pump faults. Machine learning method used in the proposed approach was compared with different methods such as stacked LSTM, stacked GRU, Gaussian DBN, and several variants of sparse de-noising autoencoders in terms of accuracy. The proposed approach significantly outperformed the compared methods [155].

A vision-based digital twin that supported threat assessments for construction site disasters was proposed in [156]. The context of disaster risk encoded into deep learning models was used for identifying and analyzing characteristics and effects of disasters in the construction site of the digital twin models. Two case studies were used, and data were collected by UAVs, smartphones, and the cameras of tablets for evaluating the proposed approach's performance. Instance segmentation was accomplished using deep learning methods. Utilized deep learning methods included AlexNet, VGG19, ResNet-18, and ResNet-50, and they were compared in the segmentation task in terms of accuracy. ResNet-50 outperformed all other methods. The proposed approach achieved risk-informed decision-making and alerted practitioners in the event of a hurricane which could immensely damage construction sites. The approach can also help in rapid scene understanding for site monitoring [156].

In [157], a robot arm digital twin approach was proposed. The paper provided simulation and communication architectures between virtual agents and physical representations of virtual agents with the deployment of the proposed approach. A robot arm was created using several smart equipment to establish communication with its environment, and PPO was used for training the digital twin. The proposed approach might be used to test scenarios that include hardware sensors to guide the physical actions of a system in trained virtual space. The deployed approach can establish connectivity between the physical and virtual components of digital twin. The framework's generalization ability for tackling virtual-physical connections may be well-suited for other digital twin application fields [157].

Industrial robots are adept due to intensive training. Their training process may probably require more time, be highly expensive, and include safety concerns. Digital twin deployment in such situations will likely produce favorable results [158]. In [158], a digital twin approach was proposed using DRL for an assembly-oriented industrial grasping robot. The DRL algorithm-trained system was transferred to a physical robot in the study. Two parallel training systems (real robotic system and its digital replica) were formed during the deployment phase. An industrial robotic assembly scenario including several robotic arms was considered in the paper. The DRL algorithm (DQN) used real time pictures from an RGB-D camera placed on the assembly area. The proposed digital twin of the industrial assembly system was built on a robot-simulator that enabled communication with the physical robot. A digital twin-based sim-to-real transfer approach was proposed for linking virtual and real systems by correcting real output with virtual ones. The proposed approach contributed to the adaptability and flexibility of robots in real industrial environments with different environmental scenarios such as illumination, occlusion, and complex task scenes [158].

In [159], a full life cycle digital twin for complex equipment was proposed by embedding machine learning into digital twin. The proposed approach combined digital twin, machine learning, and edge-cloud computing under a single framework. The digital twin approach was deployed for predictive maintenance of diesel locomotives. Data from CRRC Qishuyan Locomotive Co. were used for the implementation, and the proposed approach was compared with LASSO, SVR, XGBoost, and their combination. Performance comparisons of the machine learning methods were accomplished in terms of RMSE, MAR, and R2 metrics. The combined method for the digital twin framework outperformed all other methods in the comparisons [159]. Applying and embedding machine learning in digital twin highlights the potential of integrating machine learning in digital systems for predictive maintenance.

In [160], a digital twin framework was proposed, incorporating cloud computing and deep learning for real-time monitoring and proactive maintenance of structural health monitoring. The proposed framework applied for a case study of a real bridge structure, Nam O, in Vietnam. To collect vibration data of the bridge, a network of triaxle accelerometers was located at truss connections in the bridge. The data were used to implement deep learning method. Testing confirmation and validation of the cloud platform was accomplished with the bridge structure data. Integration of deep learning, fog computing, cloud computing, and digital twin for structural health monitoring of physical systems is promising for advancing physical health monitoring systems in real time [160].

A beam selection framework was formed in [161]. The aim was to reduce beam training overheads to enable the efficient operation

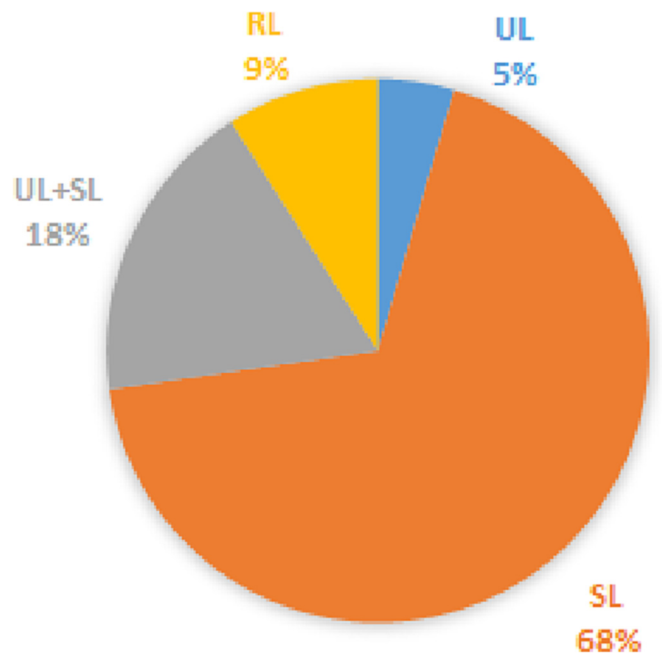

Fig. 11. Learning types applied in intelligent transportation systems.

of time sensitive IoT applications in industrial environments. An accurate map-based channel model of an environment was created using digital twin, and a beam predictor was trained to reduce the beam search space for potential space set configurations. Predictions for a set of beam configurations between IoT devices, the access point, and base stations were performed using a machine learning model. The proposed framework was deployed in an industrial case scenario using IoT devices connected to an mmWave network in a factory vehicle that conducted remote control operations [161].

In [162], a digital twin application for handover parameter optimization scheme in an ultra-dense network was performed, and a DQN method based on digital twin was proposed. Through the DQN, the handover parameter optimization scheme based on

Table 7
Research on digital twins.

Application Field	Paper	Year	Problem	Learning Type	Task in ML	Used Method(s)
Digital Twin	[146]	2021	Healthcare system management	SL	Classification	CNN, MLP, LSTM, SVR
	[147]	2022	Predictive modeling in wind turbines	SL	Regression	TCNN + KNN
	[148]	2022	Ship maneuvering prediction	SL	Regression	LSTM + GRU
	[149]	2021	Non-linear MDOF systems modeling	SL	Regression	GPR
	[150]	2021	Damage detection in structures	SL	Classification	SVM, DT, KNN, EBT Discriminant Variants
	[151]	2022	Predictive modeling in environment	SL	Regression	RF
	[152]	2022	Oil pipeline risk estimation	UL & SL	Clustering and classification	Dirichlet Process Clustering + Canopy Clustering + SVR
	[153]	2021	Multi-scale dynamical system modeling	SL	Regression	GPR + MCMC
	[154]	2019	Production optimization in petrochemical industry	SL	Regression	RF, AdaBoost, XGB, GBDT, LGBM, ANN
	[155]	2021	Intelligent fault diagnosis for machinery	UL	Data compression	Sparse de-noising autoencoder
	[156]	2022	Risk assessment for construction site disaster preparedness	SL	Segmentation-classification	CNN
	[157]	2021	Robot arm simulation	RL	RL	PPO
	[158]	2022	Industrial robot grasping simulation	RL	RL	DQN
	[159]	2022	Predictive maintenance of complex equipment	SL	Regression	Lasso, SVR, XGB, and hybrid model
	[160]	2022	Structural health monitoring	SL	Classification	CNN
	[161]	2022	Beam selection for time sensitive industrial IoT	SL	Regression	MLP
	[162]	2023	Digital twin for handover optimization	RL + SL	RL and classification	DQN and LSTM
	[163]	2023	UAV target search model training	RL	RL	QMIX
	[164]	2023	State of charge prediction of battery energy storage system	SL	Regression	RF, ANN, LSTM, GRU, AdaBoost

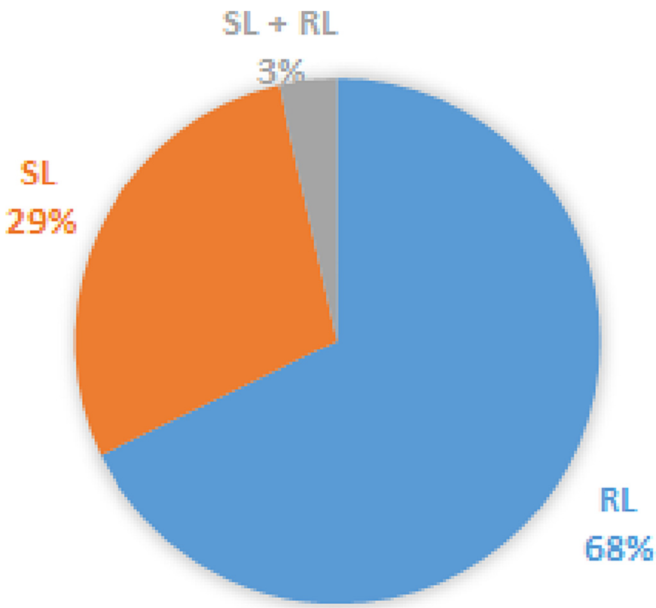

Fig. 12. Learning types applied in smart energy.

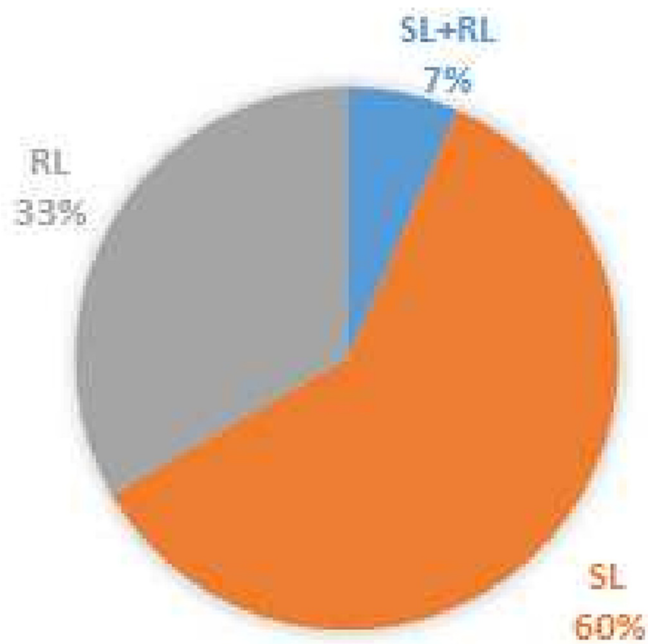

Fig. 13. Learning types applied in cyber security.

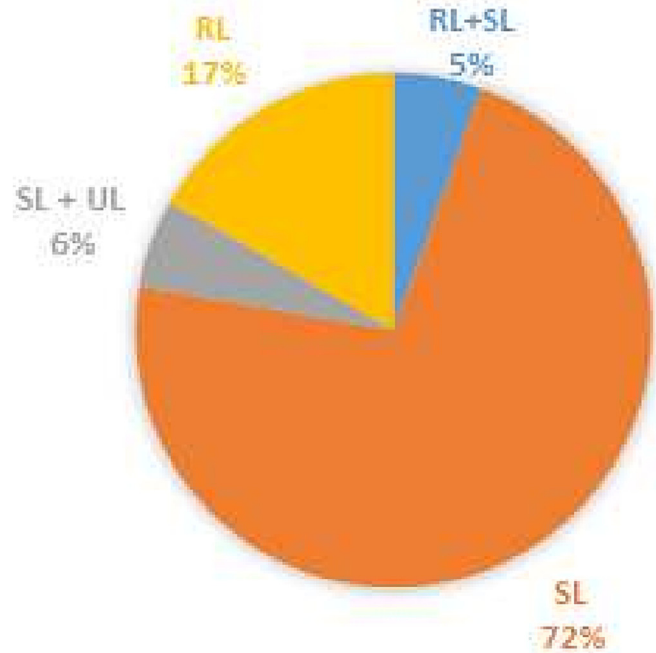

Fig. 14. Learning types used in digital twin applications.

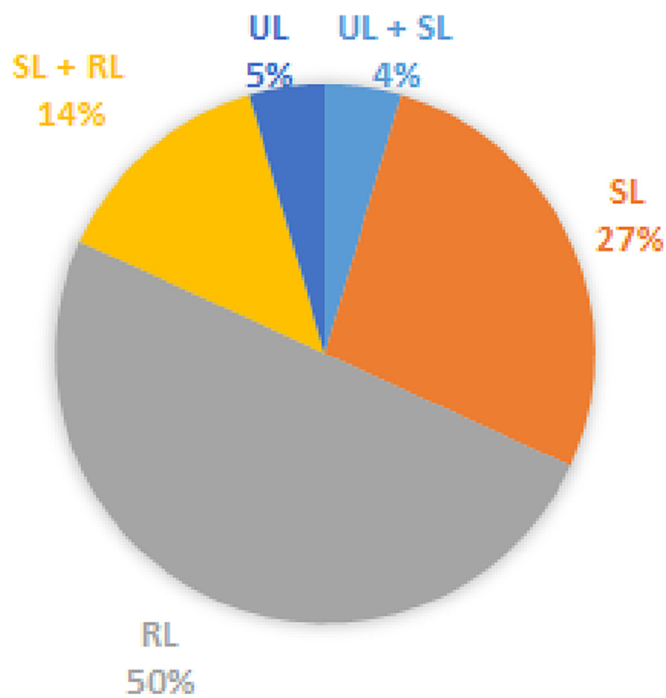

Fig. 15. Learning types applied in UAVs.

LSTM-assisted digital twins was performed which digital twins were used for prediction of reward value under the assumed handover parameters. For different wireless signal fading conditions, a DQN handover parameter selection method was formed, and the LSTM-assisted digital twin enhanced performance of the handover parameter optimization scheme by further increasing system efficiency and convergence effect. The digital twin was used for providing some needed real-time data for the handover parameters such as reference signal received power, to predict reward for reinforcement learning deployment. LSTM method was also used with the digital twin in the study to predict success of the handover, and for whether ping-pong handover occurred as per reference signal received power series. Simulation data were used for the study, and this utilized approach and non-digital twin enhanced DQN approach were compared. According to results obtained in the paper, the proposed approach significantly contributed to robustness of conventional DQN, and convergence efficiency. It also produced more effective handover rate with respect to its conventional counterpart by means of the LSTM-assisted digital twin.

In [163], a digital twin use in combination with multi-agent deep reinforcement learning approach to solve a target search problem for multi-UAVs environment was studied in this paper.

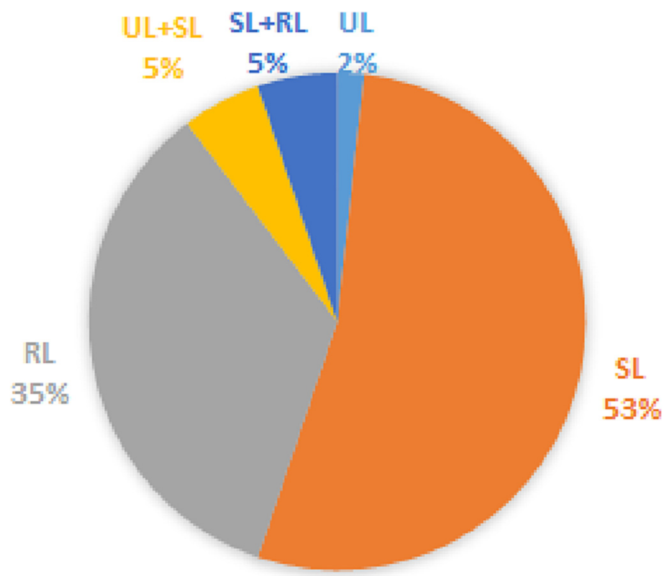

Fig. 16. Total learning types applied.

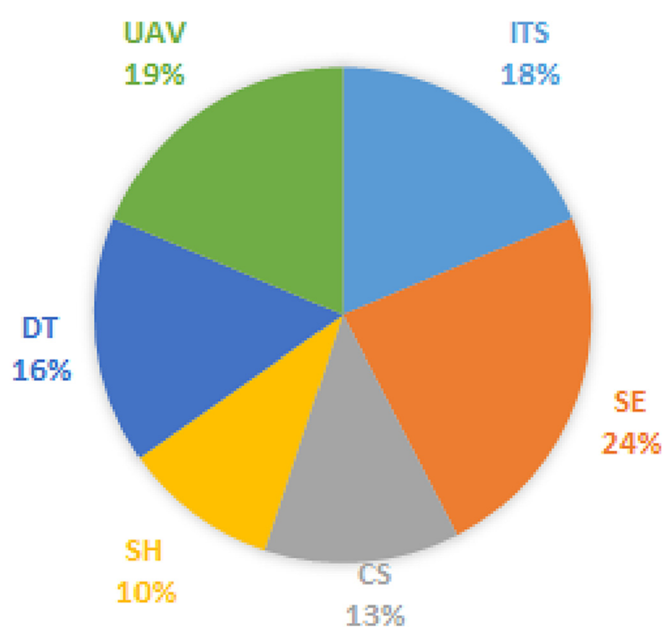

Fig. 17. Machine learning applications in various use cases.

A digital twin-driven training framework was formed that facilitated centralized training, continuous evolution, and decentralized execution for the proposed multi-agent deep reinforcement learning approach. In the training stage of the proposed approach, multiple digital twin environments provided data for centralized training of the decision model, and facilitated execution of the target search for UAVs in distributed manner. The proposed approach was compared against two baseline methods in terms of some algorithm performance metrics. After then, the proposed approach was compared against some existing schemes for the problem in terms of search rate, coverage rate, number of collisions, and episode length. As per obtained results in the paper, in most of the comparisons, the proposed approach outperformed the rest of the methods compared.

In [164], a digital twin for a battery energy storage system by providing frequency containment reserve for normal operation in Nordic region was used. The twin using real frequency in Nordic region was utilized to generate dataset, and several machine learning methods for a set of state of charge for battery energy storage systems' forecast were then compared with digital twin-generated and real battery energy storage system operation data. Random forest, LSTM, feed-forward neural network, AdaBoost, GRU, and SVR methods were deployed to develop the battery storage systems' digital twin. Different forecasting horizons with the used data were conducted, and random forest and AdaBoost methods were found the best performing methods among the methods used in most of the predictions as per results obtained in the paper.

Table 7 presents available studies on digital twins.

3.7. Discussion

This section presents the reviewed papers that offer concise information regarding machine learning and use case scenarios. Table 1 categorized previous research papers, and comparison of this paper with respect to the published papers. In this paper, each subsection has investigated the employed learning types, their corresponding visuals, and results. After giving reviewed papers and their related information, we also give discussion about their applications from the perspective of learning types and machine learning. Relevant figures are given in Figs. 11-18. Learning types used in each use case, percentage of machine learning applications in the use cases in the reviewed papers, and relevant papers publishment throughout the years are given in these figures. Discussions on the figures are also provided.

Fig. 11 highlights the rate of employing learning types in the field of intelligent transportation systems. UL, SL, and RL represent unsupervised learning, supervised learning, and reinforcement learning, respectively. The + sign represents the hybrid form of the mentioned learning types or the ML algorithms/methods. Supervised learning encompasses most use case applications with a rate of 68%. This is followed by the hybrid unsupervised + super vised learning with a rate of 18%. Reinforcement learning accounts for 9% of applications, while unsupervised learning accounts for 5%.

In intelligent transportation applications, object detection, segmentation, and vehicle/pedestrian recognition tasks that require supervised learning has made up the majority of use cases. With the advancement of V2V, V2I, and autonomous self-driving cars in 5G and B5G enabled systems, it is expected that RL applications will increase in the near future.

Fig. 12 presents the rate of application for each learning type in the smart energy field. Reinforcement learning consists of the majority of applications with a rate of 68%, it is followed by supervised learning with a rate of 29%. The remaining applications include the hybrid supervised method and reinforcement learning type with a rate of 3%. Smart homes, autonomous decision-making, decentralized decision-making, decision engines, and adaptive learning are key topics in the smart energy field. Reinforcement learning thus makes up the majority of applications in this field. Load prediction is also significantly important, especially for smart energy. Hence, supervised learning applications follow reinforcement learning applications in the smart energy field.

Fig. 13 presents the rate of applications of learning types in the cyber security field. Since detection and identification tasks are significant in cyber physical systems, the high rate of supervised learning applications (60%) is plausible. Reinforcement learning applications are also found in many studies on cyber security applications. As seen in Fig. 13, Sole RL applications accounts for 33 % while the hybrid one accounts for 7%. A noteworthy issue is that anomaly detection can be applied as an unsupervised learning type since unsupervised learning has not been employed in the reviewed papers for this field.

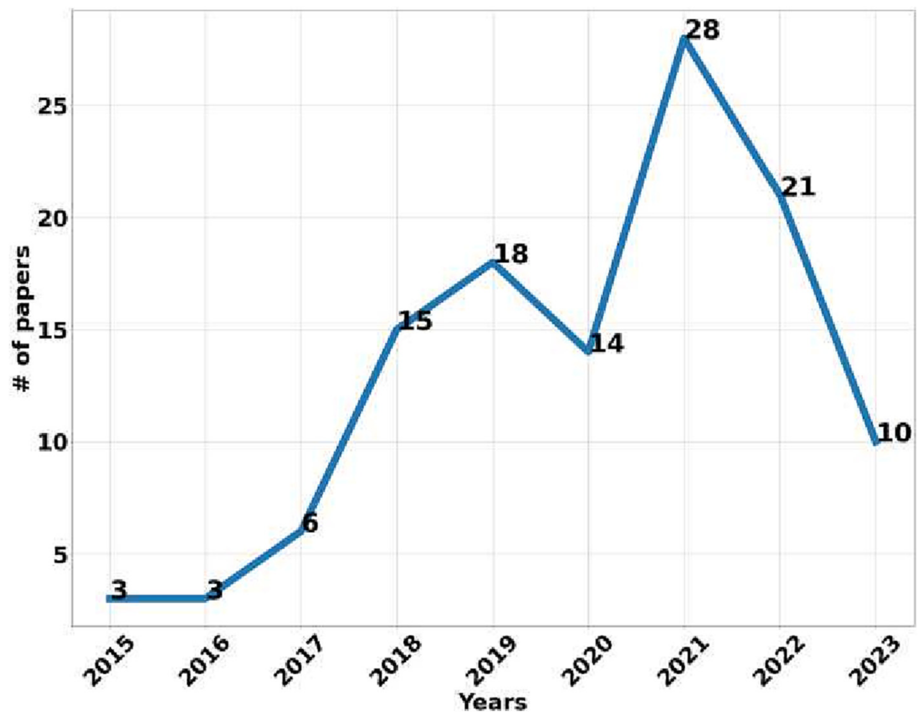

Fig. 18. Annual use case applications in total.

Supervised learning covers all smart health applications in the reviewed papers; therefore, unsupervised learning is not presented for this field. Classification and detection of diseases, human activity recognition, and diagnosing diseases all require regression or classification tasks. Therefore, all smart health applications in the reviewed papers have used the supervised learning type for either regression or classification tasks.

Fig. 14 presents the learning types used in digital twin applications. In digital twin applications, the supervised learning type accounts for 72% of applications, followed by reinforcement learning with a rate of 17%. Hybrid form of supervised learning with unsupervised one accounts for 6% of applications while hybrid supervised and reinforcement learning applications accounts for 5%. Digital twin enables simulations of large physical systems and monitors their processes. Regression and classification tasks are needed for these processes. For instance, structural damage classification, load prediction in wind turbines, and oil pipeline risk estimation use cases will require these tasks, hence, the supervised learning type for digital twins account for the majority of applications in the reviewed papers. Robot simulations have recently emerged in industrial fields. Training robots with simulations require reinforcement learning applications since they perform simulations in the environment of an agent. As shown in Fig. 14, reinforcement learning applications are relatively low in digital twin, however, applications are likely to exponentially increase with future mobile communication networks.

Fig. 15 presents the rate of learning types applied for unmanned aerial vehicles. Since autonomous decision-making is extremely crucial for UAVs, reinforcement learning will be the first key enabler. Reinforcement learning applications in UAV use cases account for 50%, while its hybrid application with supervised learning accounts for 14%. Supervised learning is also noteworthy in this field and accounts for 27% of applications. Several inspections, detections, and health monitoring tasks assisted by UAVs will require regression, classification, and/or segmentation. Supervised learning thus follows reinforcement learning in UAV use cases. Fig. 16 presents the total rate of learning types applied.

Supervised learning applications in the reviewed papers account for 53%, followed by reinforcement learning with a rate of 35%. The remaining applications are the hybrid learning type which accounts for 12%. From Fig. 16, the percentage of supervised learning application is noteworthy. The trial–error learning type, which is reinforcement learning, also has a prominent position in applications, and is expected to grow since new technologies will require intensive autonomous decision-making and optimal control. Reinforcement learning is the most viable option for this task.

Fig. 17 presents the machine learning deployments in various use cases. In the figure, DT represents digital twin, SH is smart health, CS is cyber security, SE is smart energy, and ITS is intelligent transportation systems. From the aspect of machine learning used in the reviewed papers, smart energy and UAVs are the first two leading fields, respectively. This is followed by ITS and digital twin, both with an equal rate. Smart health and cyber security are two fields with the least machine learning deployments with respect to the other fields.

In addition to the use cases of specific learning types, the annual change of the total use case applications is illustrated in Fig. 18. A steadily increasing trend is apparent until year 2020, and a surge in machine learning applications can subsequently be seen. A decrease in applications during 2020 may be due to the effect of the global pandemic. Research is now expected to increase, exceeding that of year 2021. Papers published for the use cases in the first quarter of 2023 make promise for ML applications in these future mobile network-enabled fields. Supervised and reinforcement learning are mostly the prevalent machine learning types deployed, and unsupervised learning is rarely used as compared to them. This may be due to classification, segmentation, semantic parsing, regression, prediction, autonomous decision-making, and determining the optimal strategy are mostly dominant tasks in the use cases. Finding hidden patterns in data is rare in the use cases, unsupervised learning deployments are thus rare. With the advancements in IoT by 5G and B5G mobile communication systems, data volumes will significantly grow, and physical systems will turn into more cyber physical systems. New problems will emerge throughout different fields as well. As a result, the need for intelligent methods will subsequently increase. Innovative algorithmic developments for new problems may further boost the application of machine learning throughout various fields. Requirements are expected to increase in the near future to perform operations in cyber physical systems with better performance. It is apparent that the literature will consist of numerous machine learning applications in the near future for various fields enabled by future mobile communication systems.

4. Challenges of AI and ML applications

Digitalization and big data surges enabled by future mobile communication systems are transforming individual lives and business areas. Data obtained from different IoT sources (such as smart sensors, smartphones, wearable devices, antennas, microcontrollers, etc.) have been increasing on a daily basis, and physical systems are evolving into more cyber physical form. Digitalization is maturing in every aspect of daily life. It is expected that digitalization and big data surges will increase as 5G and B5G enabled technologies become more apparent in the near future. In this digitalized environment, machine learning with powerful algorithms will become a viable option for various application fields, from intelligent transportation systems to smart health. However, several limitations and challenges will emerge when using machine learning in different applications in general. This section highlights the limitations, challenges, and several potential solutions of AI and ML applications for different areas.

4.1. Big data

In 5G and B5G mobile communication systems, the data volume is expected to exponentially grow with the IoT concept. Machine learning will reap the benefit of this growth. A subset of deep neural networks will take advantage of such growth since data volume expansion will significantly boost their performance throughout vast applications and across various fields. Big data opens numerous opportunities for the application of machine learning algorithms; however, it will lead to challenges for machine learning applications. High volume, velocity, variety, and veracity of big data problems are significant problems that must be resolved [165].

4.1.1. High volumes of big data

High data volumes may hinder real-time or near real-time performance since it will create issues associated with data volume for computing all learning types. The use of multiple computers or processors for the learning process may reduce computational complexity and memory allocations. Advanced hardware solutions, such as graphical processing units (GPUs), tensor processing units (TPUs), and massively parallel processing (MPP) may help practitioners by introducing faster computations compared to conventional CPU computations with high data volumes. Hardware-based machine learning solutions produced by Google [166], IBM [167], and Stanford [168] may be viable options for the issue of high data volumes. Since efficiency, real-time, or near real-time decision-making are critical for several applications due to safety concerns (such as autonomous self-driving cars), handling high data volumes with advanced hardware solutions that facilitate low latency and efficiency in decision-making systems will boost the performance of machine learning algorithms, and this fact is not only valid for intelligent transportation systems, but also for smart energy systems, cyber security, UAVs, etc. System performance will be enhanced with real-time decision-making in smart energy systems and real-time cyber-attack detection in cyber physical systems. The performance of UAV operations will increase, boosting the stability of power system management in smart energy. Thus, integrating machine learning, cloud computing, fog computing, and mobile edge computing may be viable options for handling high data volumes according to application requirements.

4.1.2. Variety of big data

Data variety is another challenge of the big data concept. In future mobile communication systems, data collected from different devices are significant source of big data variety in IoT systems. Noise, software bugs, human errors, statistical biases, and lack of data lineage are other sources, and intelligent transportation systems may be affected from this challenge. The available sensors may collect structured, semi-structured, or unstructured data. Thus, data may differ in standardization and distribution, giving rise to diverse types of data. Such data will likely create challenges for algorithm deployment since it will require extensive preprocessing before becoming suitable to feed machine learning algorithms. The variety of data may halt efficiency and performance when applying machine learning algorithms due to problematic input data. A potential solution would be to investigate data representations from each data source, then feed the learned features into models at different levels [165]. This variety of big data poses challenge for intelligent transportation systems, and it may also pose risks for cyber-security since it deals with data and their authentication as well. In addition, UAV autonomous decision-making process with data collected from different sources needs to be handled efficiently to make robust training for algorithms.

4.1.3. Veracity of big data

Veracity of big data is another issue in the big data concept since it concerns the accuracy and quality of data. Missing pieces of information and data inaccuracies may cause machine learning algorithms to perform poorly. This may subsequently lead to catastrophic outcomes in certain cases. For instance, an autonomous driving system trained by inaccurate data will learn its environment through inaccurate situations, thereby causing fatal collisions when implemented. Inaccurate data usage for machine learning may also be risky in the smart healthcare field. The wrong diagnosis of a disease or misclassification of tumors may be dangerous in healthcare operations. Inaccurate data inclusion to a cyber-attack detection mechanism will disrupt the detection mechanism, resulting in wrong outcomes. Hence, it is crucial to manage this problem to improve the decision-making process of machine learning algorithms. Enacting regulations to prove the authenticity of data as well as validating standards for relevant application fields will reduce the risks associated with the veracity of data in the big data concept. Robust machine learning that facilitates generalization will further reduce the associated risks. This type of problem is not only valid and does not pose risks for one use-case, they are related to each use-case mentioned in the paper with the same level.

4.1.4. Velocity of big data

Velocity is related to the speed of streaming data and its analysis to produce an outcome. In some cases, static models may fail to make reliable inference under high velocity of data since they remain unchanged during inference and perform their tasks with learned input data settings. Automatically learning from incoming data during the inference process may be risky for conventional machine learning models, resulting in misleading outcomes. Machine learning algorithms that can adapt to perform online learning will yield more reliable and robust results in real-time or near real-time scenarios, which is significant in numerous fields [169]. Online learning performance is linked to advanced hardware solutions for machine learning methods. To resolve this challenge, online learning and speed issues must be simultaneously considered in the design process of hardware solutions. The velocity of big data becomes crucial especially for real-time decision-making requiring systems. Intelligent transportation systems including D2D, V2V communications etc., cyber-security systems, smart grids including several components in their system acting cooperatively, UAV systems especially multi-agent UAV ones require handling velocity of big data when real-time decision making is needed. This challenge is also related to computational burdensome problem that can be solved with practical lightweight computational hardware for AI and ML methods.

4.2. Robustness of models

In machine learning, acquiring plausible and trustworthy results will either hinder or boost large-scale deployment of machine learning algorithms. Robust machine learning models are related to big data issues in some respect since they are linked to other challenges, such as security and privacy. Adversarial attacks will corrupt the performance of machine learning methods. Data poisoning, evasion attacks, and model extraction are several adversarial incidents that threaten the performance of machine learning methods. Data poisoning injects bad data to databases. With this injection, a machine learning model is adversely affected since it is trained with corrupted data, thereby producing false and misleading results. Evasion attacks fool a system by concealing content of malware code or data to evade infiltration into the system. Model extraction attempts to learn a black box model by extracting data used for training the model. A targeted model can be learned and easily replicated with this type of attack. This will subsequently lead to vulnerability of the model. Hence, several attacks may pose different risks regarding machine learning types.

Conventional machine learning models use static features and predefined labels that may be vulnerable to deliberate attacks. The evasion attacks, that contaminate data in supervised learning, are difficult to be detected and distinguished will result in unexpected outcomes. Poisoned features with evasion attacks will raise challenges for supervised learning since performance quality will deteriorate due to the use of low-quality feature sets. Feature selection establishes input–output relation in supervised learning, hence implementing automated feature selection rather than manual will be a solution for poisoned data. This automated feature selection is useful for high volumes of data since it will save data processing time. Another solution is to employ data augmentation to acquire more robust training for deployments. Evasion attacks may also contain test sample manipulations. Automated feature selection may not fully hinder the functionality of the manipulation; however, it will reduce the risk to some extent. Addressing this problem with data security and privacy will produce more promising results. The vulnerability of unsupervised learning to adversarial attacks is less when compared to supervised learning. However, the vulnerability of reinforcement learning is comparable to supervised learning. Trained under several challenging conditions (such as lack of data sanity or injection of faulty data from sensor readings), agent(s) of reinforcement learning will not perform well, hence decision-making in real-time may be misleading. Adversarial data attacks may also influence decision-making process of the agents. For instance, defective data injected to train a reinforcement learning agent in an autonomous driving may cause fatal traffic accidents. This may also be possible for UAV applications. For smart energy, system stability can be disrupted by such attacks. An aggressive attack that deceives recognition systems of intelligent transportation systems may also pose a risk for the entire system by congesting communication between machines and infrastructures. In the context of reinforcement learning, robust, interpretable, fair, responsible, and defensive algorithm utilization is crucial since autonomous decision-making will significantly influence different use cases. Ensuring data stability alongside powerfully equipped algorithms will enhance the robustness of reinforcement learning to combat different types of attacks [23]. Overfitting is a conventional challenge for machine learning models. Algorithmic solutions (such as adding regularization, batch normalization, maximum and/or average pooling operations, dropout utilizations, several validation dataset strategies, and data augmentation) reasonably address the overfitting challenge since they strengthen machine learning algorithms.

4.3. Energy and computation costs

Energy requirements and computational cost of hardware solutions are other challenges of machine learning applications. UAV use-case, cyber security, intelligent transportation system, smart grids are seen the mostly affected use cases by this challenge when they use deep learning in particular with large amount of data. Machine learning algorithms, deep learning, and deep reinforcement learning algorithms, in particular, will use high volumes of data and high-capacity models. They will subsequently require high-capacity hardware in the big data era enabled by future mobile communication systems. Smart sensors, smart batteries, transceiver units, and smart phones will stream tremendous amounts of data in a short time. Local computations for machine learning algorithms will also consume high energy. Advanced hardware solutions (such as GPUs, TPUs, and MPP units) contribute to the speed of machine learning algorithms, yet they require high energy consumption and computational cost. Lightweight hardware solutions that can be placed on any device for the related use-case may be an option to overcome this challenge in some respect. Energy efficient hardware solutions for machine learning are considered as an open challenge. Offloading in mobile edge computing may be a solution for the energy requirements of machine learning algorithms depending on applications.

4.4. Security and privacy

The challenges and limitations of machine learning applications in the future mobile communication systems are interrelated issues. Thus, the solutions for these challenges are interrelated as well. The big data concept transforms every industry, and bringing novel opportunities. However, concerns will emerge at the same time as well. Data privacy and security is a hot topic in the big data concept. This challenge is very crucial for smart health and cybersecurity use cases in particular. Corrupted and unsecure data processed by ML and AI techniques may result in catastrophic results for many use cases. Hence, measurements to provide security and privacy of data are of significant issues in this sense. This is expected to gain significance with the expansion of the next generation networks. In this context, the security and privacy of machine learning models based on their robustness is another crucial issue. Poisoned data, adversarial attacks infiltrating databases, clouds, nodes, and model extractions in the future mobile communication-enabled systems must be resolved by intelligent, secure, and reliable solutions. Their effects may otherwise lead to colossal damage. For instance, untrusted and poisoned data may trigger false alarms in large scale systems by urging needless operations, destroying system reliability and sustainability. They may further affect autonomous driving, disrupt personalized healthcare services, etc. The adverse effects of poisoned data, cyber-attacks, and model extractions can be stopped depending on the robustness of the machine learning model applied. Securing data will significantly enhance performance of both use case systems and machine learning models. Integrated solutions of machine learning

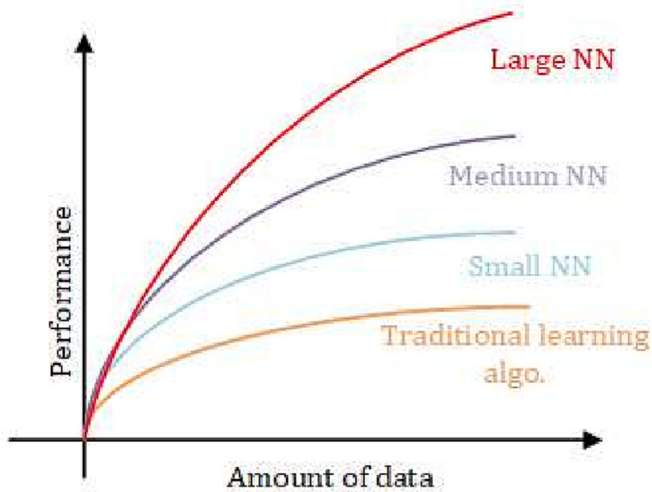

Fig. 19. Performance comparison of different neural networks and traditional learning algorithms with respect to data amount [170].

robustness and security will yield the most promising results for any use case application. Blockchain technology based on cryptography and data decentralization to ensure trustable transactions are currently seen viable options for guaranteeing the security and privacy of data. The integration of blockchain to applied frameworks is expected to facilitate data security and privacy in 5G and B5G era.

4.5. Low latency

Real-time or near-real time decision-making may be the most important issue in several machine learning applications. For instance, UAV positioning in disaster management will require real-time decision-making. For non-urgent cases, UAV training and testing will reap benefits of the real-time decision-making by enhancing performance. Another example of the importance of the real-time decision-making would be V2I and V2V communications in intelligent transportation systems. Cyber security systems also need for low latency in order to perform in an undisrupted manner. These will require real-time or near real-time performance using AI and machine learning algorithms. Hence, this challenge must be addressed for consistent management during use cases. Mobile edge computing and fog computing are two potential solutions for low latency requirements in machine learning applications assisted by 5G and B5G mobile communication systems. Edge computing enables low latency by transferring cloud services to intermediate nodes closer to application layer(s), thereby reducing the reliance on a cloud network [23]. However, this solution comes with its own challenge. Data in a single node will be limited in a centralized network, hence, the quality of decision-making will be somewhat low in this computing alternative with respect to the cloud network. This is also valid for fog computing. The trade-off between choosing the right option depends on use cases.

5. Future research directions

The previous section presented the challenges of applying machine learning for different use cases along with potential solutions. This section highlights several future research directions of AI and ML applications for the different use cases by considering the various challenges.

5.1. Deep learning

Deep learning is a subset of neural networks, rather than a learning type. With the surge in big data enabled by IoT in 5G and B5G communication systems, powerful hardware (such as GPUs, TPUs, and MPP units) as well as novel algorithmic developments (deep learning) have emerged as dominant solutions for most machine learning application issues. Their sophisticated

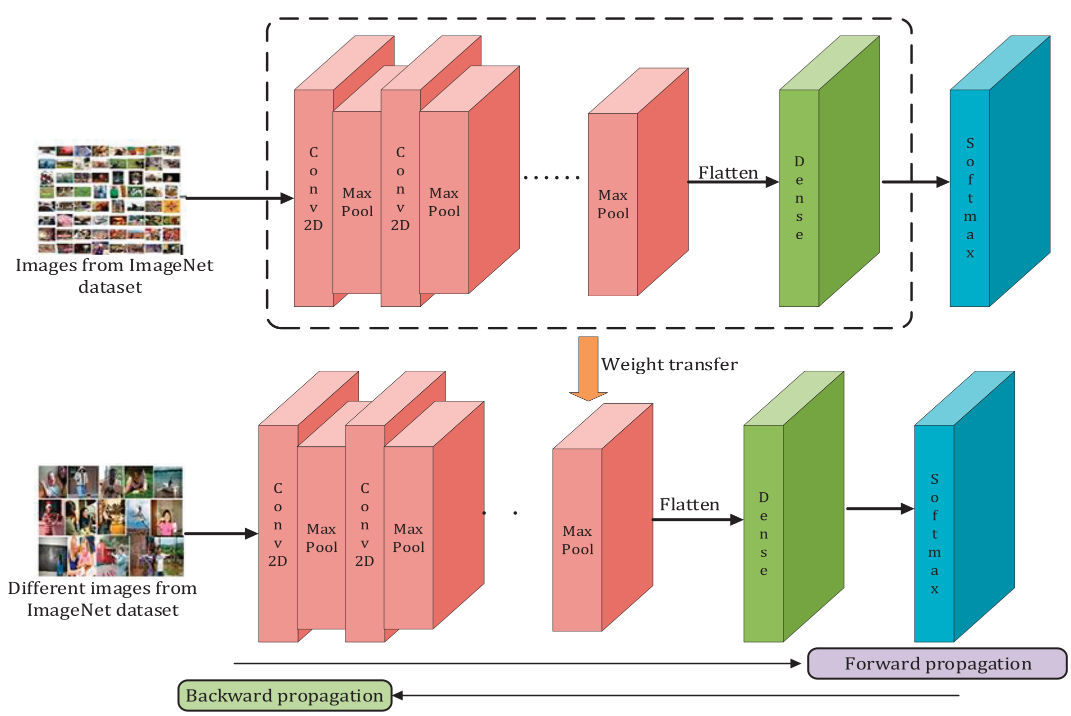

Fig. 20. An example of the transfer learning process.

mechanism that resembles the functions of the brain combined with enormous amounts of data may be the reason behind deep learning success. Conventional machine learning algorithms perform well up to an extent, depending on data amounts, to provide consistent performance. However, the performance of deep learning algorithms significantly improves with large amounts of data [170]. This is showcased in Fig. 19.

After acquiring a set amount of data, the learning of conventional learning algorithms will stop since the curve flattens out as shown in Fig. 19.

Small neural networks, which have a small number of units, layers, and hyperparameters as compared to conventional algorithms, perform slightly better in the task of supervised learning, as shown in Fig. 19 [170], and the relation between large amounts of data and deep neural network performance can be seen in the same figure.

Training large neural networks with tremendous amounts of data will boost their performance. This shows the importance of acquiring large amounts of data for efficient deep neural networks, as displayed in the figure. The use of deep learning with big data in IoT enabled by 5G and B5G mobile communication systems will produce more promising results for different application fields, surpassing conventional machine learning algorithms. Throughout the literature, the benefit of applying deep learning in various fields is clear. Deep learning is less dependent on hand-crafted features since it conducts automatic feature extraction using its inner mechanism(s), providing end-to-end learning with less domain expertise required. This feature also makes them attractive for large scale deployments. Deep learning is also transforming reinforcement learning. Using deep neural networks in reinforcement learning enhances the performance of reinforcement learning. Sim-to-real transfer is a significant issue in reinforcement learning since a reinforcement agent simulates the environment through its training, then applies it to real-world cases. With the deployment of deep reinforcement learning, the performance of sim-to-real transfer will be further enhanced with the support of deep learning.

5.2. Transfer learning

Transfer learning is a possible solution for machine learning applications. It is a process that uses knowledge gained as a result of training process for deep neural networks. The gained knowledge is then applied to a different but related domain(s). Fig. 20 presents an example of transfer learning. In the figure, an adaptation of a deep neural network is trained with the ImageNet dataset to perform classification for the Stanford 40 HAR dataset, which is employed as the transfer learning.

The weights from the pre-trained deep neural network (excluding the last layer) are transferred for another deep neural network training. This new network then conducts the classification. Three major types of transfer learning are present: fixed feature extractors, fine-tuning, and pre-trained models. In the first case, the last fully connected layer of deep neural network is removed, and the remaining part of the network is used for the feature extraction of a new dataset. In the second case, weights of a pre-trained network are fine-tuned by maintaining backpropagation operations. In the third case, since training deep learning models is a time-consuming process, the pre-trained models can be saved by checkpoints, and then used for fine-tuning or for the same domain deployment. As seen from the transfer learning types, this strategy will save time in deep learning applications, and it will further contribute to energy-related solutions as well as reduce the computational cost of deep learning algorithms. Hence, transfer learning seems to be a viable option for different application fields with big data enabled by 5G and B5G mobile communication systems.

5.3. Federated learning

Federated learning is one of the hot topics in the context of machine learning. With the wake of 5G and B5G networks, different devices will use the new mobile network communications for which low latency, high data rates, and massive and intensive connectivity are significant pillars. IoTs, wearable devices, smart phones, intelligent machines in plants, machine-to-machine devices are some examples of the devices that will reap the benefits of these future mobile network systems. In massively connected devices, the extension of distributed machine learning, federated learning, gets machine learning and deep learning algorithms trained on data in the edge devices such as laptops, wearable devices, smart phones, etc. thereby moving the computation in local that the data generated. As a result of this type of learning, latency requirement is met, and it also contributes to data privacy and security. In addition, federated learning does not require to move data from edge devices to a cloud thereby making computations with data from different data sources and updating parameters of machine learning and deep learning in a distributed manner [171]. With massively deployed smart devices, smart machines, and IoT systems, it is expected that federated learning use with the future mobile network systems will mature in the future.

5.4. Blockchain

Massively connected devices have been producing enormous amount of data, and this amount will also expand in the future mobile networks-enabled systems. In these systems, data privacy and trust will gain more importance. Hence, this data and privacy issue needs to be addressed through novel technologies. Blockchain technology is one of these technologies that may respond to data privacy and trust issue in the future mobile networks-enabled systems [171,172]. Deep learning deployment with big data produces desirable outcomes with respect to conventional machine learning deployment, however, many deep learning deployments are dependent on centralized servers, and this may result in less reliability, security, trust, and, operational transparency [173]. Using these two immersive technologies, deep learning and blockchain, will create a synergistical effect in the future mobile networks-enabled systems in the sense of data privacy and trust with enormous amount of data. Hence, operational efficiency will be boosted by means of this synergistical efficiency of integrated use of blockchain and deep learning [173,174].

6. Conclusion

This paper provides a comprehensive assessment of machine learning applications in various fields enabled by the future mobile communications-enabled systems. Introductory information on machine learning types has been presented. Machine learning types and their groundbreaking evolution are highlighted to provide further insight. Various use cases of machine learning applications have been examined. The use cases include intelligent transportation systems, smart energy, smart healthcare, cyber security, digital twins, and UAVs. The journal papers that only discuss such use cases using machine learning algorithms are highlighted in this paper. A comprehensive summary of the reviewed papers is provided to elaborate on the machine learning algorithms used for each use case. The discussion of the papers is further accomplished to present the learning types employed in the application fields. This may assist practitioners for further developing and employing machine learning algorithms in different fields.

A categorization of the relevant studies is also presented, including the years of publication, problem definition, learning types and task, and used machine learning algorithm(s). The paper has also addressed several challenges of different machine learning applications in the future mobile communications-enabled systems. The potential solutions for these challenges were discussed accordingly. The paper introduced the necessary future research directions for upcoming studies as well. Big data management, model robustness, energy and computation costs, low latency, and security and privacy are the highlighted challenges of machine learning applications for the different fields. Advanced hardware utilization-based solutions, several algorithmic developments (-such as automated feature selection, online learning, fair and responsible model generation, etc.), offloading, mobile edge computing, fog computing, federated learning, and blockchain technology are some solutions that address the mentioned challenges. For future research directions, deep learning is the emerging field in machine learning. From the computational aspect, federated learning is considered as a promising solution, and it is a growing area for future research. With massively collected data environment, data privacy and security issue is of significant issue. Hence, blockchain technology combined with deep learning in enormous amount of data collected environments will possibly be an emerging area for future research. Supervised learning and reinforcement learning are the most used learning types in most of the applications, and they benefit from deep neural networks. The deployment of deep learning algorithms for different use cases are expected to exponentially grow with the expansion of big data and IoT assisted by 5G and B5G mobile communication systems. Transfer learning is another emerging field in future deployments of machine learning applications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research has been produced benefiting from the 2232 International Fellowship for Outstanding Researchers Program of TÜBİTAK (Project No: 118C276) conducted at Istanbul Technical University (ITU). The paper is also supported in part by Universiti Teknologi Malaysia (UTM) under the Contract Research of IC5G Research and Development Platform for Malaysian Industry, Research Grant of R.J130000.7609.4C87.

APPENDIX

The abbreviations and acronyms first introduced in the text, and, for convenience, the list of abbreviations used in this paper is summarized in Table 8.

Table 8
Summary of abbreviations.

Abbreviation	Definition
3-D	Three dimensional
3GPP TR	3rd Generation Project Partnership Technical Requirements
5G	5th Generation
A2C	Advantage Actor Critic
A3C	Asynchronous Advantage Actor Critic
ASD	Anomaly Symptom Detection
AI	Artificial Intelligence
AGI	Artificial General Intelligence
ANN	Artificial Neural Network
APSIM	The Agricultural Production Systems sIMulator
AUC	Area Under Curve
B5G	Beyond 5th Generation
BS	Base Station
CAD	Computer Aided Drawing
C-LSTM	Centralized Long-Short Term Memory
CNN	Convolutional Neural Network
CS	Cyber Security
CVD	Cardiovascular Disease
D2D	Device-to-Device
DBSCAN	Density-based Spatial Clustering of Applications with Noise
DBN	Deep Belief Network
DDPG	Deep Deterministic Policy Gradient
DQN	Deep Q Network
DRL	Deep Reinforcement Learning
DS2OS	Distributed Smart Space Orchestration System
DSAE	Deep Stacked Auto-Encoder
DiT	Digital Twin
DOF	Degree of Freedom
DT	Decision Tree
ECG	Electrocardiogram
EIoT	Energy Internet of Things
ELM	Extreme Learning Machine
ESN	Echo State Network
GBM	Gradient Boosting Method
GPS	Global Positional Systems
GRU	Gated Recurrent Unit
HAR	Human Activity Recognition
IBM	International Business Machines
IDPS	Intrusion Detection and Prevention System
IEEE	Institute of Electrical and Electronics Engineers
IoMT	Internet of Medical Things
IoT	Internet of Things
IoV	Internet of Vehicles
ISET	Irish Smart Energy Trial
ISO	Independent System Operator
ITS	Intelligent Transportation Systems
eMBB	enhanced Mobile Broad Band
FDI	False Data Injection
FRCBM	Factored Restricted Conditional Boltzman Machine
GA	Genetic Algorithm
GPU	Graphical Process Unit
KL	Kullbakc-Leibler
KRR	Kernel Ridge Regression
kWh	kiloWatt/hour
LOS	Line-of-Sight
LSTM	Long-Short Term Memory
LR	Linear Regression
Lg.R	Logistic Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARL	Multi-agent Reinforcement Learning
MCC	Matthew's Correlation Coefficient
MDMS	Manager's Decision-Making System
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MLP	Multi-layer Perceptron
mMTC	Massive Machine Types Communications
MPP	Massively Parallel Processing
MRI	Magnetic Resonance Imaging
MRE	Mean Relative Error
NAD	Network Anomaly Detection
NAR	Non-linear Autoregressive
NARXNET	Non-linear Autoregressive Network with Exogenous Variable
NY	New York
PJM	Pennsylvania-Jersey-Maryland
PoI	Point of Interest
POMDP	Partially Observable Markov Decision Process
PSO	Particle Swarm Optimization
RCBM	Restricted Conditional Boltzman Machine
R-CNN	Regions with Convolutional Neural Network
RF	Random Forest
RGB	RedGreenBlue

Table 8 (*continued*)

Abbreviation	Definition
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
ROC	Received Operator Curve
RoI	Region of Interest
RL	Reinforcement Learning
SAE	Stacked Auto-Encoder
SAF R-CNN	Scale Aware Fast R-CNN
SDN	Software-Defined Radio
SE	Smart Energy
SGCC	State Grid Cooperation of China
SH	Smart Health
SL	Supervised Learning
SVR	Support Vector Regression
TCNN	Temporal Convolutional Neural Network
TD	Temporal Difference
TDD	Time Division Duplex
TORCS	The Open Race Car Simulator
TPU	Tensor Processing Unit
TRPO	Trust Region Policy Optimization
UK	United Kingdom
US	United States
uRLLC	Ultra-Reliable and Low-Latency Communication
UAV	Unmanned Aerial Vehicle
UL	Unsupervised Learning
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VGG	Visual Geometry Group
VIR	Variance Interpretation Ratio
VNF	Virtual Network Function
VPP	Virtual Power Plant
WSN-IoT	Wireless Sensor Network Internet of Things
YOLO	You Only Look Once

References

[1] A. L. Samuel, "Programming computers to play games," in *Advances in Computers*, vol. 1, Elsevier, 1960, pp. 165–192.
[2] T. M. Mitchell and T. M. Mitchell, *Machine learning*, vol. 1, no. 9. McGraw-hill New York, 1997.
[3] S. Pang, J.J. del Coz, Z. Yu, O. Luaces, J. Díez, Deep learning to frame objects for visual target tracking, Eng. Appl. Artif. Intell. 65 (2017) 406–420.
[4] D. Peer, S. Stabinger, S. Engl, A. Rodríguez-Sánchez, Greedy-layer pruning: Speeding up transformer models for natural language processing, Pattern Recognit. Lett. 157 (2022) 76–82.
[5] I. Yazici, O.F. Beyca, D. Delen, Deep-learning-based short-term electricity load forecasting: A real case application, Eng. Appl. Artif. Intell. 109 (2022) 104645.
[6] E. Kara, M. Traquair, M. Simsek, B. Kantarci, S. Khan, Holistic design for deep learning-based discovery of tabular structures in datasheet images, Eng. Appl. Artif. Intell. 90 (2020) 103551.
[7] C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, L. Hanzo, Machine learning paradigms for next-generation wireless networks, IEEE Wirel. Commun. 24 (2) (2016) 98–105.
[8] J. Peters, S. Vijayakumar, S. Schaal, Reinforcement learning for humanoid robotics, in: in *Proceedings of the third IEEE-RAS international conference on humanoid robots*, 2003, pp. 1–20.
[9] M. Qazi, K. Tollas, T. Kanchinadam, J. Bockhorst, G. Fung, Designing and deploying insurance recommender systems using machine learning, Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 10 (4) (2020) e1363.
[10] Z.N.K. Swati et al., Brain tumor classification for MR images using transfer learning and fine-tuning, Comput. Med. Imaging Graph. 75 (2019) 34–46.
[11] N. Kasabov and S. Pang, "Transductive support vector machines and applications in bioinformatics for promoter recognition," in *International Conference on Neural Networks and Signal Processing, 2003. Proceedings of the 2003*, 2003, vol. 1, pp. 1–6.
[12] J. Chen, B. Yuan, and M. Tomizuka, "Model-free deep reinforcement learning for urban autonomous driving," in *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, 2019, pp. 2765–2771.
[13] F. Zantalis, G. Koulouras, S. Karabetsos, D. Kandris, A review of machine learning and IoT in smart transportation, Futur. Internet 11 (4) (2019) 94.
[14] D. Sirohi, N. Kumar, P.S. Rana, Convolutional neural networks for 5G-enabled intelligent transportation system: A systematic review, Comput. Commun. 153 (2020) 459–498.
[15] Z. Ullah, F. Al-Turjman, L. Mostarda, R. Gagliardi, Applications of artificial intelligence and machine learning in smart cities, Comput. Commun. 154 (2020) 313–323.
[16] S.S. Ali, B.J. Choi, State-of-the-art artificial intelligence techniques for distributed smart grids: A review, Electronics 9 (6) (2020) 1030.
[17] V.P. Rekkas, S. Sotiroudis, P. Sarigiannidis, S. Wan, G.K. Karagiannidis, S.K. Goudos, Machine Learning in Beyond 5G/6G Networks—State-of-the-Art and Future Trends, Electronics 10 (22) (2021) 2786.
[18] A.K. Dogra, J. Kaur, Moving towards smart transportation with machine learning and Internet of Things (IoT): A review, J. Smart Environ. Green Comput 2 (2022) 3–18.
[19] L. Hurbean, D. Danaiata, F. Militaru, A.-M. Dodea, A.-M. Negovan, Open Data Based Machine Learning Applications in Smart Cities: A Systematic Literature Review, Electronics 10 (23) (2021) 2997.
[20] H. Sharma, A. Haque, F. Blaabjerg, Machine learning in wireless sensor networks for smart cities: a survey, Electronics 10 (9) (2021) 1012.
[21] A. Kumbhar, P.G. Dhawale, S. Kumbhar, U. Patil, P. Magdum, A comprehensive review: Machine learning and its application in integrated power system, Energy Reports 7 (2021) 5467–5474.
[22] M. Farhoumandi, Q. Zhou, M. Shahidehpour, A review of machine learning applications in IoT-integrated modern power systems, Electr. J. 34 (1) (2021) 106879.
[23] A. Talpur, M. Gurusamy, Machine learning for security in vehicular networks: A comprehensive survey, IEEE Commun. Surv Tutorials, 2021.
[24] W.S. McCulloch, W. Pitts, A logical calculus of the ideas immanent in nervous activity, Bull. Math. Biophys. 5 (4) (1943) 115–133.
[25] D.O. Hebb, The organization of behavior: a neuropsychological theory, Science editions (1949).
[26] A. M. Turing, "Computing machinery and intelligence," in *Parsing the turing test*, Springer, 2009, pp. 23–65.
[27] S. Muggleton, Alan Turing and the development of Artificial Intelligence, AI Commun. 27 (1) (2014) 3–10.
[28] F. Rosenblatt, The perceptron: a probabilistic model for information storage and organization in the brain, Psychol. Rev. 65 (6) (1958) 386.
[29] I.M. Cockburn, R. Henderson, S. Stern, The impact of artificial intelligence on innovation: An exploratory analysis, in: The economics of artificial intelligence: An agenda, University of Chicago Press, 2018, pp. 115–146.
[30] M. Pelillo, Alhazen and the nearest neighbor rule, Pattern Recognit. Lett. 38 (2014) 34–37.
[31] D. E. Rumelhart, R. Durbin, R. Golden, and Y. Chauvin, "Backpropagation: The basic theory," *Backpropagation Theory, Archit. Appl.*, pp. 1–34, 1995.
[32] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning representations by back-propagating errors, Nature 323 (6088) (1986) 533–536.
[33] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (8) (1997) 1735–1780.
[34] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86 (11) (1998) 2278–2324.
[35] A. Krizhevsky, I. Sutskever, G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Adv. Neural Inf. Process. Syst.*, vol. 25, 2012.
[36] T. Kano, S. Sakti, and S. Nakamura, "Transformer-based direct speech-to-speech translation with transcoder," in *2021 IEEE Spoken Language Technology Workshop (SLT)*, 2021, pp. 958–965.
[37] G. Tiwari, A. Sharma, A. Sahotra, R. Kapoor, "English-Hindi neural machine translation-LSTM seq2seq and ConvS2S," in *2020 International Conference on Communication and Signal Processing (ICCSP)*, 2020, pp. 871–875.
[38] I. Yazici, L. Temizer, O.F. Beyca, Short term electricity load forecasting with a nonlinear autoregressive neural network with exogenous variables (NarxNet), in: *Industrial Engineering in the Big Data Era*, 2019, pp. 259–270.
[39] N. Grira, M. Crucianu, N. Boujemaa, Unsupervised and semi-supervised clustering: a brief survey, A Rev. Mach. Learn. Tech. Process. Multimed. content 1 (2004) 9–16.
[40] R. Hadsell, S. Chopra, Y. LeCun, "Dimensionality reduction by learning an invariant mapping," in *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, 2006, vol. 2, pp. 1735–1742.
[41] V. Chandola, A. Banerjee, V. Kumar, Anomaly detection: A survey, ACM Comput. Surv. 41 (3) (2009) 1–58.
[42] P.V. Klaine, M.A. Imran, O. Onireti, R.D. Souza, A survey of machine learning techniques applied to self-organizing cellular networks, IEEE Commun. Surv. Tutorials 19 (4) (2017) 2392–2431.
[43] R.S. Sutton, A.G. Barto, Reinforcement learning: An introduction, MIT press, 2018.
[44] L. Guevara, F. Auat Cheein, The role of 5G technologies: Challenges in smart cities and intelligent transportation systems, Sustainability 12 (16) (2020) 6469.
[45] G. Hu et al., Self-powered 5G NB-IoT system for remote monitoring applications, Nano Energy 87 (2021) 106140.
[46] M. Chen, U. Challita, W. Saad, C. Yin, M. Debbah, Artificial neural networks-based machine learning for wireless networks: A tutorial, IEEE Commun. Surv. Tutorials 21 (4) (2019) 3039–3071.
[47] J. Yang, Y. Han, Y. Wang, B. Jiang, Z. Lv, H. Song, Optimization of real-time traffic network assignment based on IoT data using DBN and clustering model in smart city, Futur. Gener. Comput. Syst. 108 (2020) 976–986.
[48] G. Amato, F. Carrara, F. Falchi, C. Gennaro, C. Meghini, C. Vairo, Deep learning for decentralized parking lot occupancy detection, Expert Syst. Appl. 72 (2017) 327–334.
[49] M. Munoz-Organero, R. Ruiz-Blaquez, L. Sánchez-Fernández, Automatic detection of traffic lights, street crossings and urban roundabouts combining outlier detection and deep learning classification techniques

based on GPS traces while driving, Comput. Environ. Urban Syst. 68 (2018) 1–8.
[50] Y. Hou, P. Edara, C. Sun, Traffic flow forecasting for urban work zones, IEEE Trans. Intell. Transp. Syst. 16 (4) (2014) 1761–1770.
[51] Y. Lv, Y. Duan, W. Kang, Z. Li, F.-Y. Wang, Traffic flow prediction with big data: a deep learning approach, IEEE Trans. Intell. Transp. Syst. 16 (2) (2014) 865–873.
[52] W. Hu, Q. Zhuo, C. Zhang, J. Li, Fast branch convolutional neural network for traffic sign recognition, IEEE Intell. Transp. Syst. Mag. 9 (3) (2017) 114–126.
[53] K. Yu, L. Lin, M. Alazab, L. Tan, B. Gu, Deep learning-based traffic safety solution for a mixture of autonomous and manual vehicles in a 5G-enabled intelligent transportation system, IEEE Trans. Intell. Transp. Syst. 22 (7) (2020) 4337–4347.
[54] S. Natarajan, A.K. Annamraju, C.S. Baradkar, Traffic sign recognition using weighted multi-convolutional neural network, IET Intell. Transp. Syst. 12 (10) (2018) 1396–1405.
[55] Y. Tang, C. Zhang, R. Gu, P. Li, B. Yang, Vehicle detection and recognition for intelligent traffic surveillance system, Multimed. Tools Appl. 76 (4) (2017) 5817–5832.
[56] J. Sochor, J. Špaňhel, A. Herout, Boxcars: Improving fine-grained recognition of vehicles using 3-d bounding boxes in traffic surveillance, IEEE Trans. Intell. Transp. Syst. 20 (1) (2018) 97–108.
[57] J. Liang, X. Chen, M. He, L. Chen, T. Cai, N. Zhu, Car detection and classification using cascade model, IET Intell. Transp. Syst. 12 (10) (2018) 1201–1209.
[58] W. Chen, Q. Sun, J. Wang, J.-J. Dong, C. Xu, A novel model based on AdaBoost and deep CNN for vehicle classification, Ieee Access 6 (2018) 60445–60455.
[59] J. Li, X. Mei, D. Prokhorov, D. Tao, Deep neural network for structural prediction and lane detection in traffic scene, IEEE Trans. neural networks Learn. Syst. 28 (3) (2016) 690–703.
[60] X. Ma, Z. Dai, Z. He, J. Ma, Y. Wang, Y. Wang, Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction, Sensors 17 (4) (2017) 818.
[61] J.-G. Wang, L.-B. Zhou, Traffic light recognition with high dynamic range imaging and deep learning, IEEE Trans. Intell. Transp. Syst. 20 (4) (2018) 1341–1352.
[62] D. Tomè, F. Monti, L. Baroffio, L. Bondi, M. Tagliasacchi, S. Tubaro, Deep convolutional neural networks for pedestrian detection, Signal Process. image Commun. 47 (2016) 482–489.
[63] J. Li, X. Liang, S. Shen, T. Xu, J. Feng, S. Yan, Scale-aware fast R-CNN for pedestrian detection, IEEE Trans. Multimed. 20 (4) (2017) 985–996.
[64] Y. Yuan, R. Tasik, S.S. Adhatarao, Y. Yuan, Z. Liu, X. Fu, RACE: Reinforced cooperative autonomous vehicle collision avoidance, IEEE Trans. Veh. Technol. 69 (9) (2020) 9279–9291.
[65] C. Chen, H. Xiang, T. Qiu, C. Wang, Y. Zhou, V. Chang, A rear-end collision prediction scheme based on deep learning in the Internet of Vehicles, J. Parallel Distrib. Comput. 117 (2018) 192–204.
[66] A. Dairi, F. Harrou, Y. Sun, M. Senouci, Obstacle detection for intelligent transportation systems using deep stacked autoencoder and $ k $-nearest neighbor scheme, IEEE Sens. J. 18 (12) (2018) 5122–5132.
[67] H. Ye, G.Y. Li, B.-H.-F. Juang, Deep reinforcement learning based resource allocation for V2V communications, IEEE Trans. Veh. Technol. 68 (4) (2019) 3163–3173.
[68] M. Aloqaily, S. Otoum, I. Al Ridhawi, Y. Jararweh, An intrusion detection system for connected vehicles in smart cities, Ad Hoc Networks 90 (2019) 101842.
[69] S. Zhou, Z. Hu, W. Gu, M. Jiang, X.-P. Zhang, Artificial intelligence based smart energy community management: A reinforcement learning approach, CSEE J. Power Energy Syst. 5 (1) (2019) 1–10.
[70] T.A. Nakabi, P. Toivanen, Deep reinforcement learning for energy management in a microgrid with flexible demand, Sustain. Energy, Grids Networks 25 (2021) 100413.
[71] M. Khan, J. Seo, D. Kim, Real-time scheduling of operational time for smart home appliances based on reinforcement learning, IEEE Access 8 (2020) 116520–116534.
[72] A. Kathirgamanathan, E. Mangina, D.P. Finn, Development of a Soft Actor Critic deep reinforcement learning approach for harnessing energy flexibility in a Large Office building, Energy AI 5 (2021) 100101.
[73] P. Lissa, C. Deane, M. Schukat, F. Seri, M. Keane, E. Barrett, Deep reinforcement learning for home energy management system control, Energy AI 3 (2021) 100043.
[74] Y. Hong, Y. Zhou, Q. Li, W. Xu, X. Zheng, A deep learning method for short-term residential load forecasting in smart grid, IEEE Access 8 (2020) 55785–55797.
[75] V. Suresh, P. Janik, J.M. Guerrero, Z. Leonowicz, T. Sikorski, Microgrid energy management system with embedded deep learning forecaster and combined optimizer, IEEE Access 8 (2020) 202225–202239.
[76] S.A. Nabavi, N.H. Motlagh, M.A. Zaidan, A. Aslani, B. Zakeri, Deep Learning in Energy Modeling: Application in Smart Buildings With Distributed Energy Generation, IEEE Access 9 (2021) 125439–125461.
[77] M. Ahrarinouri, M. Rastegar, A.R. Seifi, Multiagent reinforcement learning for energy management in residential buildings, IEEE Trans. Ind. Informatics 17 (1) (2020) 659–666.
[78] R. Lu, S.H. Hong, M. Yu, Demand response for home energy management using reinforcement learning and artificial neural network, IEEE Trans. Smart Grid 10 (6) (2019) 6629–6639.
[79] L. Yu et al., Deep reinforcement learning for smart home energy management, IEEE Internet Things J. 7 (4) (2019) 2751–2762.
[80] E. Mocanu, P.H. Nguyen, M. Gibescu, W.L. Kling, Deep learning for estimating building energy consumption, Sustain. Energy, Grids Networks 6 (2016) 91–99.
[81] M.N.Q. Macedo, J.J.M. Galo, L.A.L. De Almeida, A.C. de, C. Lima, Demand side management using artificial neural networks in a smart grid environment, Renew. Sustain. Energy Rev. 41 (2015) 128–133.
[82] B. Yuce, Y. Rezgui, M. Mourshed, ANN–GA smart appliance scheduling for optimised energy management in the domestic sector, Energy Build. 111 (2016) 311–325.
[83] C. Guo, X. Wang, Y. Zheng, F. Zhang, Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning, Energy 238 (2022) 121873.
[84] S. Totaro, I. Boukas, A. Jonsson, B. Cornélusse, Lifelong control of off-grid microgrid with model-based reinforcement learning, Energy 232 (2021) 121035.
[85] K.G. Di Santo, S.G. Di Santo, R.M. Monaro, M.A. Saidel, Active demand side management for households in smart grids using optimization and artificial intelligence, Measurement 115 (2018) 152–161.
[86] S. Lee, D.-H. Choi, Federated reinforcement learning for energy management of multiple smart homes with distributed energy resources, IEEE Trans. Ind. Informatics 18 (1) (2020) 488–497.
[87] H.-M. Chung, S. Maharjan, Y. Zhang, F. Eliassen, Distributed deep reinforcement learning for intelligent load scheduling in residential smart grids, IEEE Trans. Ind. Informatics 17 (4) (2020) 2752–2763.
[88] A. Mathew, A. Roy, J. Mathew, Intelligent residential energy management system using deep reinforcement learning, IEEE Syst. J. 14 (4) (2020) 5362–5372.
[89] T. Li, Y. Xiao, L. Song, Integrating Future Smart Home Operation Platform With Demand Side Management via Deep Reinforcement Learning, IEEE Trans. Green Commun. Netw. 5 (2) (2021) 921–933.
[90] L. Lin, X. Guan, Y. Peng, N. Wang, S. Maharjan, T. Ohtsuki, Deep reinforcement learning for economic dispatch of virtual power plant in internet of energy, IEEE Internet Things J. 7 (7) (2020) 6288–6301.
[91] X. Zhang, D. Biagioni, M. Cai, P. Graf, S. Rahman, An edge-cloud integrated solution for buildings demand response using reinforcement learning, IEEE Trans. Smart Grid 12 (1) (2020) 420–431.
[92] A. Kumari, S. Tanwar, A reinforcement learning-based secure demand response scheme for smart grid system, IEEE Internet Things J. (2021).
[93] Q. Wei, Z. Liao, G. Shi, Generalized actor-critic learning optimal control in smart home energy management, IEEE Trans. Ind. Informatics 17 (10) (2020) 6614–6623.
[94] F. Tuchnitz, N. Ebell, J. Schlund, M. Pruckner, Development and evaluation of a smart charging strategy for an electric vehicle fleet based on reinforcement learning, Appl. Energy 285 (2021) 116382.
[95] A. Rosato, M. Panella, R. Araneo, A. Andreotti, A neural network based prediction system of distributed generation for the management of microgrids, IEEE Trans. Ind. Appl. 55 (6) (2019) 7092–7102.
[96] A.A. Alli, M.M. Alam, SecOFF-FCIoT: Machine learning based secure offloading in Fog-Cloud of things for smart city applications, Internet of Things 7 (2019) 100070.
[97] K. Khanna, B.K. Panigrahi, A. Joshi, AI-based approach to identify compromised meters in data integrity attacks on smart grid, IET Gener. Transm. Distrib. 12 (5) (2018) 1052–1066.
[98] D. An, Q. Yang, W. Liu, Y. Zhang, Defending against data integrity attacks in smart grid: A deep reinforcement learning-based approach, IEEE Access 7 (2019) 110835–110845.
[99] L.F. Maimó, Á.L.P. Gómez, F.J.G. Clemente, M.G. Pérez, G.M. Pérez, A self-adaptive deep learning-based system for anomaly detection in 5G networks, Ieee Access 6 (2018) 7700–7712.
[100] A. Takiddin, M. Ismail, U. Zafar, E. Serpedin, Deep Autoencoder-Based Anomaly Detection of Electricity Theft Cyberattacks in Smart Grids, IEEE Syst. J. (2022).
[101] D.I. Dogaru, I. Dumitrache, Cyber attacks of a power grid analysis using a deep neural network approach, J. Control Eng. Appl. Informatics 21 (1) (2019) 42–50.
[102] M. Adil, M.K. Khan, M.M. Jadoon, M. Attique, H. Song, A. Farouk, An AI-enabled Hybrid lightweight Authentication Scheme for Intelligent IoMT based Cyber-Physical Systems, IEEE Trans. Netw. Sci. Eng. (2022).
[103] P. Illy, G. Kaddoum, K. Kaur, S. Garg, ML-based IDPS Enhancement With Complementary Features For Home IoT networks, IEEE Trans. Netw. Serv. Manag. (2022).
[104] S. Latif, Z. Zou, Z. Idrees, J. Ahmad, A novel attack detection scheme for the industrial internet of things using a lightweight random neural network, IEEE Access 8 (2020) 89337–89350.
[105] L. Chen, S. Tang, V. Balasubramanian, J. Xia, F. Zhou, L. Fan, Physical-layer security based mobile edge computing for emerging cyber physical systems, Comput. Commun. 194 (2022) 180–188.
[106] L. Zhang, S. Lai, J. Xia, C. Gao, D. Fan, J. Ou, Deep reinforcement learning based IRS-assisted mobile edge computing under physical-layer security, Phys. Commun. 55 (2022) 101896.
[107] T. Li, S. Xie, Z. Zeng, M. Dong, A. Liu, ATPS: An AI based trust-aware and privacy-preserving system for vehicle managements in sustainable VANETs, IEEE Trans. Intell. Transp. Syst. 23 (10) (2022) 19837–19851.

[108] R. Fu, X. Ren, Y. Li, Y. Wu, H. Sun, M.A. Al-Absi, Machine Learning-Based UAV Assisted Agricultural Information Security Architecture and Intrusion Detection, IEEE Internet Things J. (2023).
[109] H. Sharma, N. Kumar, R.K. Tekchandani, SecBoost: Secrecy-Aware Deep Reinforcement Learning Based Energy-Efficient Scheme for 5G HetNets, IEEE Trans. Mob. Comput. (2023).
[110] S. Ding, L. Kou, T. Wu, A GAN-based intrusion detection model for 5G enabled future metaverse, Mob. Networks Appl. 27 (6) (2022) 2596–2610.
[111] L.A. Ajao, S.T. Apeh, Secure edge computing vulnerabilities in smart cities sustainability using petri net and genetic algorithm-based reinforcement learning, Intell. Syst. with Appl. (2023) 200216.
[112] N. Iqbal, F. Jamil, S. Ahmad, D. Kim, A novel blockchain-based integrity and reliable veterinary clinic information management system using predictive analytics for provisioning of quality health services, IEEE Access 9 (2021) 8069–8098.
[113] A. Gumaei, M.M. Hassan, A. Alelaiwi, H. Alsalman, A hybrid deep learning model for human activity recognition using multimodal body sensing data, IEEE Access 7 (2019) 99152–99160.
[114] M. Alhussein, G. Muhammad, Voice pathology detection using deep learning on mobile healthcare framework, IEEE Access 6 (2018) 41034–41041.
[115] Y. Chen, X. Qin, J. Wang, C. Yu, W. Gao, Fedhealth: A federated transfer learning framework for wearable healthcare, IEEE Intell. Syst. 35 (4) (2020) 83–93.
[116] T. Huynh-The, C.-H. Hua, N.A. Tu, D.-S. Kim, Physical activity recognition with statistical-deep fusion model using multiple sensory data for smart health, IEEE Internet Things J. 8 (3) (2020) 1533–1543.
[117] A. Sekhar, S. Biswas, R. Hazra, A. K. Sunaniya, A. Mukherjee, and L. Yang, "Brain tumor classification using fine-tuned GoogLeNet features and machine learning algorithms: IoMT enabled CAD system," *IEEE J. Biomed. Heal. Informatics*, 2021.
[118] L. Verde, G. De Pietro, A. Ghoneim, M. Alrashoud, K.N. Al-Mutib, G. Sannino, Exploring the use of Artificial Intelligence techniques to detect the presence of Coronavirus Covid-19 through speech and voice analysis, IEEE Access 9 (2021) 65750–65757.
[119] A. Ghoneim, G. Muhammad, S.U. Amin, B. Gupta, Medical image forgery detection for smart healthcare, IEEE Commun. Mag. 56 (4) (2018) 33–37.
[120] A. Hussain, K. Zafar, A.R. Baig, Fog-centric IoT based framework for healthcare monitoring, management and early warning system, IEEE Access 9 (2021) 74168–74179.
[121] K.N. Qureshi, S. Din, G. Jeon, F. Piccialli, An accurate and dynamic predictive model for a smart M-Health system using machine learning, Inf. Sci. (Ny) 538 (2020) 486–502.
[122] V.K. Rathi et al., An edge AI-enabled IoT healthcare monitoring system for smart cities, Comput. Electr. Eng. 96 (2021) 107524.
[123] S. Tuli et al., HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments, Futur. Gener. Comput. Syst. 104 (2020) 187–200.
[124] V.N. Nguyen, R. Jenssen, D. Roverso, Intelligent monitoring and inspection of power line components powered by UAVs and deep learning, IEEE Power energy Technol. Syst. J. 6 (1) (2019) 11–21.
[125] A.S.M. Shihavuddin et al., Wind turbine surface damage detection by deep learning aided drone inspection analysis, Energies 12 (4) (2019) 676.
[126] Y.Y. Munaye, H.-P. Lin, A.B. Adege, G.B. Tarekegn, UAV positioning for throughput maximization using deep learning approaches, Sensors 19 (12) (2019) 2775.
[127] U. Challita, A. Ferdowsi, M. Chen, W. Saad, Machine learning for wireless connectivity and security of cellular-connected UAVs, IEEE Wirel. Commun. 26 (1) (2019) 28–35.
[128] U. Challita, W. Saad, C. Bettstetter, Interference management for cellular-connected UAVs: A deep reinforcement learning approach, IEEE Trans. Wirel. Commun. 18 (4) (2019) 2125–2140.
[129] P.V. Klaine, J.P.B. Nadas, R.D. Souza, M.A. Imran, Distributed drone base station positioning for emergency cellular networks using reinforcement learning, Cognit. Comput. 10 (5) (2018) 790–804.
[130] C.H. Liu, Z. Chen, J. Tang, J. Xu, C. Piao, Energy-efficient UAV control for effective and fair communication coverage: A deep reinforcement learning approach, IEEE J. Sel. Areas Commun. 36 (9) (2018) 2059–2070.
[131] X. Liu, Y. Liu, Y. Chen, L. Hanzo, Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach, IEEE Trans. Veh. Technol. 68 (8) (2019) 7957–7969.
[132] F. Cheng, D. Zou, J. Liu, J. Wang, N. Zhao, Learning-based user association for dual-UAV enabled wireless networks with D2D connections, IEEE Access 7 (2019) 30672–30682.
[133] A. Alipour-Fanid, M. Dabaghchian, N. Wang, P. Wang, L. Zhao, K. Zeng, Machine learning-based delay-aware UAV detection and operation mode identification over encrypted Wi-Fi traffic, IEEE Trans. Inf. Forensics Secur. 15 (2019) 2346–2360.
[134] T. Li, W. Liu, Z. Zeng, N.N. Xiong, DRLR: A deep reinforcement learning based recruitment scheme for massive data collections in 6G-based IoT networks, IEEE Internet Things J. (2021).
[135] T. Yuan, C.E. Rothenberg, K. Obraczka, C. Barakat, T. Turletti, Harnessing UAVs for fair 5G bandwidth allocation in vehicular communication via deep reinforcement learning, IEEE Trans. Netw. Serv. Manag. 18 (4) (2021) 4063–4074.
[136] A.M. Seid, G.O. Boateng, S. Anokye, T. Kwantwi, G. Sun, G. Liu, Collaborative computation offloading and resource allocation in multi-UAV-assisted IoT networks: A deep reinforcement learning approach, IEEE Internet Things J. 8 (15) (2021) 12203–12218.
[137] F. Tang, Y. Zhou, N. Kato, Deep reinforcement learning for dynamic uplink/downlink resource allocation in high mobility 5G HetNet, IEEE J. Sel. areas Commun. 38 (12) (2020) 2773–2782.
[138] J. Yang, X. You, G. Wu, M.M. Hassan, A. Almogren, J. Guna, Application of reinforcement learning in UAV cluster task scheduling, Futur. Gener. Comput. Syst. 95 (2019) 140–148.
[139] D. Basu, S. Kal, U. Ghosh, R. Datta, SoftDrone: Softwarized 5G assisted drone networks for dynamic resource sharing using machine learning techniques, Comput. Electr. Eng. 101 (2022) 107962.
[140] X. Chen, X. Liu, Y. Chen, L. Jiao, G. Min, Deep Q-Network based resource allocation for UAV-assisted Ultra-Dense Networks, Comput. Networks 196 (2021) 108249.
[141] Y. Liu, J. Yan, X. Zhao, Deep reinforcement learning based latency minimization for mobile edge computing with virtualization in maritime UAV communication network, IEEE Trans. Veh. Technol. 71 (4) (2022) 4225–4236.
[142] N. Zhao, Z. Ye, Y. Pei, Y.-C. Liang, D. Niyato, Multi-agent deep reinforcement learning for task offloading in UAV-assisted mobile edge computing, IEEE Trans. Wirel. Commun. 21 (9) (2022) 6949–6960.
[143] L. Tsipi, M. Karavolos, P.S. Bithas, D. Vouyioukas, Machine Learning-Based Methods for Enhancement of UAV-NOMA and D2D Cooperative Networks, Sensors 23 (6) (2023) 3014.
[144] N. Parvaresh, B. Kantarci, A Continuous Actor-Critic Deep Q-Learning-Enabled Deployment of UAV Base Stations: Toward 6G Small Cells in the Skies of Smart Cities, IEEE Open J. Commun. Soc. 4 (2023) 700–712.
[145] G. Wu, B. Zhang, Y. Li, Intelligent and survivable resource slicing for 6G-oriented UAV-assisted edge computing networks, Comput. Commun. 202 (2023) 154–165.
[146] H. Elayan, M. Aloqaily, M. Guizani, Digital twin for intelligent context-aware iot healthcare systems, IEEE Internet Things J. 8 (23) (2021) 16749–16757.
[147] M. Fahim, V. Sharma, T.-V. Cao, B. Canberk, T.Q. Duong, Machine learning-based digital twin for predictive modeling in wind turbines, IEEE Access 10 (2022) 14184–14194.
[148] R.E. Nielsen, D. Papageorgiou, L. Nalpantidis, B.T. Jensen, M. Blanke, Machine learning enhancement of manoeuvring prediction for ship Digital Twin using full-scale recordings, Ocean Eng. 257 (2022) 111579.
[149] S. Garg, A. Gogoi, S. Chakraborty, B. Hazra, Machine learning based digital twin for stochastic nonlinear multi-degree of freedom dynamical system, Probabilistic Eng. Mech. 66 (2021) 103173.
[150] T.G. Ritto, F.A. Rochinha, Digital twin, physics-based model, and machine learning applied to damage detection in structures, Mech. Syst. Signal Process. 155 (2021) 107614.
[151] C. Pylianidis, V. Snow, H. Overweg, S. Osinga, J. Kean, I.N. Athanasiadis, Simulation-assisted machine learning for operational digital twins, Environ. Model. Softw. 148 (2022) 105274.
[152] E.B. Priyanka, S. Thangavel, X.-Z. Gao, N.S. Sivakumar, Digital twin for oil pipeline risk estimation using prognostic and machine learning techniques, J. Ind. Inf. Integr. 26 (2022) 100272.
[153] S. Chakraborty, S. Adhikari, Machine learning based digital twin for dynamical systems with multiple time-scales, Comput. Struct. 243 (2021) 106410.
[154] Q. Min, Y. Lu, Z. Liu, C. Su, B. Wang, Machine learning based digital twin framework for production optimization in petrochemical industry, Int. J. Inf. Manage. 49 (2019) 502–519.
[155] M. Xia, H. Shao, D. Williams, S. Lu, L. Shu, C.W. de Silva, Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning, Reliab. Eng. Syst. Saf. 215 (2021) 107938.
[156] M. Kamari, Y. Ham, AI-based risk assessment for construction site disaster preparedness through deep learning-based digital twinning, Autom. Constr. 134 (2022) 104091.
[157] M. Matulis, C. Harvey, A robot arm digital twin utilising reinforcement learning, Comput. Graph. 95 (2021) 106–114.
[158] Y. Liu, H. Xu, D. Liu, L. Wang, A digital twin-based sim-to-real transfer for deep reinforcement learning-enabled industrial robot grasping, Robot. Comput. Integr. Manuf. 78 (2022) 102365.
[159] Z. Ren, J. Wan, P. Deng, Machine-Learning-Driven Digital Twin for Lifecycle Management of Complex Equipment, IEEE Trans. Emerg. Top. Comput. (2022).
[160] H. V. Dang, M. Tatipamula, and H. X. Nguyen, "Cloud-based digital twinning for structural health monitoring using deep learning," *IEEE Trans. Ind. Informatics*, 2021.
[161] N. Zeulin, A. Ponomarenko-Timofeev, O. Galinina, S. Andreev, ML-Assisted Beam Selection via Digital Twins for Time-Sensitive Industrial IoT, IEEE Internet Things Mag. 5 (1) (2022) 36–40.
[162] J. He, T. Xiang, Y. Wang, H. Ruan, X. Zhang, A Reinforcement Learning Handover Parameter Adaptation Method Based on LSTM-Aided Digital Twin for UDN, Sensors 23 (4) (2023) 2191.
[163] G. Shen, L. Lei, X. Zhang, Z. Li, S. Cai, L. Zhang, Multi-UAV Cooperative Search Based on Reinforcement Learning with a Digital Twin Driven Training Framework, IEEE Trans. Veh. Technol. (2023).
[164] N. Kharlamova, S. Hashemi, Evaluating Machine-Learning-Based Methods for Modeling a Digital Twin of Battery Systems Providing Frequency Regulation, IEEE Syst. J. (2023).

[165] E. Gures, I. Shayea, M. Ergen, M.H. Azmi, A.A. El-Saleh, Machine Learning Based Load Balancing Algorithms in Future Heterogeneous Networks: A Survey, IEEE Access (2022).
[166] N. P. Jouppi *et al.*, "In-datacenter performance analysis of a tensor processing unit," in *Proceedings of the 44th annual international symposium on computer architecture*, 2017, pp. 1–12.
[167] P. A. Merolla *et al.*, "A million spiking-neuron integrated circuit with a scalable communication network and interface," *Science (80-.).*, vol. 345, no. 6197, pp. 668–673, 2014.
[168] S. Han et al., EIE: Efficient inference engine on compressed deep neural network, ACM SIGARCH Comput. Archit. News 44 (3) (2016) 243–254.
[169] A. L'heureux, K. Grolinger, H.F. Elyamany, M.A.M. Capretz, Machine learning with big data: Challenges and approaches, Ieee Access 5 (2017) 7776–7797.
[170] A. Ng, "Machine learning yearning: Technical strategy for ai engineers in the era of deep learning," *Retrieved online https//www. mlyearning. org*, 2019.
[171] S. Singh, S. Rathore, O. Alfarraj, A. Tolba, B. Yoon, A framework for privacy-preservation of IoT healthcare data using Federated Learning and blockchain technology, Futur. Gener. Comput. Syst. 129 (2022) 380–388.
[172] T. Li et al., BPT: A blockchain-based privacy information preserving system for trust data collection over distributed mobile-edge network, IEEE Internet Things J. 9 (11) (2021) 8036–8052.
[173] M. Shafay, R.W. Ahmad, K. Salah, I. Yaqoob, R. Jayaraman, M. Omar, Blockchain for deep learning: review and open challenges, Cluster Comput. (2022) 1–25.
[174] M. Singh, G.S. Aujla, A. Singh, N. Kumar, S. Garg, Deep-learning-based blockchain framework for secure software-defined industrial networks, IEEE Trans. Ind. Informatics 17 (1) (2020) 606–616.