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A Review on Machine Learning Algorithms in Smart Communication System

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ABSTRACT

Including ML techniques into smart communication systems has fundamentally changed modern wireless networks such that they are now more trustworthy, efficient, and flexible than ever before. Among the many applications of machine learning (ML) discussed in this paper are channel prediction, power allocation, IoT enabled devices, and network automation. This study aims to provide a complete summary of how present achievements in domains like neuro-fuzzy inference systems, clustering approaches, and deep reinforcement learning (DRL) tackle challenges with data processing, security, and resource management. Furthermore, the assessment identifies significant advances and areas where additional research is required, therefore supporting future developments in this subject.

Keywords: ML, Smart communication, DRL, Network automation

INTRODUCTION

Smart communication systems, which underlie next-generation wireless networks, are used in a variety of applications including IoT , communication in automobiles, and satellite networking. The exponential increase of linked devices makes optimising network performance, security, and resource allocation increasingly challenging. Among the many ways recent ML developments have provided fresh solutions for these challenges are intelligent decision-making, flexible resource management, and enhanced security measures. This work investigates the use of multiple ML algorithms in smart communication systems. Gaining knowledge of the contributions of approaches like clustering, deep learning, reinforcement learning, and neuro-fuzzy inference systems helps one to solve problems like channel prediction, power allocation, and traffic classification. By use of many significant study findings, this review examines trends, challenges, and future directions of research.

Need for Research

The need for intelligent optimisation algorithms has grown as NOMA, LEO satellite networks, and IoT ecosystems become more common. Using conventional approaches might be a major difficulty adjusting to always shifting network conditions, limited resources, and security concerns. ML-based techniques might help systems with many users distribute resources and control power. Other advantages include improved channel prediction and modulation categorisation as well as strict security policies meant to prevent smart jamming and identity theft. Moreover, these technologies automate network operations in challenging environments like O-RAN, hence lowering the need for human involvement.

Motivation

Motivating this effort is the belief that ML has the ability to address the growing complexity of modern communication networks. Here are a few noteworthy discoveries that came from the inquiry. Research on DRL was centred on NOMA system power distribution and channel forecasting under Galala et al. [1]. Camana et al. [2] updated REM in wireless networks using clustering and random forests. It is examining the implementation of federated deep reinforcement learning for edge computers in sky-based systems by Liu et al. [17]. Agricultural IoT route loss prediction using neuro-fuzzy algorithms It is time for a comprehensive study to bring everything together and look ahead to trends, as these research show how revolutionary ML algorithms may be.

Literature review

This all-encompassing analysis of current trends across several sectors reveals how AI, machine learning, and IoT have evolved game-changing responses to common problems in automation, communication, and farming.

In Power Domain NOMA systems, Gaballa and Abbod (2023) introduced a basic DRL algorithm for channel prediction [1]. Using DRL, this approach enhanced the performance of the wireless communication system and prediction accuracy.

Published in 2023 by Gaballa et al. [2], one study on the advantages of MISO-NOMA systems using reinforcement learning for channel prediction and power allocation was Its lowered interference and enhanced energy efficiency will enable future wireless networks.

In their investigation, Camana et al. (2023) [3] developed a REM updating approach by means of random forest and clustering approaches. Our approach improves spectrum management and network performance by appropriately updating the radio environment map using machine learning models.

Phaiboon and Phokharatkul (2023) [4] examined route losses in a ruby mango orchard using an ANFIS and found Their method effectively managed environmental challenges during the construction of wireless networks, therefore obtaining great prediction accuracy in rural areas.

With deep learning and CSI, Ribouh et al. (2022) [5] aimed to find vehicle settings. This approach made it possible to predict environmental circumstances and thereby increase system dependability, hence guiding trustworthy wireless communication in automobile networks.

Harper et al. [6] presented in 2023 a DNN based automatic modulation categorisation method. Their approach showed how to distinguish between many modulation techniques, therefore enhancing wireless communication systems.

Zhang and Zhang (2023) [7] created a cascade network with the aim of just appreciating LDPC codes. Especially for low-density parity-check codes, this method greatly enhanced both decoding performance and error correction.

Lamilla et al. (2023) [8] concentrated on OAM in their presentation of an optical encoding model powered by machine learning). Their studies showed its potential for high-capacity transmission and effective optical encoding.

Cho and Song (2022) [9] described a fast decoding method for Reed-Muller codes using an auto-decoder using an auto-decoder. Applications needing both short-length and high-rate coding would find the method to be perfect given its outstanding reductions in computational complexity.

Gupta et al. (2023) [10] presented an intelligent irrigation system dependent on IoT by means of soil moisture prediction derived on machine learning. In precision agriculture, their method proved effective in both water use and accuracy.

Pu et al. (2022) [11] proposed an imperfect spectrum sensing method as a way of stopping intelligent interference in wireless communication. This method provided constant communication in demanding surroundings and enhanced spectrum detection accuracy.

Goyal et al. (2024) [12] utilising IoT, devised an identity theft prevention solution for industrial automation. Their enhanced data security and reliability in industrial IoT systems came from using blockchain technology.

Ding et al. (2023), [13] developed a method for routing in LEO satellite networks utilising fast-convergence reinforcement learning. Dealing with important problems in satellite communication, their method reduced latency and enhanced routing efficiency.

Venkateshwari et al. (2023) [14] employed time series forecasting of data from IoT in their analysis of smart city technical design. Their approach produced sensible suggestions for bettering metropolitan infrastructure and distributing limited resources.

Zhang et al. (2023) [15] proposed a deep reinforcement learning-based strategy to maximise the bandwidth and power distribution concurrently. This approach found the sweet spot between power constraints and resource use, therefore effectively achieving high system efficiency.

Rao et al. (2024) [16] developed a state-of- the-art deep learning algorithm to categorise content in IoT ecosystems. Their method was shown to be more accurate and efficient in classifying for large volumes of IoT data.

Liu et al. (2022) [17] proposed a federated deep reinforcement learning architecture for the offloading computation and collaboratively deploying AeBSs in aerial edge computing networks. This approach improved resource use and helped to lower computing latency.

Gupta et al. (2024) [18] concentrated on performance and accuracy enhancement of machine learning and IoT-based agricultural precision AI systems. Their method provided helpful information for agricultural management and improved the accuracy of forecasts.

Camana et al. (2024) [19] was maximised beamforming using deep learning in rate-splitting multiple-access systems with wireless information and power transfer. Their approach raised both power management and communication efficiency.

Veeraiah et al. (2024) [20] investigated IoT applications in creating engineering systems to illustrate how IoT has the capacity to enhance commercial and industrial automation using advanced IoT frameworks.

Sharma et al. (2024) [21] built a machine learning model to forecast future manufacture of sustainable solar power. Their technology created from IoT uses sensor data collected from the distribution and administration of power.

Recently Hamdan et al. (2023) [22] reviewed O-RAN network automation in light of They showed how artificial intelligence may enable networks to become more adaptable and efficient.

John et al., 2024 [23] looked into new wireless technologies in order to better route IoT. They demonstrated using contemporary routing techniques that IoT networks may be more stable and scalable.

Baek et al. (2023) [24] put forth a multi-task classification method for application traffic using task linkages. This approach allowed them to raise classification accuracy at the same time as lowering the processing load in network management.

Lalitha Kumari et al. (2023) [25] introduced a deep learning deep learning method for object categorisation in high-resolution optical images. Their approach proved flexible by performing really outstanding performance on optical image classification challenges.

Table 1: Literature Review

Ref	Author / Year	Journal details	Objective	Methodology	Accuracy	Conclusion
[1]	Gaballa et al. (2023)	Sensors, 23, 9010	Simplify DRL for channel prediction in Power Domain NOMA System.	Simplified deep reinforcement learning approach.	High prediction accuracy; specific value not provided.	Demonstrates efficiency of RL for channel prediction in NOMA.
[2]	Gaballa et al. (2023)	Sensors, 23, 1383	Study the impact of integrating RL for channel prediction and	RL combined with power allocation techniques.	Improved power allocation and channel	Integration improves system efficiency and

			power allocation in MISO-NOMA.		prediction accuracy.	resource allocation.
[3]	Camana et al. (2023)	Applied Sciences, 13, 5362	Propose an REM update methodology based on clustering and random forest.	Clustering and random forest models applied for REM updates.	Enhanced REM update accuracy; specific metric not provided.	Demonstrates improvement in resource management using clustering.
[4]	Phaiboon (2023)	J. Sens. Actuator Netw., 12, 71	Apply ANFIS for path loss prediction in a Ruby Mango plantation.	ANFIS	Achieves low prediction error; quantitative values not mentioned.	Validates ANFIS as a robust approach for path loss prediction in agricultural environments.
[5]	Ribouh et al. (2022)	Sensors, 22, 9018	Identify vehicular environments using channel state information and DL.	DL for channel state information analysis.	High classification accuracy; specific values not mentioned.	Demonstrates DL's potential for accurate vehicular environment identification.
[6]	Harper et al. (2023)	Electronics, 12, 3962	Automatic modulation classification with DNN.	DNN for modulation classification.	Classification accuracy exceeds 90%.	DNN effectively classify modulation types.
[7]	Zhang et al. (2023)	Electronics, 12, 1979	Cascade network for blind LDPC code recognition.	Cascade network architecture.	Accuracy exceeds baseline methods by a significant margin.	Effective in blind recognition of LDPC codes.
[8]	Lamilla et al. (2023)	Sensors, 23, 2755	Optical encoding model using orbital angular momentum with ML.	ML-powered optical encoding model.	High encoding accuracy; specific metrics not mentioned.	Proves the feasibility of ML for optical encoding.
[9]	Cho & Song (2022)	Applied Sciences, 12, 9225	High-speed decoding for Reed-Muller codes using auto-decoders.	Auto-decoder methodology.	Faster decoding with high accuracy.	Promotes high-rate and short-length Reed-Muller codes.
[10]	Gupta et al. (2023)	IEEE ICTACS	IoT-based intelligent irrigation with ML for soil moisture prediction.	ML models for moisture prediction integrated into IoT.	Accuracy exceeds 90%.	Efficiently optimizes irrigation systems using IoT.

Problem Statement

Even with notable progress, the implementation of ML algorithms in smart communication systems still presents some challenges. Main challenges include adjusting to rapid changes in network conditions, especially in NOMA, LEO satellites, and vehicle communications. Regarding huge IoT networks and federated learning, scalability is also another issue requiring solution. This one focusses entirely on the processing and communication over overheads. One cause of worry has been shown to be security hazards. Strong ML models are needed to fight sophisticated hazards as intelligent jamming and identity theft. Decision-making procedures should remain transparent and ML models should provide insightful analysis. Dealing with these challenges demands a thorough examination of present approaches as well as the development of new ones.

Future Scope

The rapid developments in machine learning, AI, and IoT have created many chances for further research and applications in many different fields. Particularly in complex scenarios such as MIMO-NOMA systems, channel estimation, resource allocation, and interference management, AI-driven prediction models in wireless communication may help to enhance all around. With the development of complex reinforcement learning techniques, network efficiency in terrestrial and satellite communication networks may be much enhanced. Expansion of IoT-based precision farming technologies including real-time weather predictions and improved soil health monitoring opens more sustainable agricultural possibilities. New frameworks like federated learning and blockchain are developing to address IoT ecosystem data sharing, privacy, and security challenges. Furthermore leading to the creation of communication systems with hitherto unheard-of degrees of security and capacity is research on quantum communication and optical encoding. Future research might look at AI driven predictive maintenance and energy optimisation systems for sustainable power management. Integration of renewable energy sources is becoming ever more important. From the application of deep learning for autonomous decision-making in transit systems, smart cities, and industrial automation, deep learning will have transforming consequences on city planning and infrastructure development. Different sectors must keep working together and using fresh technologies in creative ways if we are to address world issues and raise the quality of living.

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