A Survey of Machine Learning Algorithms for 6G Wireless Networks

Abstract
Integrating Artificial Intelligence/Machine Learning (AI/ML) into wireless technology aims to reduce costs, optimize network performance, and create new revenue streams. By replacing traditional algorithms with deep learning AI techniques, power consumption has been reduced, and system performance has improved significantly. ML algorithms enable high automation levels, application-based traffic steering, dynamic network slicing, and ubiquitous connectivity across 6G communication platforms. This chapter provides a comprehensive review of ML techniques applicable to 6G wireless networks and highlights open research problems that require timely solutions.

Introduction
The exponential growth in bandwidth demand and data traffic necessitates efficient high-speed wireless communication networks. To meet these requirements, intelligent algorithms, advanced physical layer solutions, and higher-frequency spectral bands are essential. Tera-Hertz (THz) bands have emerged as a promising solution to enable ultra-broadband wireless communication and mitigate spectrum scarcity issues. While traditional wireless systems rely heavily on mathematical models, ML techniques have gained momentum for achieving quality-of-service functionalities with advanced solutions. ML algorithms replace heuristic or Brute Force Algorithms, optimize localized tasks and provide solutions beyond the reach of existing mathematical models. Dynamic deployment of ML algorithms is envisioned to enhance performance and utilization.

ML Algorithms in Wireless Communication
ML algorithms play a vital role in wireless communication tasks, including classification, regression, and intelligent agent interaction with the wireless environment. These algorithms operate in three different versions: supervised learning, unsupervised learning, and reinforcement learning. Non-parametric Bayesian methods, such as the Gaussian approach, handle small, incrementally growing data sets, but their complexity is higher than parametric methods. Kernel Hilbert Space-based solutions have shown promising results in generating significantly improved data rates compared to 5G networks, with lower approximation error and computational simplicity. Federated Learning (FL) is a distributed ML algorithm that enables mobile devices to collaboratively learn a shared ML model without exchanging data. FL is being further analyzed for various applications, including orientation, intrusion detection, mobility, and extreme event prediction. Reinforcement Learning algorithms assist in coding scheme selection, modulation, beamforming, power control, and physical layer optimization.

Supervised Learning and Unsupervised Learning Algorithms
Machine learning (ML) algorithms can be classified into supervised and unsupervised learning. The main difference between these two classes lies in the availability of labeled training data. In supervised learning, the algorithms predict and classify predetermined attributes based on input and output variables. This process continues until the algorithm achieves a satisfactory level of performance. Examples of supervised learning algorithms include linear regression, random forest, and support vector machines (SVM). These algorithms are commonly used for tasks such as prediction, classification, and resource allocation in wireless communication.

Semi-Supervised Machine Learning
Semi-supervised learning algorithms involve a large amount of input data (X) and a small amount of labeled output data (Y). These algorithms bridge the gap between supervised and unsupervised learning.

Unsupervised Learning
Unsupervised learning involves pattern recognition without a target attribute. It uses all variables as inputs and is suitable for clustering and association mining. Clustering algorithms identify inherent groupings within unlabeled data, while association mining algorithms identify relationships between attributes. Unsupervised learning helps create labels in the data that can be used for subsequent supervised learning tasks. Examples of unsupervised learning algorithms include K-means clustering and the Apriori algorithm.

Reinforcement Learning
Reinforcement learning (RL) is a fundamental ML paradigm focusing on decision-making and maximizing cumulative reward in an environment. RL does not require labeled input/output pairs and aims to find a balance between exploration and exploitation. RL finds applications in game theory, control theory, simulation-based optimization, multi-agent systems, swarm intelligence, and wireless communication. RL algorithms use Markov Decision Processes (MDP) to model the environment and employ dynamic programming techniques.

RL algorithms can be categorized into various types.

Associative Reinforcement Learning: Combines the features of stochastic learning automata tasks in a closed-loop interaction with the environment.Deep Reinforcement Learning: Extends RL by using deep neural networks to approximate or estimate states without explicitly designing the state space. Deep RL has gained attention, particularly in learning tasks such as playing ATARI games.

Inverse Reinforcement Learning: Aims to imitate observed behavior, often close to optimal, without explicitly defining a reward function.Safe Reinforcement Learning: Focuses on learning policies that maximize the expected return while ensuring reasonable system performance and safety constraints.

Federated Learning

Federated learning (FL) is a distributed ML algorithm that addresses privacy concerns in traditional centralized ML algorithms. It enables devices to learn a shared ML model without exchanging data among devices. Instead, each device trains a local FL model using its collected data, and the data center integrates these local models to generate a global FL model. FL aims to protect data owners' privacy and allows for accurate generalized models across multiple devices.

Kernel Hilbert Space

To address high interference and improve data rates in 6G, solutions based on Reproducing Kernel Hilbert Space (RKHS) are effective. RKHS methods offer computational simplicity, low approximation error, and scalability. These methods can mitigate impairments caused by non-ideal hardware and apply to various 6G challenges, including detection, tracking, and localization. RKHS-based approaches combined with feature extraction methods can enhance the performance of models used in 6G wireless communications.

Cognitive Radio

Cognitive radio technology enables dynamic spectrum allocation by autonomously adapting transmission strategies based on environmental sensing and learning. It adjusts system transmission parameters, such as bandwidth, transmits power, carrier frequency, and modulation scheme, to optimize performance while protecting primary users. Cognitive radio can facilitate Dynamic Spectrum Allocation (DSA) efficiently and has the potential to be integrated.

Considerations and Implications

Implementing ML algorithms at end-user devices requires considering parameters such as cost, size, and power. Furthermore, optimizing the physical realization of the design and determining the inputs to the model are important considerations in simulating and prototyping ML at end-user devices. As a component of AI, ML plays a crucial role in 6G wireless communication by leveraging historical data to solve problems, extract knowledge, and enable faster and more efficient management of processes.

Future Applications and Dynamic Spectrum Management

ML is poised to revolutionize wireless communication networks, enabling applications such as Augmented Reality (AR), Virtual Reality (VR), holographic telepresence, eHealth, wellness applications, Massive Robotics, and Pervasive connectivity in smart environments. ML will facilitate real-time analysis, zero-touch operation, and control in 6G networks. In addition, mobile devices can report ML actions and predictions to aid efficient resource management. Dynamic spectrum management, addressing the scarcity and underutilization of available spectrum, relies on concepts like Cognitive Radio, Symbiotic Radio, and Blockchain Technology. These techniques manage spectrum allocation and address data security, optimization, power efficiency, and cost efficiency.

Conclusion:

ML algorithms offer significant potential for enhancing wireless communication in 6G networks. Their integration enables intelligent decision-making, resource optimization, and improved user experiences. However, further research is required to address the open problems in this field and develop timely solutions to ensure the successful implementation of ML in 6G wireless networks.

References:

Amanpreet S., Narina,T., & Aksha , S. (2016). A review of supervised machine learning algorithms. 3rd International
Conference on Computing for Sustainable Global Development (INDIACom), Corpus ID:27775741

Amruthnath, N., & Gupta, T. (2018). A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. 5th International Conference on Industrial Engineering and Applications (ICIEA).
DOI:10.1109/iea.2018.8387124.

Chowdhury, S., & Schoen, M. P. (2020), Classification using Supervised Machine Learning Techniques, Intermountain Engineering Technology and Computing (IETC).
DOI:10.1109/ietc47856.2020.924921.

Dalal R., and Kushal, R. (2018). Review on Application of Machine Learning Algorithm for Data Science. IEEE 3rd International Conference on Inventive Computation Technologies (ICICT), 270-273. DOI:10.1109/icict43934.2018.9034256.

Du, J., Jiang, C., WANG, J., Ren, Y., & Debbah, M. (2020). Machine Learning for 6G Wireless Networks: Carry-Forward- Enhanced Bandwidth, Massive Access, and Ultrareliable/Low Latency. IEEE Vehicular Technology Magazine. DOI:10.1109/mvt.2020.3019650.

Guo, W. (2019). Explainable artificial intelligence (XAI) for 6G: Improving trust between human and machine. arXiv preprint arXiv:1911.04542.

Hewa, T., Gurkan, G., Kalla, A., & Ylianttila. (2020). The Role of Blockchain in 6G: Challenges, Opportunities and Research Directions, 2nd 6G wireless Summit (6G SUMMIT), DOI: 10.1109/6GSUMMIT49458.2020.9083784.

Hong, X., Jing, W., & Jianghong, S. (2014). Cognitive radio in 5G: a perspective on energy-spectral efficiency trade–off. IEEE communications Magazine. DOI: 10.1109/MCOM.2014.6852082.

Iqbal H. S. (2021). Machine Learning: Algorithms, Real World Applications and Research Directions. SN Computer Science, 2:160 Available on https://doi.org/10.1007/s42979-021-00592-x

Kien, T., Long Ton, T., & Nguyen, G.M.T. (2020). Plant Leaf Disease Identification by Deep Convolutional Autoencoder as a Feature Extraction Approach. Proceedings of The IEEE 17th International Conference on Electrical Engineering / Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), paper ID: #1570639150, Thailand, Available on https://ieeexplore.ieee.org/document/9158218/

Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated Learning: Challenges, Methods, and Future Directions. IEEE Signal Processing Magazine, 37(3), 50–60. DOI:10.1109/msp.2020.2975749.
Marmol, C., Pablo, F.S., Aurora, G.V., Jose, L., Hernandez, R., Jorge, B., Gianmarco B., & Antonio, S. (2021). Evaluating Federated Learning for Intrusion Detection in Internet of Things: Review and Challenges Enrique. arXiv:2108.00974v1. Mingzhe, C., Deniz, G., Kaibin, H., Walid, S., & Mehdi, B.(2021). Distributed Learning in Wireless Networks: Recent Progress and Future Challenges. IEEE Journal on Selected Areas in Communications, 39(12): 3579 – 3605. DOI: 10.1109/JSAC.2021.3118346.
Mollah, M.B., Zeadally, S., & Azad, M.A.K. (2019). Emerging wireless technologies for Internet of Things applications:
Opportunities and challenges, Encyclopaedia of Wireless Networks. Springer International Publishing Cham, pp. 1–11. Salh, A., Audah, L., & Shah, NSM. (2020). A Survey on Deep Learning for Ultra-Reliable and Low-Latency Communications Challenges on 6G Wireless Systems. Proceedings of Future of Information and Communication Conference (FICC)
2021, arXiv: 2004.08549v3.
Sheena, A. & Sachin, A. (2017). Machine learning and its applications: A review. International Conference on Big Data
Analytics and Computational Intelligence (ICBDAC). DOI: 10.1109/ICBDACI.2017.8070809
Shrestha, A., & Mahmood, A., (2019). Review of Deep Learning Algorithms and Architectures. IEEE Access, 7, 53040–
53065. DOI:10.1109/ACCESS.2019.2912200.
Syed, J.N., Shree, K.S., Shurjeel, W., Mohammad, N., & Md. Asaduzz, A. (2019). Quantum Machine Learning for 6G
Communication Networks: State-of-the-Art and Vision for the Future. IEEE Access, 7: 46317-46350.
Vasileios, P.R., Sotirios, S., Panagiotis, S., Shaohua, W., George, K. K., & Sotirios K.G.(2021). Machine Learning in Beyond 5G/6G Networks—State-of-the-Art and Future Trends. Electronics, 10, 2786.Available on https://doi.org/10.3390/
electronics10222786.

Yogesh, K., Komalpreet K., & Gurpreet, S. (2020). Machine Learning Aspects and its Applications Towards Different Research Areas. IEEE International Conference on Computation, Automation and Knowledge Management (ICCAKM). DOI: 10.1109/ICCAKM46823.2020.9051502
Zhao, Y., Zhai, W., Zhao, J., Zhang, T., Sun, S., Niyato, D., & Yan Lam, K. (2020). A Survey of 6G Wireless Communications: Emerging Technologies. arXiv:2004.08549v3.
Zhao, Y., Zhai, W., Zhao, J., Zhang, T., Sun, S., Niyato, D., & Yan Lam, K. (2021). A Comprehensive Survey of 6G Wireless Communications. arXiv:2101.03889v2.