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Deep learning Techniques for Enhancing Smart Wireless Networks: A Review

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Abstract

Deep learning has proven to be an effective tool for improving the performance of wireless networks, for addressing many network's important problems, including routing, security, spectrum sensing, resource allocation, and localization. Furthermore, integrating deep learning tools into networks can greatly increase the network's capacity to adapt to changing into smart environments and improve the overall stability and robustness of the system. As the demand for large network nodes and huge amounts of information, it can be used to determine and identify the network characteristics (such as best path, hotspots node, interference distribution, congestion points, traffic bottlenecks, spectrum availability, etc.) by analyzing a large number of network parameters (such as energy consumption, delay, lifetime, loss rate, packet overhead, etc.). This paper presents a review of recently published research that used different deep learning models to enhance the performance of wireless networks. In addition, the review focused primarily on the following topics in this field: user localization, routing, security, big data, mobility, network control, and other applications such as Wi-Fi and channel communication. This article aims to help the readers' awareness of the most recent proposed models and algorithms in deep learning-driven wireless networks, as well as to identify relevant unresolved challenges that could be addressed in future studies.

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1. Introduction

In recent years, there has been considerable attention for intelligent methods from researchers due to their potential to enhance wireless networks [1]. Currently, many authors are tended to focus on combining Deep Learning (DL) with wireless networks to make transferring information's in to the system more intelligent and reliable. At the same time, the increasing variety and use of wireless networks coupled with the increased necessity for large data applications, have led to the most efficient use of DL to improve the performance of wireless networks. Furthermore, the large amount of heterogeneous data traffic in the network requires efficient methods that can learning and process this data in a fast and robust way. From these perspectives, DL could address and solve various challenges in wireless networks, such as resource management, routing, security, coverage, pattern recognition, localization, and big data [2]. By applying deep learning methods, including the neural layer for feature detection and trying to produce effective detection of cyber threats, researchers are creating the basis for building flexible and intelligent systems. In most of the applications, the integration of deep learning techniques in wireless networks provides real-time analysis and fast resource allocation, but also for the

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improvement of security aspects, network functions, and highly specific solutions for different types of mobile contexts. Furthermore, approaches based on reinforcement learning, such as stateless Q-learning variants, allow intelligent wireless networks to adapt channel usage and transmission power dynamically according to throughput to enhance performance [3].

Traditional wireless networks face challenges such as latency, high energy consumption, and security issues due to the large amount of data generated at the network edge. Deep learning algorithms and frameworks have the potential to address these challenges by enabling tasks such as user associations, power allocation, bandwidth assignment, user selections, and cloud computing technologies at the edge [4]. In contrast, AI-driven networks aim for self-operational, self-configurational, and self-managed systems to deliver highly reliable and low-latency communication. Additionally, innovations like the DL-MAC protocol leverage deep learning for intelligent channel access and rate adaptation, significantly improving spectrum efficiency in Wi-Fi networks. The way towards Intelligent Wireless Networks represents a higher step advancement over traditional wireless networks, providing improved efficiency, reliability, and intelligence in network operations [5].

Deep learning (DL) finds extensive applications in wireless networks, particularly in tasks like wireless signal analysis for indoor localization [6] [7]. DL models are trained using measurement data of wireless signals to predict signal characteristics accurately. However, the process of generating high-quality DL training datasets from real-world experimental environments presents significant challenges in terms of both effort and duration, hindering the application of the latest DL models in wireless network research. To address this challenge, construction of tools like DeepWiSim, a wireless signal simulator based on ray-tracing, streamlines the DL process, encompassing data generation, model training, and evaluation. This approach facilitates the efficient production of high-quality simulated wireless signal measurement data, which is then used for training and evaluating DL models [8]. This advance simplifies the use of DL in wireless networks by easing data generation and training. Figure 1 presents a taxonomy of deep learning applications in wireless networks.

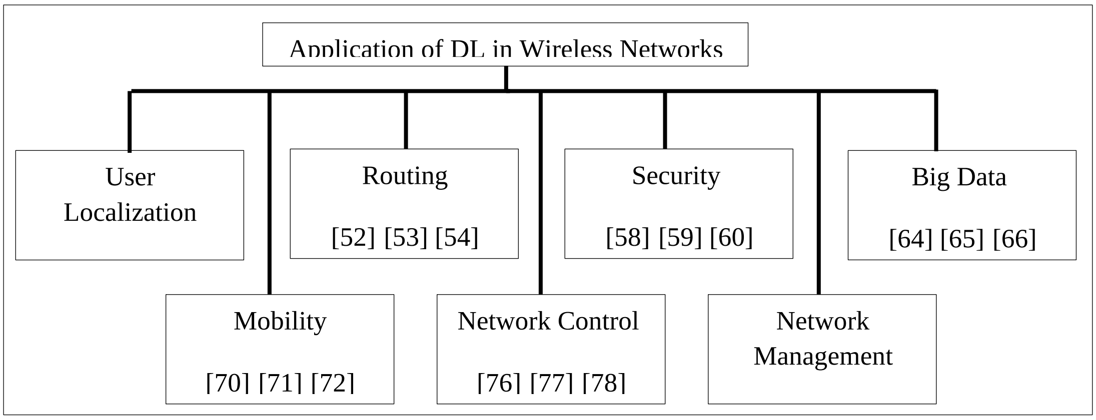

Figure. 1 Application of DL in the field Wireless Networks

This paper presents a review of deep learning techniques in the domain of intelligent wireless networks. Furthermore, it examines various research domains where deep learning can be applied in wireless systems, aiming to inspire and guide researchers in this field. Deep learning (DL) has emerged as a powerful tool for intelligent and data-driven decision-making in a wide range of applications [9]. In the context of wireless communications, deep learning has the potential to simplify network design and improve performance by leveraging the vast amounts of data generated in modern wireless systems [10]. Table 1 presents a comparison of existing surveys and this work.

Roadmap: The rest of this paper is structured as follows: Section 2 gives an overview of deep learning. Architectures of deep learning for wireless networks are presented in Section 3. Furthermore, section 4 introduces various related works for the use of AI approaches for improving wireless networks. In section 5, we focus on future directions and open issues. Our conclusions are drawn in the final part of the review, section 6.

1.2 Search Strategy and Literature Sources

Literature searches were conducted across multiple digital libraries and databases, including Google Scholar, ScienceDirect, IEEE Xplore, the ACM Digital Library, the IET Digital Library, Wiley Online Library, Springer Nature, and SpringerLink. Queries combined keywords and phrases such as “DL with wireless network,” “DL security models for wireless network,” “artificial intelligence for enhanced network,” “DL for wireless network management,” and “review on DL

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for wireless network," which initially returned approximately 155 articles. After removing duplicates and screening abstracts for relevance, 82 articles were selected for full-text review; following full-text examination, 25 articles were excluded due to overlapping methodologies or prior publication, leaving 57 papers included in this review (IEEE Xplore: 23 papers; Wiley: 10 papers; Springer: 10 papers; Google Scholar: 6 papers; ResearchGate: 5 papers; MDPI: 3 papers).

Table 1: Summary of existing surveys for Deep Learning in Intelligent Wireless Networks

Refs. (Author)	Year	Scope						
		Localization	Routing Protocols	Security	Big Data	mobility	Network Control	Other
Mao et al. [18]	2018	✓	✓	×	×	×	✓	×
Zhang et al. [10]	2019	✓	×	✓	×	✓	✓	×
Sun et al. [19]	2019	✓	✓	×	✓	✓	✓	×
Ali et al. [20]	2020	×	×	✓	×	×	×	×
Hussain et al. [21]	2020	×	×	×	×	×	✓	×
Kumar et al [22]	2020	×	×	✓	×	×	×	×
Sharma et al. [23]	2021	×	×	×	✓	×	×	✓
Li et al. [24]	2021	×	×	×	✓	×	×	×
Nguyen et al. [25]	2022	✓	×	✓	×	×	✓	×
Salau et al. [26]	2022	×	×	×	✓	×	✓	×
Yazici et al. [27]	2023	×	×	✓	✓	✓	×	×
Iyer et al. [28]	2023	×	×	×	×	×	✓	×
Rodriguz et al. [29]	2023	×	×	✓	×	×	×	×
Zhou et al. [30]	2024	×	×	×	×	×	✓	✓
Hammadi et al. [31]	2024	×	×	✓	✓	✓	✓	×
Sun et al. [32]	2024	×	×	×	×	✓	✓	×
Gupta et al. [33]	2025	✓	×	×	×	×	✓	✓
Kori et al [34]	2025	×	×	×	×	×	✓	✓
This Review		✓	✓	✓	✓	✓	✓	✓

2. Deep Learning Background

Deep learning (DL), a subfield of machine learning, has witnessed significant progress and extensive application in bioinformatics [11][12], medicine field [13], speech recognition, and wireless networks [14]. It permits computers to acquire knowledge from experience using large datasets [15]. Deep learning is constructed with multiple layers, allowing for a classified structure of data and enabling the process of feature extraction as data passes through the model [16] [17]. DL classification can be classified into three main categories: supervised learning, unsupervised learning, and semi-supervised learning. In supervised learning, the input samples with the corresponding labels are provided to train the model. Unsupervised learning includes training models on unlabeled data.

The model independently discovers patterns, structures, or relationships from the unlabeled input data to learn by itself. In semi-supervised learning, labelled and unlabeled data are combined for training. The model learns patterns from the labeled training data to make predictions on the unlabeled data [35].

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The Convolutional neural network (CNN) is the well-known and popular approach used in the domain of DL, which is used to automatically extract the pertinent features without human supervision [36]. The benefits of employing CNNs involve their ability to automatically extract relevant features, efficiently process spatial information, achieve translation invariance, and build hierarchical representations. The architecture of CNN [37], as shown in Figure 2, is typically composed of multiple layers that work together to analyze and extract features from input data. A CNN architecture consists of the following main layers:

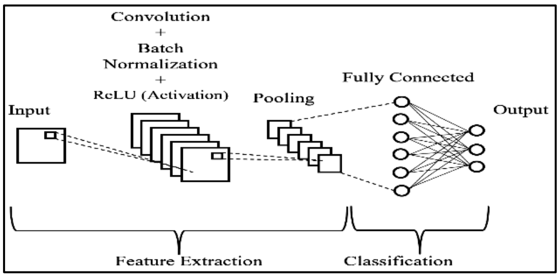

Figure 2. Basic CNN architecture [36].

1. Convolutional Layers: These layers apply a set of learnable filters known as kernels to the input image. The filters learn to detect different features, such as edges, shapes, or textures, by convolving the filter over the input and calculating the dot product between the filter and the input. This process generates a feature map that represents the most relevant and discriminative aspects of the input data.
2. Pooling Layers, including max pooling and average pooling, are essential components in deep learning architecture, as they diminish the spatial dimensions of feature maps, reduce the amount of features, and lower computational complexity.
3. Activation Layers: These layers play a crucial role in deep learning since they work in hidden layers to solve hard problems and send and analyze data throughout the deep learning algorithm.
4. Fully Connected Layers: added to the end of the CNN architecture. These layers connect each neuron from the previous layer to all neurons in the current layer, primarily for classification purposes.
5. Normalization Layers: In order to improve the network's performance during training, Normalization Layers, such as Batch Normalization, are frequently inserted between the convolutional and activation layers.

2.1. Advantages of Deep Learning in Wireless Networking

Many benefits and advantages that deep learning provides in the area of networks will be highlighted in this section. The ability of deep learning to automatically extract task features from huge amounts of data is one of its most crucial characteristics. By eliminating the need for human design, the learning process significantly improves the manual feature formulation process. This feature is important in network systems, because processing and reduction are one of the most feasible required when having a large amount of information. Furthermore, Deep learning models can improve adaptive signal processing techniques, leading to better data transmission and reception. This process optimizes and enhances the channel equalization, which leads to data rate and reliability improvement. More Advanced deep learning models can identify and correct errors in communication channels more efficiently than traditional methods. At the same time, the strength point added to the wireless network, models can predict and detect network failures or anomalies, allowing for proactive maintenance. Another key for the resource's allocation, DL algorithms enable dynamic allocation based on demand and improve overall network efficiency [38].

A further important DL technique can enhance the security of networks through identify cybersecurity threats in real-time. First, DL models can examine normal network behavior and identify deviations that may indicate security threats, and continuous monitoring of network traffic helps detect unusual patterns quickly. Furthermore, DL can be more useful in energy consumption for wireless networks, such as dynamic power control and sleep scheduling, which leads to enhanced energy efficiency across the network. For scalability, DL models can manage the increasing complexity of networks, such as those seen in 5G and IoT environments, and can adapt to new network structures without extensive re-topologizing [39].

3. Deep Learning Architectures For Wireless Networks

The integration of deep learning architectures into wireless networking has emerged as a transformative approach, significantly enhancing the efficiency, security, and adaptability of communication systems. Various architectures, each with unique strengths, have been developed to address specific challenges within this domain [40]. Convolutional Neural Networks (CNNs) are widely utilized for their capabilities in spatial feature extraction. In wireless networks, they facilitate tasks such as channel estimation and interference detection, where the ability to analyze multidimensional signals is crucial. Similarly, Recurrent Neural Networks (RNNs), particularly their advanced form, Long Short-Term Memory networks (LSTMs), excel in processing sequential data. These architectures are instrumental in predicting network traffic patterns and user behaviors over time, enabling more efficient resource allocation and congestion management

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[41]. The following are some of the deep learning architectures that have been used in wireless networks:

- Convolutional Neural Networks (CNNs): CNNs have been used for modulation classification, channel estimation, and interference mitigation.
- Recurrent Neural Networks: RNNs, and especially LSTMs, have shown effectiveness in enabling predictive capabilities and modeling time-series data in wireless channels.
- Generative Adversarial Networks: GANs have been employed for synthetic data generation, enabling strong model training even when the dataset size is small.
- Deep Reinforcement Learning: DRL merges reinforcement learning with deep learning to facilitate smart decision-making in dynamic wireless networks.

4. Related Work

- **Deep Learning-Driven User Localization**

Localization is the technique used to find the physical or estimated location of a node in the network [42]. It is a critical factor in many types of networks where nodes are generally deployed in an ad-hoc manner, for instance, in Mobile Ad-hoc Networks (MANET), Vehicular Ad-hoc Networks (VANET), Wireless Sensor Networks (WSN), and underwater sensor networks. Thus, the locations of nodes are required to communicate and transfer information effectively between nodes [43].

In node localization, a number of deep-learning techniques have been proposed to improve localization algorithms. Abebe et al. [44] utilize classification and regression to achieve 99.15% of device localization accuracy in the Internet of Things (IoT). The authors create a data record that contains all reachable received signal strengths (RSSs) and basic service set identifiers (BSSIDs). Regression is then used to fill in the missing RSS values. And in the final step, use a DNN to determine device locations in indoor environments.

Therefore, to enhance the accuracy of anonymous node localization, Li et al. [45] have proposed Kernel Extreme Learning Machines based on Hop-count Quantization (KELM-HQ) algorithm. In this localization approach, the point of anchor nodes is identified as reference information. For the input training parameter, the KELM-HQ used the locations of the anchor’s node and the number of hops between anchors and the anonymous node. The localization error rate of KELM-HQ was 34.6% when compared with the fast-SVM algorithm [45]. Kegang et al. [46] proposed a deep learning-based wireless positioning method that accurately locates devices in complex environments, accounting for obstacles and path loss. The method utilizes received signal strength and coordinates of receiving nodes to determine the source position. To address limited training data, a data augmentation technique generates new samples based on existing data, enhancing the positioning system's robustness. Simulation results confirm the promising positioning performance of the proposed scheme. This approach not only increases the capacity of the RSSI database but also improves the training effect of the deep learning model for indoor positioning [47]. Oumaima et al. [48] propose the use of a new technique called Cascade Extreme Learning Machine to enhance the accuracy of localization in Range-Free Wireless Sensor Networks. The authors apply the Cascade-ELM algorithm in isotropic WSNs with the aim of minimizing localization errors and providing accurate geographic information about node positions. Simulation results demonstrate that the Cascade-ELM algorithm outperforms other algorithms based on smart computing techniques in terms of effectiveness. Additionally, this algorithm can improve node localization accuracy in real-world scenarios involving large-scale WSNs implementing Range-Free approaches. Deep learning in intelligent wireless networks has been used to increase the accuracy and enhance the performance of range-free node localization algorithms [49]. A real-time outdoor localization technique named LocUNet, designed for use in dense urban cellular networks, has been discussed by Cagkan et al. [50]. This method leverages pathloss information and does not depend on computational complexity improvements at user devices. It leverages approximated path loss radio maps of all base stations and the reported signal strength of devices. LocUNet also includes RadioUNet, which is a deep learning pathloss function simulator over urban areas, and offers a precise pathloss estimation at various points on a densely gridded map. This solution addresses the challenge of accurate outdoor localization in high-density urban cellular networks based on real-time pathloss information and deep learning techniques using LocUNet and RadioUNet. An analysis of predicted results indicates that the presented approach shows more accuracy and adaptability than other known practical models, such as Egli and Free-Space path loss [51].

- **Deep Learning-Driven Intelligent Routing in Wireless Networks**

Deep learning techniques are applied in wireless networks to intelligently predict the most efficient routing path. The intelligent routing has demonstrated superior performance when compared to traditional routing algorithms, particularly in terms of load balancing and network lifetime under various conditions [52].

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Farzad et al. [53] have introduced a new clustering routing protocol that depends on a reinforcement learning approach. This protocol aims to decrease energy depletion and prolong the network lifetime. In each round, one of the nodes is selected to be the CH based on DL. Furthermore, in this routing process, the number of cluster members increases as the distance between the clusters and the Base Station (BS) increases. The sensing nodes do not need to be aware of the BS because CH sensors have a multi-hop communication with the BS. Bomin et al. [54] proposed Tensor-based Deep Belief Architectures (TDBAs) to improve delay and package loss rates for the network. To select the next hop, TDBAs use packet number, instance time, and buffer size as input to the model. Therefore, based on these parameters and through training the DL model, the best path from the source to the destination is constructed. To address the issue of route instability caused by node movement, Ali et al. [55] have suggested a routing protocol based on the Q-Learning strategy. The most suitable neighbor node is selected using a reinforcement algorithm. It predicts the nature of the relationship of the chosen node with the target node. Joao et al. [56] have suggested a routing algorithm based on DL to overcome the usual path selection issue that always selects the shortest path. Thus, reducing the load on the nodes in the shortest path. Via the use of a Deep Neural Network (DNN) network capable of identifying the best route for every packet of information, and a post-processing routing approach to derive an appropriate path from the DNN's outputs. Zheheng et al. [57] proposed the block-based deep learning intelligent routing strategy (DLBR) for the complex network to enhance routing accuracy and latency. DLBR partitions the network recursively into small multiple sub-areas and trains parameters of deep learning models in each area so that the best path is found in each sub-area from any node to the destination based on the evaluation function.

- **Deep Learning-Driven Network Security**

Deep Learning has emerged as a powerful technique for enhancing network security in wireless networks. By leveraging the capabilities of Deep Learning algorithms, wireless networks can effectively detect and mitigate various types of cyber-attacks [58].

Vinayakumar et al. [59] introduced a DNN methodology to design an intelligent intrusion detection system (IDS) for the identification and classification of cyberattacks in the network. The study also assessed the effectiveness of multiple machine learning algorithms on malware datasets that are publicly accessible and proposed a fusion DNN framework named scale-hybrid-IDS-AlertNet, which is highly scalable and suitable for real-time analysis of network traffic data and host activities to notify possible cyberattacks proactively. Marouane et al. [60] suggested an efficient DL-based jamming multi-stage attack detection algorithm. There are two classifiers employed to detect jamming in this approach. The first classifier is an MLP, and the second classifier is a KSVM. The testing using WSN-DS (Wireless Sensor Networks DataSet) has shown that this solution has an accuracy of 94.51% and a false negative rate of 7.84%, which helps enhance security. Tianxi et al. [61] proposed a method in the field of monitoring network security using deep learning and image analysis to detect a type of security attack that cannot be detected by monitoring network security through traditional methods. In order to accomplish this, they obtained network security power, extracted features from it, and fed it to a neural network model for training. They also succeed in gaining the non-invasive network security monitoring and enhancement of the network security efficacy by 24%, boosting the general security performance. Gowdhaman et al. [62] introduced an intrusion detection system that is based on DNN. The main goal of this model is to overcome the security problem faced by wireless networks, which includes issues related to limited resources nodes, distribution methods, and transmission channels. Furthermore, improves intrusion detection capabilities by utilizing a cross-correlation approach to find effective features from the dataset and incorporate them into the DNN model. Dhanya et al. [63] introduced effective machine learning and deep learning techniques for detecting various types of network intrusions and attacks, utilizing the UNSW-NB15 dataset. Their experiments, conducted on this dataset, achieved an impressive accuracy of 99.05% using a Decision Tree classifier. These results highlight the significant role of deep learning approaches in improving network security and identifying different threat types. The growing prevalence of cyberattacks has underscored the importance of leveraging machine learning and deep learning algorithms to enhance network protection and response strategies.

- **Deep Learning for Big Data in wireless networks**

The rapid growth of wireless networks has resulted in the generation of substantial volumes of data, creating a need for advanced analytical methods to derive actionable insights. Deep learning, a key branch of artificial intelligence, has emerged as a robust technique for the processing and analysis of big data within wireless environments. This approach leverages its capability to identify intricate patterns and make accurate predictions, thereby enhancing critical facets of wireless networks, including performance

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optimization, cybersecurity, and efficient resource allocation. As the demand for effective data management intensifies, the integration of deep learning in this domain is increasingly essential for overcoming the challenges associated with large-scale data analysis, as evidenced by recent studies in the field [64].

A new artificial intelligence technique proposed by Jing et al. [65] for spatiotemporal modeling and prediction in cellular networks using big system data to efficiently learn temporal and spatial patterns. They propose a hybrid deep architecture model that uses an autoencoder-based deep model for spatial data embedding and Long Short-Term Memory units for temporal pattern learning to achieve efficient spatiotemporal modeling in cellular networks. Experimental outcomes based on a big data set gathered from China mobile show the power of the developed model in actual data from a big wireless carrier. Yu et al. et al. [66] presented DCAPR (Deep CNN-Assisted Personalized Recommendation), a novel hybrid recommendation framework designed for mobile users in wireless networks. This framework exploits convolutional neural networks (CNN) to combine multisource heterogeneous data, including image features, textual semantic features, and mobile social user trajectories. The proposed DCARP enhanced the accuracy and performance in providing user-specific recommendations to mobile device users. Khan et al. [67] highlighted the efficacy of deep learning techniques in extracting valuable insights and uncovering hidden patterns from the big data generated by network traffic. Their research underscores the importance of deep learning architectures and intelligent automation in modeling complex data distributions, with potential applications across healthcare, retail, finance, and the automotive sectors. The study development of robust and efficient systems to collect, analyze, and disseminate real-time sensory data generated by the network to healthcare professionals. Pradeep et al. [68] introduced an intelligent model employing deep learning techniques for classifying large datasets within a patient network. Their work highlights the model's potential to analyze patient data gathered from a sensor network, particularly in the medical field. The vast amounts of data collected from biomedical sensors can significantly enhance patient monitoring and treatment. Moreover, they illustrate how the integration of deep learning and big data strategies can empower organizations to build sustainable market value over time. George et al. [69] present a thorough review of the literature surrounding the Internet of Manufacturing Things (IoMT), focusing on deep learning-enhanced smart process planning, robotic wireless sensor networks, and algorithms for managing geospatial big data. Their analysis includes 346 sources published from 2018 to 2022, highlighting significant findings related to IoMT. The paper underscores the necessity for future research to investigate dynamic scheduling and production execution systems that could benefit from deep learning-driven smart process planning and data-informed decision-making, along with advancements in robotic wireless sensor networks.

- **Deep Learning for mobility node in wireless network**

Deep learning algorithms are employed to improve the performance, security, efficiency, and reliability of wireless networks, effectively addressing the challenges posed by mobile nodes. The constant movement of mobile nodes within a wireless network introduces complexities in network resource management and performance optimization. Deep learning for mobility nodes in wireless networks is used for mobility prediction, location tracking, network traffic management, and channel quality prediction [70].

Dinal et al. [71] presented an encoder-decoder based sequence-to-sequence deep learning framework to accurately predict future wireless signal strength changes using past signal strength data. They investigate two configurations of the deep learning model, utilizing LSTM and GRU as their inner cell structures, demonstrating the robustness of the deep learning model by accurately predicting future channel conditions under various network configurations, sampling rates, mobility patterns, and communication standards. The performance of the proposed model using deep learning outperforms the two baselines, auto-regression and linear regression. Montoya et al. [72] presented a multi-objective mathematical optimization framework to identify optimal communication routes between source nodes and a central base station in mobile wireless sensor networks, considering dynamic network conditions where all nodes are mobile, with the objective of minimizing overall communication latency and energy consumption. They introduce a prediction distributed routing protocol that leverages Markov chain-based prediction to dynamically select communication routes that minimize energy consumption in mobile networks. A deep learning approach has been used to predict the future locations of nodes in a mobile network and identify potential communication disruptions caused by node movements. The proposed method shows a good performance achieved by Markov Chains and Deep Learning approaches. Various mobility models, such as random walk, random direction, Gauss-Markov, and recurrent self-similar Gauss-Markov (RSSGM), were utilized by Shatha et al. [73] to evaluate the performance of several machine learning classification algorithms, such as decision trees (DT), logistic regression (LR), k-nearest neighbors (K-NN), linear discriminant analysis

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(LDA), Gaussian naïve Bayes (GNB), and support vector machines (SVM). It reported that the DT performed with 98% accuracy rate for 5000 steps. This study highlights the effectiveness of various mobility models and DL algorithms in predicting the mobility of wireless mobile nodes, aimed at improving communication technologies and optimizing network design. Shuai et al. [74] proposed a two-stage topology-aware deep learning (TADL) model to enhance wireless networks. This model employs graphical neural network techniques to accurately encode network topology, allowing the learning algorithm to uncover significant patterns and relationships. The TADL model utilizes a two-phase training process, which consists of a graph embedding unit and a link usage prediction module, to identify crucial links for optimal scheduling. This approach enables the model to accommodate diverse topologies and improves the effectiveness of the learning targets. The TADL framework demonstrates near-optimal performance while significantly reducing computation time, eliminating the need for retraining. Yijie et al. [75] developed a deep learning framework to explore the connection between the movement patterns of mobile nodes and the efficiency of routing protocols in drone networks. The neural network is trained using five motion metrics that define the relationships among nodes and various network-level features. Consequently, the model demonstrates high accuracy in classifying new data across a range of motion characteristics. This approach streamlines the process of selecting mobility models and routing protocols for diverse application scenarios, eliminating the need for repeated experiments to assess network performance.

- **Deep Learning-Driven Network Control**

Deep learning-driven network control represents a transformative approach to managing and optimizing network performance. By leveraging advanced algorithms, this methodology enables the analysis of complex data patterns and enhances decision-making processes within network systems. The application of deep learning techniques facilitates improved efficiency, security, and adaptability in network management, addressing the challenges posed by increasing data traffic and dynamic network conditions. As networks evolve, the integration of deep learning into control mechanisms is essential for achieving robust and responsive network operations [76].

A comprehensive overview of recent advancements and practical applications of deep learning in wireless network presented by Wu et al. [77]. Their work explores the convergence of wireless networks and artificial intelligence, focusing on the challenges faced by researchers in intelligent communications and the enhancement of wireless system performance. The paper advocates for the application of deep learning techniques to improve compression efficiency and expedite the transmission process in massive MU-MIMO systems, utilizing time-varying channels for feedback on channel state information (CSI). Kumae et al. [78] introduced a framework known as DLTIF, designed to model cyber threat intelligence and identify various threat types within IoT-enabled Maritime Transportation Systems (MTS) using deep learning techniques. This approach enhances the security of IoT-enabled MTS against cyberattacks by providing early warning signals and supporting security analysts in implementing effective defense strategies. The DLTIF framework incorporates three key components: a deep feature extractor (DFE), CTI-driven detection (CTIDD), and CTI-attack type identification (CTIATI). Together, these components achieve a detection accuracy of up to 99%, significantly surpassing traditional methods. Javeed et al. [79] proposed a framework that integrates Software-Defined Networking (SDN) with deep learning to enhance secure communication and detect threats within the Internet of Things (IoT). Through a comparative analysis with existing benchmark classifiers, the authors demonstrate the superior performance of their hybrid model, which is trained on the CICIDS dataset. This framework achieves an impressive accuracy of 99.87% and a recall rate of 99.96% by utilizing advanced classifiers such as Cu-DNNGRU and Cu-BLSTM. A confidence-aware deep learning solution presented by Ganewattha et al. [80] for predicting wireless channel utilization (CU) within shared spectrum bands, overcoming the challenge of uncertainty in DL models when dealing with new unseen data. Learninger-decoder-based Bayesian deep learning model is employed to produce prediction intervals to capture uncertainties in wireless channel utilization. A novel metric score based on CU predictions is utilized to develop an adaptive resource allocation algorithm. The stability of the proposed resource allocation algorithm is analyzed, and it is shown to converge to a Nash equilibrium after a certain number of iterations. Zhou et al. [81] proposed deep learning-driven distributed communication systems for a cluster online educational platform, considering human-computer interaction. The system integrates Q-learning under a deep neural network structure, cluster computing model, and human-computer interaction with movement tracking models. The proposed algorithm accurately extracts information and ensures transmission efficiency, outperforming the latest platforms in terms of accuracy. The paper also discusses the parallelism of the distributed system,

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which reduces processing bottlenecks and improves cost-effectiveness.

- **Other Applications**

To improve WiFi network management efficiency, Xiaolong et al. [82] propose a method that dynamically adjusts the scanning cycle of WiFi hotspots based on real-time signal strength. By acquiring real-time signal strength and comparing it to previous values, the method determines if a WiFi hotspot meets a target condition. The scanning cycle is adjusted accordingly, optimizing network management. In the way to reduce the human IT costs associated with maintaining the network and improve the predictability and reliability of IT systems, Jingguo et al. [83] introduced an artificial intelligence module to serve in this field. In this proposed method, the authors train the machine learning models with a variety of system data, including logs, network traffic data, and sensor data. This method provided a solution for automated network maintenance by utilizing deep learning to evaluate and analyze the huge amount of operational network information. Anita et al. [84] have proposed a new spectrum awareness model using deep learning techniques to improve wireless network performance. The model focuses on three different types of transmissions (LTE, UMTS, and WLAN) for training and validation. The deep learning model is trained on data from these different transmissions and has been shown to achieve up to 100% accuracy and complete predictive power. The main goal of this model is to improve spectrum awareness, which in turn optimizes the allocation and utilization of limited spectrum resources. This optimization ultimately leads to improved network efficiency and performance. Liang et al. [85] presented a paper proposing an approach based on deep learning for fault localization in optical networks, thus enhancing the efficiency of the overall network. In this work, the authors train and verify deep learning models with various variables using the preprocessed dataset to identify the optimal values for the model. The suggested solution provides an accuracy rate higher than 95%. Swapna et al. [86] introduced a method that utilizes deep learning (DL) techniques to enhance channel performance in uplink massive MIMO communication. This approach focuses on reducing the challenge of channel estimation via employing a fully connected neural network (NN) architecture for accurate estimation. The channel estimation error is analyzed over a large number of node antennas for various scenarios. Furthermore, the results indicate that as the number of antennas increases, the normalized mean square error (NMSE) decreases. A summarized overview of the relevant literature is presented in Table 2.

5. Future Direction And Open Issues

The potential use of artificial intelligence in wireless networks looks positive, especially as demand for greater data rates and more effective utilization of resource management increases. Key areas of focus include enhancing cognitive radio networks, optimizing resource allocation in heterogeneous networks, and integrating deep learning within open radio access networks (O-RAN). Furthermore, the list below outlines the primary directions and challenges in this emerging field:

- Fusion of Deep Learning with Physical Layer Management: Future study should focus on enhancing the functions of cognitive radio networks (CRNs) in the physical layer. This includes improving channel decoding, modulation, and detection processes, which are crucial for an effective communication system [87].
- Security: as wireless networks grow more sophisticated, they confront a range of security threats, including eavesdropping and jamming. Future research should investigate how deep learning can strengthen security measures, such as employing anomaly detection to identify malicious activities within the network. This domain is crucial given the rising number of connected devices, which increases the vulnerability of networks to attacks [88].
- Enhancing Energy Efficiency: Research should also explore how deep learning can contribute to developing energy-efficient cognitive systems. This includes optimizing cooperative sensing approaches and addressing energy consumption challenges. Integrating deep learning with graph-based neural networks could significantly improve overall system efficiency [89].
- Quality of Service (QoS) Provisioning: Future studies should investigate how deep learning can automate routine tasks in CRNs to ensure better QoS. This involves developing predictive control schemes that balance energy management and QoS provisioning, especially as network traffic increases [90].
- Adaptive Deep Learning Techniques: There is a need for adaptive deep learning algorithms that can respond to changing network conditions [91].

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Table 2. Summary of related works surveyed in section 4.

Domain	Author	Year	Model	Objective	Dataset	Metric	Limitations
User Localization	Abebe et al. [44]	2018	DNN	accurate localization	RSSI	Accuracy=99.15%	Not taken into consideration the computational complexity, scalability to very large or highly dynamic environments
	Li et al. [45]	2020	SVM	Enhance the accuracy of anonymous node localization	Not Describe	Accuracy=87 %	limited scalability for large network
	Kegang et al. [46]	2021	Not Describe	accurately locates devices in complex environments	RSSI	Accuracy=92 %	Not taken into consideration on overfitting
	Oumaima et al. [48]	2022	Cascade-ELM	minimizing localization errors	Not Describe	Accuracy=90 %	high training time
	Cagkan et al. [50]	2023	LocUNet	outdoor localization	RadioLocSeer	Accuracy=95 %	Radio maps require frequent updates to remain accurate in urban environments with moving obstacles.
Intelligent Routing	Farzad et al. [53]	2015	Not Describe	decrease energy depletion	Not Describe	Accuracy=90 %	Focus on energy only; ignores latency and reliability trade-offs
	Bomin et al. [54]	2017	TDBAs	improve delay and package loss rates	Applied Internet Data Analysis	Accuracy=95 %	Tensor-based DL requires significant memory and high-dimensional data, which is difficult for edge devices to handle.
	Ali et al. [55]	2017	Q-Learning	reducing data packet transmission time	Not Describe	Accuracy=93 %	Reinforcement learning (RL) in MANETs suffers from slow convergence during

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							high-speed node mobility.
	Joao et al. [56]	2019	DNN	overcome the usual path selection issue that always selects the shortest path.	GEANT	Accuracy=98 %	Generalization issues; a model trained on one network topology often fails when the network graph changes.
	Zheheng et al. [57]	2020	DLBR-CNN method	enhance routing accuracy and latency.	real data from another network	Accuracy=96 %	Static partitioning reduces adaptability
Network Security	Vinayakumar et al. [59]	2019	DNN	detect and classify cyberattacks effectively	malware datasets	Accuracy=93.5%	use large labeled datasets
	Marouane et al. [60]	2020	C-RAN	detect and classify four types of jamming attacks	WSN-DS	Accuracy=94.51%	Multi-stage detection increases system overhead and may lead to false positives under legitimate high-traffic bursts.
	Tianxi et al. [61]	2021	DNN	detect attacks that cannot be found at the network level	Not Describe	Accuracy=93 %	Real-time monitoring with DL is often constrained by the high packet-per-second rate
	Gowdhaman et al. [62]	2022	DNN	Proposed DNN Intrusion Detection System	Not Describe	Accuracy=95 %	Energy consumption not considered
	Dhanya et al. [63]	2023	SVM, Adaboost, XGBoost, Random Forest	identifying network attacks	UNSW-NB15	Accuracy=98.44%	Energy consumption not considered
Big Data	Jing et al. [65]	2017	LSAEs, GSAE, LSTMs	improve prediction accuracy in cellular networks.	China Mobile	MSE = 0.042 and 0.031 for downlink traffic load and uplink, respectively.	limiting the model's ability to generalize to different cellular environments
	Yu et al. [66]	2019	DCAPR	develop a deep prediction model.	Gowalla dataset	Precision= 0.1528, Recall= 0.1567,	Implementing DL in the "RF Loop" is

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						F1= 0.1547	extremely hardware-intensive for standard embedded processors.
	Khan et al. [67]	2019	Feed-Forward Network	analyze the patient's data collected by WBANs	data generated by WBANs	Not Described	Privacy concerns; limited real-world validation
	Pradeep et al. [68]	2021	Not Described	develop an intelligent model to classify large data in WBANs	patient data generated by WBANs	Not Described	Energy consumption not considered
	George et al. [69]	2022	Not Described	analyze the integration of DL techniques on the (IoMT)	Not Described	Not Described	Not taken into consideration the computational complexity
Mobility	Dinal et al. [71]	2019	LSTM, GRU	accurately predict variations in wireless channel quality.	signal strength data collected over 4G LTE, WiFi, Zigbee, WiMAX, and an industrial network setting	Seq-to-seq LSTM=38%. Seq-to-seq GRU=45.3%	Prediction accuracy is limited by the short coherence time of wireless channels in high-mobility environments.
	Montoya et al. [72]	2021	mathematical optimization model	finding optimal communication paths between source nodes and a sink	distance, and energy consumption	Accuracy=98.42%	Combining Markov Chains and DL increases mathematical complexity and power consumption.
	Shatha et al. [73]	2022	Random Walk, Random Direction, Gauss-Markov, Recurrent Self-Similar Gauss-Markov	Investigate the effectiveness of mobility models.	user locations, current and previously connected access points	Accuracy= 98% with the DT classifier.	Models may struggle with "cold start" problems when a new node enters the network with no history.
	Shuai et al. [74]	2022	GNN	facilitate wireless network optimization	random dataset, grid dataset	approximation ratio= 0.97, time reduction= 0.42	Topology-aware models require global network knowledge, which is difficult to maintain

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							in decentralized setups.
	Yijie et al. [75]	2023	BPNN	enhance performance in UAV networks	GM, RWP, RPMG	Accuracies=87.18%, 84.38%, and 87.41% for GM, RWP, and RPMG test data, respectively.	Limited scalability
Network Control	Wu et al. [77]	2020	Not described	investigate the importance of DL in the field of wireless communications.	Not described	Not described	Communication overhead between the edge and cloud can negate the latency benefits of the DL model.
	Kumae et al. [78]	2021	DLTIF	improve the accuracy and efficiency	ToN-IoT	Accuracy=99 %	Maritime environments face unique satellite latency issues not always accounted for in standard IoT frameworks.
	Javeed et al. [79]	2021	SDN-enabled DL driven framework	detect and secure an IoT environment from attacks	CICIDS2018	Accuracy = 99.87%, Recall = 99.96%.	SDN controllers can become bottlenecks or targets for DDoS attacks, compromising the DL-driven security.
	Ganewattha et al. [80]	2022	Encoder-decoder based Bayesian DL model	improve the efficiency, reliability, and stability of resource allocation	synthetic and real CU data	MAPE = 8.02%, 9.84%	Shared spectrum bands involve complex legal/policy constraints that increase overhead
	Zhou et al. [81]	2022	HCI model	improve the efficiency of online educational platforms.	MR	Not described	Human-computer interaction (HCI) metrics are often subjective and difficult to quantify for model training.
Other	Xiaolong et al. [82]	2017	HAPLA	improve positioning accuracy, adaptability	Not Describe	Accuracy=97 %	Hybrid Wi-Fi hotspots require

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				, and solve the problem of blind spots in indoor localization			dense deployment and are prone to signal interference from non-Wi-Fi devices.
	Jingguo et al. [83]	2022	AIOps	improve prediction ability, stability, and reduce IT costs	logs, monitoring information	Not Describe	lack specific implementation details for wireless protocols.
	Anita et al. [84]	2022	CNN	prediction model for the recognition of networks	LTE, UMTS, and WLAN	Accuracy=99%	Spectrum awareness models often fail in "hidden terminal" scenarios where interference is not locally detectable.
	Liang et al. [85]	2023	DNN	improves the fault localization in optical networks	Not Describe	Accuracy=95%	Fault localization in optical networks requires extremely high-speed sampling to catch transient signal drops.
	Swapna et al. [86]	2023	DL-FCNN	channel estimation in uplink massive MIMO communication	channel DS	Not Describe	Massive MIMO FCNN architectures require high-dimensional matrix operations that increase hardware cost/heat.

6. Conclusions

This paper has reviewed the use of deep learning in wireless networks. Furthermore, demonstrates that deep learning represents a powerful tool for enhancing the performance of intelligent wireless networks. Through highlighting the key research studies that utilized deep learning to improve the performance of wireless networks, it becomes clear that deep learning techniques can significantly contribute to improving efficiency, reducing interference, and enhancing resource management. We have reviewed several methods used, including improvements in routing, security, big data, control, localization, management, and other applications. This study is the first step towards enhancing privacy and security in deep learning applications for wireless networks while developing more efficient algorithms to reduce computational demands.

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