Pervasive and Mobile Computing

A Comprehensive Survey on Machine Learning Techniques in Opportunistic Networks: Advances, Challenges and Future Directions

--Manuscript Draft--

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Abstract:	Machine Learning (ML) is growing in popularity and is applied in numerous fields to solve complex problems. Opportunistic Networks are a type of Ad-hoc Network where a contemporaneous path does not always exist. So, forwarding methods that assume the availability of contemporaneous paths does not work. ML techniques are applied to resolve the fundamental problems in Opportunistic Networks, including contact probability, link prediction, making a forwarding decision, friendship strength, and dynamic topology. The paper summarizes different ML techniques applied in Opportunistic Networks with their benefits, research challenges, and future opportunities. The study provides insight into the Opportunistic Networks with ML and motivates the researcher to apply ML techniques to overcome various challenges in Opportunistic Networks.
Suggested Reviewers:	Gordhan Jethva g.jethava@gmail.com
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Cover letter

April 10, 2023

Dear Editors,

I am submitting a manuscript for consideration for publication in Computer Communications. The manuscript is entitled “A Comprehensive Survey on Machine Learning Techniques in Opportunistic Networks: Advances, Challenges and Future Directions”.

The article comprehensively surveys Machine Learning (ML) Techniques in Opportunistic Networks. It summarizes different ML techniques applied in Ad-hoc Networks and Opportunistic Networks. The existing surveys in Adhoc and Opportunistic networks focus mainly on mobility models, routing protocols, simulation tools, and challenges. Our survey goes beyond a traditional survey that merely describes and compares available approaches. For this reason, this survey provides several significant guidelines for both students and researchers desiring to explore Opportunistic Networks with Machine Learning. In presenting these explanations, our survey provides a workflow to apply machine learning for opportunistic communication. In addition, it presents a detailed description of the related paper with its concepts, models, simulators, functionalities, and advantages. The authors have also made the comparative analysis in tabular form to explain existing ML-based routing protocols briefly.

We declare that the manuscript is original and has not been published before.

Thank you very much for your consideration.

Yours Sincerely,
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Authors' Reply

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Title	**A Comprehensive Survey on Machine Learning Techniques in Opportunistic Networks: Advances, Challenges and Future Directions**
Authors	**Jay Gandhi, Zunnun Narmawala**

The authors thank the Editor-in-Chief (EIC) and the Editor for giving an opportunity to revise the manuscript and incorporate the suggestions given by reviewers, thereby improving the quality of the manuscript. All the suggestions given by the reviewers are incorporated in the revised manuscript. The corrections are depicted in **blue highlighted** colored text in the revised manuscript.

Reply to Reviewer #1

Comment to the authors:
While I appreciate the author's efforts in systemizing the literature in Machine Learning (ML) applied to Opportunistic Networks (OppNets), there are some issues that currently hinder me from recommending acceptance. After making these changes, I believe the work will be strengthened:

Comment 1: The major issue with the work stems from missing relevant work related to ML approaches applied to OppNets. Several seminal works that are directly related to the problem topic are not cited. Moreover, other adjacent network settings such as IoT (usually referred to as OppIoTs) have many related works that need to be discussed as well. Relevant articles must be cited and discussed in the paper appropriately.
Reply: Thank you for your valuable feedback. We have thoroughly revised the literature review section of our paper to address the concerns raised regarding missing relevant work related to ML approaches applied to OppNets and OppIoTs. We have added the missing relevant work as follows.

Page No.	Section	Area	Machine Learning Technique
2	3.1.1	MANETs	Supervised Learning
Protocol Name and Citation: ORuML [34], SVM,BBC [148]			

4	3.2.1	VANETs	Supervised Learning
Protocol Name and Citation: V2I [150], RF, KNN, LB [35]			

14	4.2.3	Opportunistic Networks	Supervised Learning
Protocol Name and Citation: RF-BBFT [126], iProPHET [176], ML-Fresh [64], Combo-Pre [102], ARBP [7]			

17	4.2.3	Opportunistic Networks	Reinforcement Learning
Protocol Name and Citation: DQNSec [85], DeepMPR [89], Several Q-Learning based approaches [110], [186], [45], [166], [112], [158]			

20,21	4.4.4	Opportunistic Networks	Neural Networks and Fuzzy Logic
Protocol Name and Citation: ML-BBFT [125], GTEER [164], Ant-Router [161], BRNN-LP [113], EEFLPOR [122], FCSG [92], INSS1 and INSS2 [42], Intelligent system [43]			

23	4.5.3	Opportunistic Networks	Unsupervised Learning
Protocol Name and Citation: DOIDS [204], DBSCAN-R [135], HiLSeR [19], OFCR [6]			

Comment 2: Furthermore, in the future research directions section (Section 5), under Security and Privacy, it is imperative that the authors discuss related work on intelligent approaches for securing opportunistic networks. The paper claims that "no such works exist " -- this is not correct and should be rectified. It is important to cite existing literature on security and privacy, resource utilization and energy consumption. Please use resources such as scholar.google or DBLP to identify suitable literature for citing and discussion. This lack of discussion on existing works in critical topics of relevance to opportunistic networks needs to be improved extensively throughout the manuscript since this is a survey paper.

Reply: Thank you for bringing this to our attention. We apologize for the oversight in claiming that no such works exist, and we have rectified this by conducting a thorough literature review and citing relevant papers on security, privacy, resource utilization, and energy consumption. We have covered similar works surveys using Google Scholar, DBLP, and other relevant sources. We have referred and cited the missing relevant work as follows.

Area	Citation
Security and Privacy	[50], [85], [86], [96], [204]
Resource Utilization and energy consumption	[19], [34], [52], [71], [101], [112], [122]
Opportunistic Networks Applications such as Smart city, wild-life monitoring, healthcare etc.	[31], [72], [83], [110], [141], [143]

Comment 3: A minor issue regarding presentation and formatting is the lack of subsections and subheadings throughout the paper. For example, in Section 5, each of the sub topics should be subsections with section numbers, such as 5.1 for Link Prediction, etc. The same format should be followed throughout the paper and Section 3 and 4 should be modified the same way with

significant subsection usage. I would like to emphasize that for a survey paper this is significantly important to maintain clarity and currently the paper is hard to parse due to the lack of organization.
Reply: Thank you for your feedback regarding the presentation and formatting of the paper. We have revised Section 5 to include subsections with appropriate numbering. Additionally, we have modified Sections 3 and 4 to incorporate significant subsection usage for improved clarity and organization.

Reply to Reviewer #2

Comment to the authors:

This paper is easy to read, but organization can be improved. It presents an overview of existing literature at the intersection of machine learning techniques and opportunistic networks. As machine learning algorithms are being applied to improve communication networks, it is unsurprising there is a plethora of works related opportunistic networks alone.

This paper mainly presents summaries and comparisons of existing works. More work is needed to motivate readers and merit publication in PMC. It will be necessary to discuss how ML techniques can improve acceptance and applications of opportunistic networks, with the background of existing works.

Reply: Thank you for your feedback. We have improved the organization of the paper by adding subsections. We have also focused on the impact of ML in overcoming limitations and expanding applications of opportunistic networks. We have added more papers in the literature review and a dedicated section on the significance and analysis of how ML techniques address challenges and enhance network performance. The revision is highlighted in blue color.

Comment 1: What is the justification for providing reviews of literature on ML techniques in MANET and VANETs? The shift from Section 3 and Section 4 is abrupt.
Reply: Thank you for your valuable feedback. We have addressed this concern by explicitly incorporating justification for exploring ML Techniques in MANETs and VANETs. This clarification is reflected in the "Rationale for Investigating ML Techniques in MANETs and VANETs" section (Section 3.3), where we have outlined our survey. (Page-7)

Comment 2: What are the differences among MANETs, VANETS and Opportunistic Networks, in terns of routing, energy consumption, latency etc.; Discuss which ML techniques used for MANETs and VANETS are applicable (or not) to opportunistic networks, in order to improve routing, energy consumption, latency etc.
Reply: We thank the reviewer for the comment. We have incorporated Section 3.4 to outline the differences among MANETs, VANETs, and Opportunistic Networks. Within this section, specifically in Section 3.4.4, we discussed the suitability and applicability of Machine Learning

techniques within these domains, explaining their potential to enhance routing, energy consumption, latency, and other performance metrics. (Page-9)

Comment 3: Which of the ML techniques used in Opportunistic Networks are simple improvisations of those used in MANETS and VANETS?

We extend our gratitude to the reviewer for their feedback. In Section 3.5, we justified using ML techniques in Opportunistic Networks. In subsection 3.5.1, we address Comment 3, explaining which ML techniques used in Opportunistic Networks are simple improvisations of those used in MANETs and VANETs.

Comment 4: Which of the ML techniques used in Opportunistic Networks are unique compared those used in MANETS and VANETS?.
Reply (Comment 3 and 4): Thank you for the feedback. In Section 3.5, we justified using ML techniques in Opportunistic Networks. In subsection 3.5.2, we specifically address Comment 4, discussing unique ML techniques employed in Opportunistic Networks compared to those used in MANETs and VANETs. (Page-10)

Comment 5: Validation tool in all cases is 'simulation'. Are there examples of real implementations? How can ML techniques make real deployments and real-life applications possible.
Reply: Thank you to the reviewer for their valuable comment. In Section 5, we have incorporated discussions on real-world applications and the validation of ML techniques beyond simulation. In Section 5.3, we emphasize the importance of transitioning from simulated environments to real-world deployments, and we highlight how ML techniques can facilitate practical implementations. (Page-23-24-25)

Comment 6: There are two major challenges to the widespread use of Opportunistic Networks- 1) lack of an incentivizing mechanism for users and 2) lack of business models for service providers. Can ML techniques help address these challenges?
Reply: Thank you for valuable feedback. In Section 5.2, we have addressed two major challenges hindering the widespread adoption of Opportunistic Networks: the need for more incentivizing mechanisms for users (section-5.2.1) and the absence of viable business models for service providers (section-5.2.2). Through our analysis, we explore how ML techniques can potentially mitigate these challenges by facilitating the development of innovative solutions. (Page-25)

Comment 7: How will ML techniques impact the application of Opportunistic Networks in real applications (e.g., UAVs, entertainment, health and wellbeing)?
Reply: We thank the reviewer for the comment. In Section 5.1, we have addressed the impact of ML techniques on applying Opportunistic Networks in various real-world domains. By integrating

ML algorithms into Opportunistic Networks, we demonstrate the potential for enhanced performance and efficiency in these applications. (Page-23-24-25)

All the suggestions of honorable reviewers have been addressed, and hence we hope that the modified version of the paper meets the requirements for possible publication in the ***Pervasive and Mobile Computing Journal***. However, the authors will be happy to incorporate any further suggestions for improving the paper's quality.

A Comprehensive Survey on Machine Learning Techniques in Opportunistic Networks: Advances, Challenges and Future Directions

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ABSTRACT

Machine Learning (ML) is growing in popularity and is applied in numerous fields to solve complex problems. Opportunistic Networks are a type of Ad-hoc Network where a contemporaneous path does not always exist. So, forwarding methods that assume the availability of contemporaneous paths does not work. ML techniques are applied to resolve the fundamental problems in Opportunistic Networks, including contact probability, link prediction, making a forwarding decision, friendship strength, and dynamic topology. The paper summarizes different ML techniques applied in Opportunistic Networks with their benefits, research challenges, and future opportunities. The study provides insight into the Opportunistic Networks with ML and motivates the researcher to apply ML techniques to overcome various challenges in Opportunistic Networks.

1. Introduction

Opportunistic Networks are a type of sparse Ad-hoc Networks, and because of that, the contemporaneous path between source and destination does not always exist. So, there is an inherent delay in delivering messages to destination [22] [119] [80]. In this type of network, message transmission between source and destination is accomplished opportunistically when nodes encounter each other. The messages are transferred in a store-carry-forward fashion, and multiple copies of a message are spread in the network to improve delivery chances and reduce delay [47]. Example applications that can tolerate long delays and lower message delivery probability are space communication, wildlife monitoring, vehicular networks, and many more [22] [119] [47]. Because of the dynamic and complex nature of Opportunistic Networks, the traditional routing protocols of the Opportunistic Networks can be improved using ML techniques.

ML techniques are applied in many fields to solve complex problems. ML allows the model to learn decision-making from data without using pre-defined rules. ML techniques fall mainly into three categories: Supervised, Unsupervised, and Reinforcement Learning. These techniques can be used in the field of Opportunistic Networks to leverage their potential [189], [65] [141] [165].

This paper gives a comprehensive survey of advances made by ML in the field of Opportunistic Networks. A concise survey of MANETs and VANETs routing protocols that use ML is presented to depict ML techniques' progression in Ad-hoc Networks. Then, the paper focuses on techniques to optimize the performance of Opportunistic Networks using Supervised Learning, Unsupervised Learning, Reinforcement Learning, Neural Networks, and Fuzzy Logic. The focus is ML techniques for link prediction between neighbouring nodes, buffer occupancy, node mobility statistics, congestion control, contact probability, node energy, friendship strength amongst nodes, selfish nodes, overhead, and resource management. In the literature, ML techniques like Naïve Bayes, Artificial Neural Networks, Recurrent Neural Networks, Decision Trees, Q-learning, Fuzzy Logic, and Trajectory Data Mining are used to improve Ad-hoc Networks performance in general and Opportunistic Networks in particular.

The contributions of this paper are as follows: Section 2 discusses existing review and survey articles for the topic and highlights the article's usefulness. Section 3 presents the ML-based routing protocols for Ad-hoc Networks. Section 4 discusses the recent advances of ML techniques in the field of Opportunistic Networks. Section 5 analyses the feasibility of ML integration in Opportunistic Networks in real-world. Section 6 identifies the research challenges and future directions. Finally, Section 7 gives the concluding observations.

2. Related Work

The motivation for this survey comes precisely from the observation that selecting an appropriate ML approach is a challenging task to enhance the performance of networks. The existing surveys in Adhoc and Opportunistic Networks focus mainly on mobility models, routing protocols, simulation tools, and challenges. To choose the ML approach precisely, researchers require a large-scale survey of existing ML-based protocols deployed with diverse network scenarios. This paper aims to survey the ML approaches in Adhoc and Opportunistic Networks comprehensively. We identify the gaps in the present state-of-the-art and propose possible future directions. Consequently, this survey will assist researchers in conceiving a well-performing, reliable, realistic, and scalable ML-based opportunistic communication framework.

There exist various relevant and detailed surveys on Opportunistic Networks in the literature. In papers [120, 30], the authors survey routing protocols, mobility models, and

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Table 1
Comparison with existing survey papers in the area of Opportunistic Networks

Points covered in existing survey	[20]	[30]	[120]	[153]	[169]	[179]	[198]	Our Contribution
ML based MANET and VANET Routing Protocols								✓
Details of Mobility Models and Dataset used in Experiments	✓			✓	✓		✓	✓
Incorporation of ML Techniques with Opportunistic Networks								✓
Overview of Simulation Tools and Experiment Setup	✓	✓	✓		✓	✓		✓
Category wise Survey of ML techniques in Opportunistic Networks								✓
Research Challenges and Future Directions		✓	✓	✓		✓	✓	✓

simulation tools available for Opportunistic Networks. In paper [20], the authors have assembled the impacts of mobility on routing protocols from the literature. In papers [198, 153], the authors survey how social networking concepts are applied in Opportunistic Networks in the literature. In paper [169, 179], researchers mainly focus on vehicular networks. The existing surveys help to answer a few questions, such as, "How a node density, traffic pattern, and other network parameters affect networks' performance?", "Which simulation tool is better for a given scenario?", "How to get mobility models and real traces?", "What is the impact of social behaviour on the performance of the network?" and "Which routing protocol is suitable for the given scenario?".

Our survey goes beyond a traditional survey that merely describes and compares available approaches. For this reason, this survey provides several significant guidelines for both students and researchers desiring to explore Opportunistic Networks with ML. In presenting these explanations, our survey provides a workflow to apply ML for opportunistic communication. Also, it presents a detailed description of the related paper with its concepts, models, simulators, functionalities, and advantages. The authors have also made the comparative analysis in tabular form to explain existing ML-based routing protocols briefly.

3. ML-based Routing Protocols for Ad-hoc Networks

This section presents a brief survey of ML-based routing protocols for Ad-hoc Networks, specifically MANETs, and VANETs. The section does not contain an exhaustive survey but incorporates essential contributions to the field. The purpose of introducing the section is to create a background for ML techniques used in the broader area of Ad-hoc Networks.

3.1. ML-based Routing Protocols for MANETs

Mobile Ad-hoc Networks (MANETs) aim at leveraging connection opportunities between mobile devices without using any infrastructure support. In MANETs, the exchange of messages between source and destination happens via multiple hops due to the short transmission range of mobile devices. Unlike Opportunistic Networks, in MANETs, it is assumed that a contemporaneous path between source and destination always exists. Due to dynamic topology, node failures, limited bandwidth, and resource constraints, the link or route between nodes may become unavailable and end in transmission failure. So, finding reliable and efficient routes in MANETs is a challenge. The traditional routing protocols used in MANETs can be improved by applying ML techniques to overcome these challenges. In this section, we discuss the evolution of ML in MANETs. It will help researchers to select a suitable ML approach depending on the specific scenario.

3.1.1. Supervised Learning-based protocols in MANET

We have studied MANET routing protocols that employ supervised learning techniques. These algorithms are trained using labelled datasets, enabling them to make informed routing decisions. These protocols aim to enhance network efficiency and reliability by leveraging supervised learning.

ORuML [34]: The paper proposes ORuML, a novel routing algorithm for wireless networks that utilises ML techniques. Traditional routing protocols like AODV and DSR have been widely studied in MANETs, but ORuML introduces a fresh approach by integrating ML with routing decisions. Previous research has explored ML in networking for intrusion detection and traffic classification tasks. However, ORuML stands out for its focus on classifying network nodes based on characteristics like battery power and available storage, using algorithms like K-nearest neighbour (KNN), Support Vector Machine (SVM), and Multinomial Logistic Regression (MLR). This paper's contribution lies in the comparative analysis of these algorithms for network node classification and the integration of ML into routing for efficient message delivery. Challenges remain in scaling ML-based routing to more extensive networks and optimising performance under varying conditions.

SVM-BBC [148]: The paper introduces Supervised Vector Machine with BrownBoost Classification (SVM-BBC) to enhance data delivery efficiency in Mobile Ad-hoc Networks (MANETs). Existing research emphasises energy-efficient routing methods but needs more awareness during data delivery. The SVM-BBC method addresses this gap by employing supervised SVM to identify neighbouring nodes based on link quality and energy consumption, subsequently utilising the Enhanced BrownBoost classifier for efficient data transmission. The novelty lies in combining these models to achieve significant data delivery improvements while minimising energy consumption. The proposed method is validated through theoretical analysis and experimental results, demonstrating notable enhancements in data delivery rate, time, and energy consumption compared to conventional approaches.

3.1.2. Reinforcement Learning-based Protocols in MANET

We have explored routing protocols in MANETs that utilise reinforcement learning algorithms. These protocols dynamically adjust routes based on network conditions, improving adaptability and efficiency. By leveraging reinforcement learning, these protocols aim to enhance the robustness of MANET routing in dynamic environments.

DRQ-Routing [97]: The paper proposes the DRQ Routing protocol that learns the optimal routing policy that sustains network congestion and gives better packet delivery time. DRQ applies dual reinforcement learning to learn the routing policy much faster than Q-routing [108]. The DRQ protocol learns to make forwarding decisions by forward and backward exploration. The forward exploration is similar to Q-routing, where a node gets the information from the neighboring node when sending packets. In contrast, backward exploration utilizes the information collected while receiving the packets from the neighboring nodes. The backward exploration makes adaption more accurate because additional network exploration helps protocol in learning. DRQ-routing learns the optimal routing policy twice as fast as the Q-routing protocol. Also, the routing policies learned by DRQ-routing are better than the Q-routing regarding the average packet delivery ratio in the higher network load scenario.

Q-MAP [177]: Multicasting plays a vital role in wireless Ad-hoc Networks. The paper proposes the Q-MAP multicast routing protocol based on multi-agent reinforcement learning to construct an on-demand multicast route. Reinforcement learning improves the network's performance after each task according to the reward received from the environment. The protocol also helps in resource reservation by optimal use of resources while sending messages between source and destination. The Q-MAP uses a Join Query Packet (JQP) comprising network and packet information. The primary purpose of sending a JQP packet between the source and destination is to find the optimal path while updating the reward in Q-learning. The Q-MAP protocol is not based on centralized control and gives minimum latency by parallel computation using multi-agent reinforcement learning.

Q-Routing [32]: The paper aims to exploit the interplay between mobility and routing. Based on reinforcement learning, the proposed Q-routing protocol continuously adapts to link failure and congestion by selecting the optimal route with the least delivery time. Q-routing learns to avoid the congested path and chooses the alternate path. The prime aim of the proposed approach is to achieve the maximum delivery ratio possible using Q-table maintained at each node by the Q-learning algorithm. The authors evaluate Q-routing performance under various network scenarios with rapid changes in network topology. The authors compared the Q-routing protocol with the directional routing protocol, and the result shows that reinforcement learning can effectively handle node mobility and make good packet routing decisions.

WARP [147]: The authors proposed the Wireless Adaptive Routing Protocol, Version 5 (Warp-5), to make a more reliable message-forwarding decision in heterogeneous networks using a new metric. The metric includes the effects of heavy network traffic and environmental noise. The WARP-5 protocol presents the cross-layer predictor to select the route in networks by calculating the statistical estimate based on recent experience. The approach uses the route request and replies packet to explore the route rapidly compared to random exploration. For validating the proposed protocol in a dynamic and unpredictable environment, the simulation includes noise and congestion in the network. The simulation results show that the WARP-5 protocol constructs a better route than existing shortest-path routing protocols or Q-Routing protocols in Wireless Ad-hoc Networks.

RL [66]: The paper proposed a reinforcement learning-based routing protocol compatible with the network changes due to the high mobility of nodes. The proposed algorithm finds the shortest path by taking the message transmission decision based on the link stability between the nodes using Q-learning. Q-learning aims to select the best suitable neighbour node at any specific time to deliver the message to the destination node. The Q-learning learns the pattern of node mobility and estimates the values of forwarding action that helps to choose the suitable node based on a higher Q-value. The simulation result shows that the reinforcement learning protocol performs better than conventional MANET protocols.

3.1.3. Neural Network and Fuzzy Logic-based protocols in MANET

We have examined MANET routing protocols that leverage neural networks and fuzzy logic controllers. These protocols aim to optimise routing paths and improve delivery ratios by employing advanced decision-making mechanisms. By combining neural networks and fuzzy logic, these protocols enhance the effectiveness of routing in MANETs.

FMRM [134]: The authors proposed the fuzzy control-based multipath routing algorithm-FMRM in MANET. Multipath routing finds multiple paths between source and destination but is challenging for dynamic topology. The FMRM uses fuzzy controllers to reduce route reconstruction and effectively select multiple paths. The prime goal of the FMRM algorithm is to develop the fuzzy controller that helps to decrease the number of route reconstructions in the MANET. The fuzzy controller explores the implicit and explicit relationships between the nodes and the Ad-hoc environment to develop the fuzzy control rule, which helps decision-making. The FMRM algorithm efficiently selects the multiple paths, which increases the packet delivery ratio and decreases the end-to-end delay. The simulation carried out in NS-2 [60] with high load conditions shows the effectiveness of FMRM protocol in multipath routing.

QURA [200]: The authors proposed the ML-based routing protocol named QURA for the Next-generation Wireless Networks (NWNs). The protocol uses principal component analysis (PCA) for parameter reduction and then the Neural Network to make an intelligent routing decision. The ML-based routing protocol predicts the Queue Utilization of the next time slot to choose the node with more resources to carry the packet using the neural network. The performance of the proposed QURA protocol is compared with the shortest path algorithm and Queue Utilization Bellman-Ford (QUBF) protocol [75]. The result shows that the QURA protocol enhances the network's performance in terms of throughput, delay, and packet loss ratio.

3.1.4. Unsupervised Learning-based protocols in MANET

We have analysed the MANET routing protocol that utilises unsupervised learning techniques. These algorithms detect patterns and structures within the network, enhancing scalability and adaptability in dynamic environments. By leveraging unsupervised learning, these protocols aim to improve the efficiency and robustness of MANET routing.

HCRP-HD [115]: In this paper, the Hybrid Clustering Routing Protocol (HCRP-HD) is proposed to detect the holes in the network. The HCRP-HD consists of two phases: hole detection and packet routing. The detection process tries to generate a connected graph to improve the network lifetime by incorporating graph metrics and a soft clustering algorithm. The network parameters such as node degree, closeness and betweenness centrality, page rank, and local cluster coefficient are used in the clustering process. The hole detection improves the network lifetime, which helps in packet routing via connected graphs. The HCRP-HD protocol is compared with three different protocols, namely THD [62], BDP [202], and LEACH-T [8]. The simulation result shows that HCRP-HD increases hole detection accuracy up to 98% and eliminates the network disconnectivity of more than 80% of the network lifetime.

3.1.5. Comparative Analysis of ML Techniques in MANETs

Summary of ML-based Protocols for MANETs: The existing ML techniques used in Ad-hoc Networks' routing protocols can mainly be categorized into reinforcement learning, neural networks, and clustering methods. The main objectives of using ML techniques in MANETs are: Choose the optimal path, predict the vehicle's location, reduce congestion and transmission delay, and increase delivery probability. Table 2 shows a comparative analysis of the ML-based routing protocols in MANETs. It also summarizes the commonly used datasets, simulation tools, and competing existing routing protocols.

3.2. ML-based Routing Protocols for VANETs

There is a growing interest in Vehicular Ad hoc Networks (VANETs) because of their potential usage in applications like road safety, driver assistance, autonomous driving, entertainment service, traffic monitoring, roadside business advertisement, and many more. Researchers are fascinated by VANETs due to their challenging characteristics, such as highly dynamic vehicle mobility, varying speeds, and varying vehicle density. So, designing protocols to provide efficient and reliable delivery, which is a minimum QoS requirement for VANET applications, is quite challenging. Over the years, many routing protocols have been proposed for VANETs. However, most protocols are designed for a specific environment/scenario or work under specific assumptions like the availability of location information. ML techniques can help protocols learn to adapt to changing environments, and application needs better than traditional protocols. In this section, we discuss the evolution of ML in VANETs.

3.2.1. Supervised Learning-based protocols in VANET

We have analysed VANET routing protocols utilising supervised learning techniques, where algorithms are trained with labelled data to make informed routing decisions, enhancing reliability and efficiency in vehicular communication.

GMLR [207]: For efficient communication in VANETs, the paper proposes a greedy forwarding algorithm named Greedy Machine Learning Routing (GLMR). It is based on Support Vector Machine (SVM). The SVM processes the vehicles' data and generates a metric to make the routing decision. Unlike most of the routing protocols in VANETs, GLMR does not depend only on GPS. A neighbor node is selected as a forwarding node based on the direction of the node and the distance between the next-hop node and the forwarding node. The simulation results show that GLMR reduces the delay and packet loss in VANETs compared to GPSR protocol [87].

V2I [150]: The paper proposes a novel approach to enhance Vehicle-to-Infrastructure (V2I) communication in Vehicular Ad hoc Networks (VANETs) by integrating ML and software agent techniques. The proposed model aims to improve the efficiency of intelligent transport systems by providing safety warnings and reducing collisions. Leveraging ML techniques and software agents addresses the inherent imprecision and uncertainty in VANETs. The proposed agent-based model incorporates static and mobile agents and employs decision tree and Q-Learning algorithms to classify events and identify destination vehicles. This approach optimises bandwidth utilisation, packet delivery ratio, and end-to-end delay in V2I communication.

RF, KNN, LR [35]: The authors focuses on evaluating the performance of ML techniques, including Random Forest (RF), Logistic Regression (LR), and k-nearest Neighbor (KNN), in predicting efficient routing protocols based on feature information extracted from real-time vehicles. The study addresses the gap in identifying vehicle features by utilizing a novel dataset compiled from NS-2 [60] and SUMO [95]. By comparing the performance of ML techniques against traditional routing protocols, the paper highlights the potential of ML in improving the effectiveness and reliability of VANETs. Future research directions include exploring the integration of artificial intelligence (AI) techniques to en-

Table 2
Comparative Analysis of ML Techniques in MANETs

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
1997	DRQ-Routing [97]	Dual Reinforcement Learning	Backward and Forward exploration of Q-learning used to update Q-value	Learns the optimal policy faster, Sustain high network load	Q-Routing [108]	Different network topologies	Custom
2002	Q-MAP [177]	Reinforcement Learning	Multi-agent reinforcement learning algorithms used for multicast routing	Minimizes the latency and chooses optimal path	Multicast Routing Protocols [79]	Different Mobility Models	Custom
2004	Q-Routing [32]	Reinforcement Learning	Reinforcement Learning Controls the node mobility and packet routing decisions	Able to learn the interplay between movement and routing	Directional Routing	Random and Centroidal movement policy	Custom
2011	Warp-5 [147]	Reinforcement Learning	Q-learning dynamically selects the route to cope with congestion and noise in network	Makes better routing decision by avoiding congestion and noise	AODV [132]	Additive white Gaussian noise model	NS-2 [60]
2012	FMRM [134]	Fuzzy Logic	Multipath routing protocol based on Fuzzy controller to minimize route reconstruction	Efficiently selects multiple routes which increase delivery ratio and reduces delay	AOMDV [114], AODVM [121]	Random Way Point mobility model [21]	NS-2 [60]
2016	RL [66]	Reinforcement Learning	It takes the forwarding decision based link stability	Identifies the behavioral pattern of node and reduces transmission delay	E-Ant-DSR [33], DSR [82], ant-colony based routing [67]	Random Way Point mobility model [21]	NS-2 [60]
2019	HCRP-HD [115]	Unsupervised Learning	Improves network lifetime by detecting holes using hybrid clustering	Increases the hole detection accuracy which reduce the network disconnectivity	THD [62], BDP [202], LEACH-T [8]	Random Distribution of node in 500 * 500 m area	MATLAB [1]
2019	QURA [200]	Neural Network	PCA and Neural Network to predict the network	Load balancing based routing protocol using ML to reduce packet loss, delay and throughput	BF and QUBF [75]	Various traffic patterns	Custom
2020	ORuML [34]	Supervised Learning	ML-based Optimized Routing in wireless networks	Identifies the optimal neighboring node for efficient routing	Other ML techniques	Real Experiment	Custom [1]
2022	SVM-BBC [148]	Supervised Learning	SVM is used to classify suitable neighbour node	High data delivery and minimal time consumption	CTCP [17], ELMP [140]	Network topology (50 to 500 nodes)	NS-2 [60]

hance further VANET efficiency and scalability in diverse VANET scenarios.

3.2.2. *Reinforcement Learning-based Protocols in VANET*

We have investigated routing protocols in VANETs leveraging reinforcement learning algorithms, dynamically adjusting routes based on changing traffic conditions to improve adaptability and efficiency in vehicular networks.

PFQ-AODV [195]: PFQ-AODV uses a fuzzy constraint-based Q-learning routing algorithm. It is based on a well-known AODV [132] (ad-hoc on-demand distance vector) routing protocol. By using fuzzy logic, the protocol can handle uncertain and imprecise link information and evaluate whether forwarding a link is good or not without using traditional mathematical models. Unlike most VANET protocols, it does not use vehicles' positioning information (GPS independence) and is independent of lower layers. So, PFQ-AODV is practical and portable. The protocol considers nodes' mobility, link quality, and bandwidth for route selection. The authors have tested the protocol on real devices as well.

PbQR [195]: Establishing a reliable multi-hop transmission in VANETs is challenging. The proposed protocol PbQR (Position-based Q-Learning Routing) uses reinforcement learning to evaluate the intermediate nodes' strength to forward messages to destinations. The PbQR protocol selects the best neighbor node for forwarding the message using the quality of neighbor nodes and the position of the destination node. Each node periodically sends a hello message containing the node's position, reward table, and the number of nodes in the communication range. It also uses the node's stability and continuity factor to calculate the reward effectively. Each node updates the reward table upon receiving hello messages. The PbQR makes forwarding decisions using the position information of the neighbor and the destination node. The simulation results show that PbQR effectively finds the better path in the dynamic topology of VANETs.

Co-operative Approach [188]: Most real-world VANETs create interconnected networks of multiple vehicles. These vehicles generate multidimensional heterogeneous overlay networks, and it is not easy to communicate between them. This paper proposed the Deep Reinforcement Learning (DRL) based cooperative method to enable effective communication between virtual networks through Software Define Networking (SDN) controller. The paper's main contributions are the framework to enable communication between heterogeneous virtual vehicle networks, improving the performance of co-existing virtual networks, providing Markov solutions for fast convergence of the cooperative method, and using the DRL to maximize the total rewards. The simulation results show that the proposed approach improves heterogeneous vehicular networks' latency, loss rate, and throughput.

3.2.3. Neural Network and Fuzzy Logic-based protocols in VANET

We have examined VANET routing protocols employing neural networks and fuzzy logic controllers to optimise routing decisions and enhance communication reliability in dynamic vehicular environments.

GABR [203]: It aims to reduce packet loss by solving the broken link problem between nodes. A genetic algorithm finds the optimal global path between a source and a destination. The initial population is generated randomly over a variety of routes. According to the fitness value, it selects an optimal path to deliver a message to the destination. In GABR, adjacent vehicles use a greedy store-carry-forward approach to deliver a message. The experimental results show the superiority of GABR over CAR (connectivity-aware routing) and IBR (intersection-based routing) protocols. However, the proposed approach is complex and needs a faster speed of searching.

CRS-MP [178]: The paper proposes a centralized routing strategy with vehicle mobility prediction for VANETs, which uses artificial intelligence-based Software Defined networks (SDN). In VANETs, protocols generally use hello messages to identify/detect neighboring nodes, increasing network congestion. The proposed protocol reduces this communication cost by predicting the vehicle arrival rate using ANN. It builds a statistical traffic model by estimating traffic mobility, which helps to make efficient routing decisions. Based on the prediction, the transmission probability and the average delay can be calculated before the actual time to make forwarding decisions. The CRS-MP protocol gives a robust performance in case of frequent changes in vehicle speeds.

GA based Approach [151]: The protocol is based on the Mobicast routing protocol. It uses Genetic Algorithm for quick and real-time response to dynamic changes in topology. The fitness is calculated using the minimum average route cost per the threshold. The approach shows performance improvement in the execution time using parallel processing. The result shows the improvement over the serial algorithms to scale up the number of vehicles on the road and reduces the roadside unit for more extended coverage.

3.2.4. Unsupervised Learning-based protocols in VANET

We have studied VANET routing protocols utilising unsupervised learning techniques, autonomously detecting patterns and structures in vehicular networks to enhance scalability and adaptability in dynamic traffic scenarios.

CBDRP [170]: In this paper, the authors proposed a cluster-based directional routing protocol (CBDRP) for highway scenarios. The protocol transmits the message according to the moving direction of vehicles. The vehicles moving in the same direction are divided into several clusters. To find the stable link, the heads of the cluster are selected based on the direction of the vehicles' movement. Each head node knows to which cluster it belongs, and it is responsible for finding the path to the destination by exchanging location messages within a cluster. In CBDRP, when intermediate nodes experience link failure, they follow a store-carry-forward approach for route repair to provide link stability. The simulation results show that the CBDRP protocol is superior compared to AODV [132] and GPSR [87] in terms of delivery ratio, latency, and link stability for highway scenarios.

MARS [100]: This paper focused on reducing transmission delays and improving message transmission stability in VANET. Due to frequent changes in a link and the high mobility of vehicles, route selection is a difficult task. The proposed protocol uses the k-means clustering technique to predict the movement of vehicles and choose the appropriate path with sustainable transmission capacity to forward the messages. The k-means clustering is used to learn network information for making forwarding decisions between Road Side Units (RSU). The MARS provides mainly three evaluations/predictions, which are as follows: First, the prediction of vehicle movements. Second, the evaluation of transmission capacity, and finally, the evaluation of forwarding direction. The simulation performed in NS-2 [60] using different real datasets shows that the MARS protocol gives better reliability and efficiency in data transmission for VANETs.

CBLTR, IDVR, CORA [3]: The authors have proposed three routing protocols in this paper. First, the Cluster-Based Lifetime Routing (CBLTR) protocol aims to increase throughput and route stability. The cluster heads are selected based on the lifetime of a vehicle. Second, Intersection Dynamic VANET Routing (IDVR) aims at reducing end-to-end delay. It selects the optimal route by considering current and destination location information and the average throughput of the Set of Candidate Shortest Routes (SCSR). Finally, the Control Overhead Reduction Algorithm (CORA) limits the number of control messages by calculating the optimal period for exchanging messages to update clusters. The SUMO [95] simulator is used for traffic generation, and MATLAB [1] is used to show the improvement in performance over the protocols like CBDRP [170], AODV-CV [13], VDLA [206].

Hybrid Clustering Approach [12]: Most VANET applications require transmitting a message to the desired location within a specific period. This paper proposes two soft computing-based VANET routing protocols to meet the delay constraints. First, a hybrid clustering protocol combines a context-based and geographical clustering approach. It helps in reducing the control overhead in the network. Second, a destination-aware routing protocol for inter-cluster routing reduces the end-to-end delay and improves the message delivery ratio. It utilizes the current location of a node and its neighboring nodes to identify the suitable forwarding node. The simulation results show that the proposed hybrid clustering approach performs better than CBLTR [143], AODV-CV [13], CBR [111].

3.2.5. Comparative Analysis of ML Techniques in VANETs

In summary, ML techniques used by routing protocols in Ad-hoc Networks can be categorized as follows: Reinforcement Learning, Neural Networks, Supervised Learning, and Unsupervised Learning. The main objectives of using ML techniques in VANETs are: to learn the network behavior, reduce congestion, select an optimal path, reduce packet loss, and increase delivery probability. Table 3 shows the comparative analysis of the ML-based routing protocols in VANETs. It also summarizes the commonly used datasets, simulation tools, and competing existing routing protocols.

3.3. Rationale for Investigating ML Techniques in MANETs and VANETs

MANETs and VANETs represent prominent categories within the domain of mobile networking. These networks are characterised by their dynamic topology, limited infrastructure, and decentralised nature. It presents distinctive challenges for routing and communication. Over the years, researchers have extensively explored ML techniques to address these challenges and enhance the performance of MANETs and VANETs. ML techniques in MANETs and VANETs are discussed in our comprehensive survey on Opportunistic Networks for several reasons:

3.3.1. Common Challenges and Solutions

MANETs, VANETs, and Opportunistic Networks have common challenges such as intermittent connectivity, node mobility, limited bandwidth, and energy constraints. ML techniques have been applied in MANETs and VANETs to optimise the performance of routing protocols, predict link quality, and adapt network configurations. By reviewing the literature on ML techniques in MANETs and VANETs, we gain insights into solutions that can be adapted and extended to address similar challenges in Opportunistic Networks.

3.3.2. Technological Evolution

The evolution of ML techniques in MANETs and VANETs reflects the iterative process of refining algorithms and models to serve the specific requirements of mobile and dynamic network environments. Early research focused on basic routing and localisation tasks. At the same time, recent advancements have examined sophisticated ML-based approaches for traffic prediction and adaptive routing. By examining the trajectory of ML research in MANETs and VANETs, we can anticipate emerging trends and innovations that may influence the development of Opportunistic Networks.

3.3.3. Cross-Domain Applications

ML techniques developed for MANETs and VANETs demonstrate potential for cross-domain application in Opportunistic Networks. For instance, ML-based routing protocols designed for network conditions in MANETs can be adapted to exploit opportunistic encounters and information dissemination in Opportunistic Networks. Similarly, anomaly detection algorithms for VANETs can be utilised to identify suspicious behaviours and malicious activities in opportunistic communication scenarios. By exploring literature across different mobile networking domains, we can leverage prior research to accelerate innovation and address common challenges in Opportunistic Networks.

3.3.4. Comprehensive Perspective

We aim to provide researchers with a comprehensive understanding of ML techniques in mobile networking, encompassing diverse applications and contexts. By including literature reviews on MANETs and VANETs, we offer a holistic viewpoint emphasising the connection of research efforts across related domains. This approach enhances the depth of our survey and encourages knowledge transfer and cross-pollination of opinions among researchers working in different areas of mobile networking.

In summary, including literature reviews on ML techniques in MANETs and VANETs in our survey on Opportunistic Networks bridges the gap between different mobile networking domains. We aim to facilitate the development of innovative solutions that address the growing needs of communication environments.

Table 3
Comparative Analysis of ML Techniques in VANETs

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
2010	CBDRP [170]	Unsupervised Learning	Cluster head selects another head based on the direction of the vehicle	Finds the stable link of transmission for rapid and reliable communication	AODV [132], GPSR [87]	Highway Scenario	NS-2 [60]
2013	PFQ-AODV [195]	Reinforcement Learning, Fuzzy Logic	Fuzzy constraint-based Q-learning algorithm used for routing	Doesn't required vehicles position to for route selection	AODV [132],	Freeway scenarios, Street scenarios	NS-2 [60]
2014	MARS [100]	Unsupervised Learning	ML techniques used to predict vehicle movement	Chooses the path with sustainable transmission capacity	CLWPR [88], STAR [31]	Open Street Map [95]	NS-2 [60]
2016	GMLR [207]	Support Vector Machine	SVM is used to process the vehicle data which helps in routing	Reduces the packet loss and delay in a network	GPSR [87]	Floating Car Data (Beijing)	NS-2 [60]
2017	CBLTR, IDVR, CORA [3]	Unsupervised Learning	Cluster-based routing protocol is used to select the optimal path	Increases the throughput, route stability, reduce delay and control overhead	CBDRP [170], AODV-CV [13], VDLA [206]	Grid Topology, Highway Scenario	SUMO [95] and Matlab [1]
2018	Hybrid Clustering Approach [12]	Soft Computing	Hybrid clustering combines the context-based and geographic approach	Message delivery within certain time limit, reduces end-to-end delay	CBCLR [143], AODV-CV [13], CBR [111]	Uniform distribution of nodes	NS-2 [60], SUMO [95]
2018	GABR [203]	Genetic Algorithm	GA used to find optimized global path which also satisfies QoS requirements	Better transmission delay and loss rate	CAR [10]	Urban road scenario	Custom
2019	CRS-MP [178]	Artificial Neural Network	Uses ANN to predict the vehicles arrival rate and make efficient decision	Reduces the communication cost and reduce network congestion	Vehicle to Vehicle and Infrastructure [37]	Poisson Process [131]	NS-2 [60]
2019	PbQR [195]	Reinforcement Learning	Uses the quality of neighbor nodes and position of destination node to find a route	Finds better forwarding nodes by calculating rewards	GPSR [87], AODV [132]	Manhattan Mobility Model	NS-2
2019	Cooperative Approach [188]	Deep Reinforcement Learning	Uses DRL to improves the cooperation between the virtual networks	Improves loss rate, throughput and latency	Coalitional Routing [40], Throughput Optimal Routing [123]	Waxman–Salama model [193]	Custom
2019	GA based Approach [151]	Genetic Algorithm	Genetic algorithm based modified mobicast routing used to gain more accuracy	Gives high reliability and quick real time response to frequent topology changes	GPSR [87] CAR [10]	Street Scenarios	OpenMP [44], CUDA [152]
2021	V2I [150]	Supervised Learning	ML-based intelligent transport system to learn automatically	Avoid vehicle collision and gives safety warning	C-V2I	City Scenario	Custom
2023	RF, KNN LR [35]	Supervised Learning	Extracting features of vehicular networks using ML	safe, secure, and reliable VANET routing	ML Techniques [10]	Read-world road environment	NS-2 [60], SUMO [95]

3.4. Analysing Differences among MANETs, VANETs, and Opportunistic Networks

MANETs, VANETs, and Opportunistic Networks represent distinct paradigms within the domain of mobile networking, each characterised by unique challenges and applications. We have analysed fundamental differences among these network types, mainly focusing on routing, energy consumption, latency, and the applicability of ML techniques.

3.4.1. Routing Dynamics

MANETs operate in infrastructure-less environments where nodes rely on ad hoc routing protocols for communication. These protocols, such as AODV and DSR, facilitate dynamic route discovery and maintenance, which is suitable for scenarios with frequent topology changes. In contrast, VANETs incorporate vehicular communication with roadside infrastructure, leading to hybrid routing approaches. Vehicle-to-Vehicle and Vehicle-to-Infrastructure communication protocols enable efficient dissemination of safety messages and traffic information, incorporating ad hoc and infrastructure-based routing. Opportunistic Networks leverage intermittent connections and mobility patterns for message dissemination. Traditional end-to-end routing is impractical due to the lack of continuous paths. Instead, store-carry-and-forward or epidemic routing strategies exploit sporadic encounters for message forwarding.

3.4.2. Energy Consumption Patterns

Energy conservation is essential in MANETs, where mobile devices operate on limited battery resources. Energy-efficient routing protocols, sleep scheduling mechanisms, and adaptive transmission power control are adopted to prolong the network lifetime. Vehicles in VANETs possess varying energy capacities and require energy-aware routing strategies. Cooperative relaying and dynamic power management techniques optimise energy consumption while meeting communication requirements. Energy consumption in Opportunistic Networks varies with device mobility and communication opportunities. Message replication and context-aware techniques balance energy efficiency with message delivery probability in resource-constrained environments.

3.4.3. Latency Characteristics

The latency in MANETs arises due to the nature of topology changes and the route discovery mechanisms utilised within the network. Proactive caching and route optimisation techniques mitigate latency and improve end-to-end communication performance. VANETs impose uncompromising latency requirements, particularly for safety-critical applications such as collision avoidance. Prioritisation of safety messages, efficient dissemination protocols, and predictive modelling of vehicle movements contribute to reducing latency in VANETs. Latency in Opportunistic Networks is inherently higher due to intermittent connectivity and the reliance on store-carry-and-forward routing. ML techniques are leveraged to predict encounter probabilities and optimise message forwarding to minimise latency.

3.4.4. Applicability of ML Techniques to Opportunistic Networks

In light of the distinct characteristics, evaluating the transferability of ML techniques developed for MANETs and VANETs to Opportunistic Networks is essential. The several considerations demonstrate the potential applicability of ML in enhancing routing, energy consumption, latency, and other performance metrics in Opportunistic Networks. ML models trained on historical routing data from MANETs and VANETs can make informed opportunistic routing decisions in dynamic and intermittently connected environments. ML-based energy availability and consumption pattern predictions facilitate energy-efficient message-forwarding strategies in Opportunistic Networks. The predictive modelling of encounter probabilities and mobility patterns using ML techniques enables proactive message scheduling and transmission to minimise latency in Opportunistic Networks. ML techniques dynamically allocate resources based on network conditions and application requirements, optimising performance in Opportunistic Networks.

It is crucial to understand the differences among MANETs, VANETs, and Opportunistic Networks for effective communication strategies and deploying appropriate ML-based solutions. We provided the groundwork for identifying ML techniques to enhance performance in Opportunistic Networks.

3.5. Comparative Study of ML Techniques in MANETs, VANETs and Opportunistic Networks

In this section, we conduct a comprehensive comparative analysis of ML techniques employed in MANETs, VANETs and Opportunistic Networks. By examining ML applications' common and unique characteristics in these network types, we aim to identify the similarities, differences, and potential in leveraging ML techniques.

3.5.1. Simple Improvisations of ML Techniques

We have examined ML techniques commonly utilized in MANETs and VANETS, which are adapted and refined in Opportunistic Networks.

Supervised learning techniques have been widely utilised in MANETs and VANETs for tasks such as link quality prediction, traffic classification, and routing optimisation. In MANETs, supervised learning models are trained on labelled data to predict link quality metrics such as packet loss or delay, enabling nodes to select more reliable paths for data transmission. Similarly, in VANETs, supervised learning algorithms may classify network traffic into different categories (e.g., safety messages and entertainment data) to prioritise message dissemination based on application requirements. In Opportunistic Networks, supervised learning techniques are often adapted for predicting encounter probabilities between nodes. By analysing historical data of node movements and communication patterns, supervised learning models can estimate future encounters' likelihood, guiding message-forwarding decisions. For example, logistic regression or support vector machines trained on features such as node mobility patterns, communication frequency, and social interactions to predict the probability of encounters between pairs of nodes.

Unsupervised learning algorithms such as clustering and anomaly detection are used in MANETs and VANETs for network monitoring, topology discovery, and anomaly detection. In MANETs, clustering algorithms group nodes with similar connectivity patterns to facilitate efficient routing and resource allocation. Anomaly detection techniques identify abnormal behaviour or network events, such as sudden changes in traffic patterns or the presence of malicious nodes. In Opportunistic Networks, unsupervised learning methods are utilised for community detection and dynamic clustering of nodes based on proximity or social behaviour. These techniques dynamically enable nodes to form clusters or communities, fostering localised communication and enhancing message delivery probability. For instance, hierarchical clustering algorithms may be employed to partition nodes into communities based on their spatial and social proximity, enabling efficient message forwarding within each community.

3.5.2. *Unique ML Techniques in Opportunistic Networks*

We highlight ML techniques explicitly tailored for Opportunistic Networks, emphasizing their distinctiveness and efficacy in addressing the inherent challenges of intermittent connectivity and mobility patterns.

Reinforcement learning techniques offer a powerful framework for adaptive decision-making in dynamic and uncertain environments. While reinforcement learning has been applied in MANETs and VANETs for tasks such as route optimisation and congestion control, its application in Opportunistic Networks introduces unique challenges and opportunities. In Opportunistic Networks, reinforcement learning algorithms enable nodes to learn optimal routing policies based on feedback from network performance metrics such as message delivery ratio and delay. Nodes act as autonomous agents that take actions (e.g., forwarding messages to neighbouring nodes) to maximise cumulative rewards over time. By learning from past experiences and interactions, nodes adapt their routing strategies to changing network conditions and mobility patterns, improving message delivery probability and network efficiency.

Neural networks offer complex pattern recognition and decision-making capabilities, making them well-suited for modelling and optimising communication protocols in mobile networks. In MANETs and VANETs, neural networks have been applied for traffic prediction, routing optimisation, and anomaly detection tasks. In Opportunistic Networks, neural networks are utilised for various purposes, such as predicting encounter probabilities between nodes, optimising message dissemination strategies, and learning node preferences for message forwarding based on past interactions. For example, Recurrent Neural Networks (RNNs) may be employed to model temporal dependencies in node mobility patterns, enabling accurate prediction of encounter opportunities between pairs of nodes.

Fuzzy logic provides a flexible framework for reasoning under uncertainty, which is particularly relevant in Opportunistic Networks where connectivity and encounter opportunities are inherently probabilistic. While fuzzy logic is used in MANETs and VANETs for tasks such as adaptive routing and decision-making, its application in Opportunistic Networks introduces novel challenges and opportunities. In Opportunistic Networks, fuzzy logic is applied for dynamic thresholding, adaptive decision-making, and context-aware routing. For example, fuzzy logic controllers may adjust message forwarding probabilities based on node mobility, communication history, and encounter probabilities, ensuring robust and adaptive message dissemination in dynamic and intermittently connected environments.

Several ML techniques used in Opportunistic Networks are simple improvisations of those employed in MANETs and VANETs. However, unique approaches are also developed to the specific challenges and opportunities presented by Opportunistic Networks. By leveraging insights from both traditional and novel ML techniques, researchers can develop robust and adaptive communication solutions capable of enhancing network performance in intermittently connected environments.

4. Recent advances of ML techniques in Opportunistic Networks

This section presents the literature review of the work done in this field in the past decade. The section also describes the workflow of a ML-based approach in an Opportunistic Networks. It is classified into four main categories: Supervised Learning, Reinforcement Learning, Unsupervised Learning, Neural Networks, and Fuzzy Logic. The Fig. 1 shows the conceptual map of the study that describes algorithms and main tasks performed in each category. The proposed approaches aim to improve performance parameters like delivery probability, overhead ratio, hop count, and average latency. The survey will help researchers choose appropriate ML techniques depending on the problem.

4.1. Workflow of Machine Learning in Opportunistic Networks

ML workflow is categorized into 6 phases: Problem Formulation, Data Collection, Feature Extraction, Develop Model, Model Validation, and Deploy Model. The Fig. 2 presents the incorporation of ML workflow for the Opportunistic Networks. The section briefly explains ML phases in terms of Opportunistic Networks.

Problem Formulation: Recently, ML has been applied in numerous aspects of Opportunistic Networks to predict the node's contact opportunity, node movement, route stability, and similarity between nodes. The initial step of ML is to recognise the problem that needs to be solved [130]. It is the procedure to recognise the network's attributes, characteristics, behaviour, nodes movement, and node density. Based on the problem and its functioning domain, diverse problem-solving approaches, such as classification, clustering, reinforcement learning, etc., can be determined. The

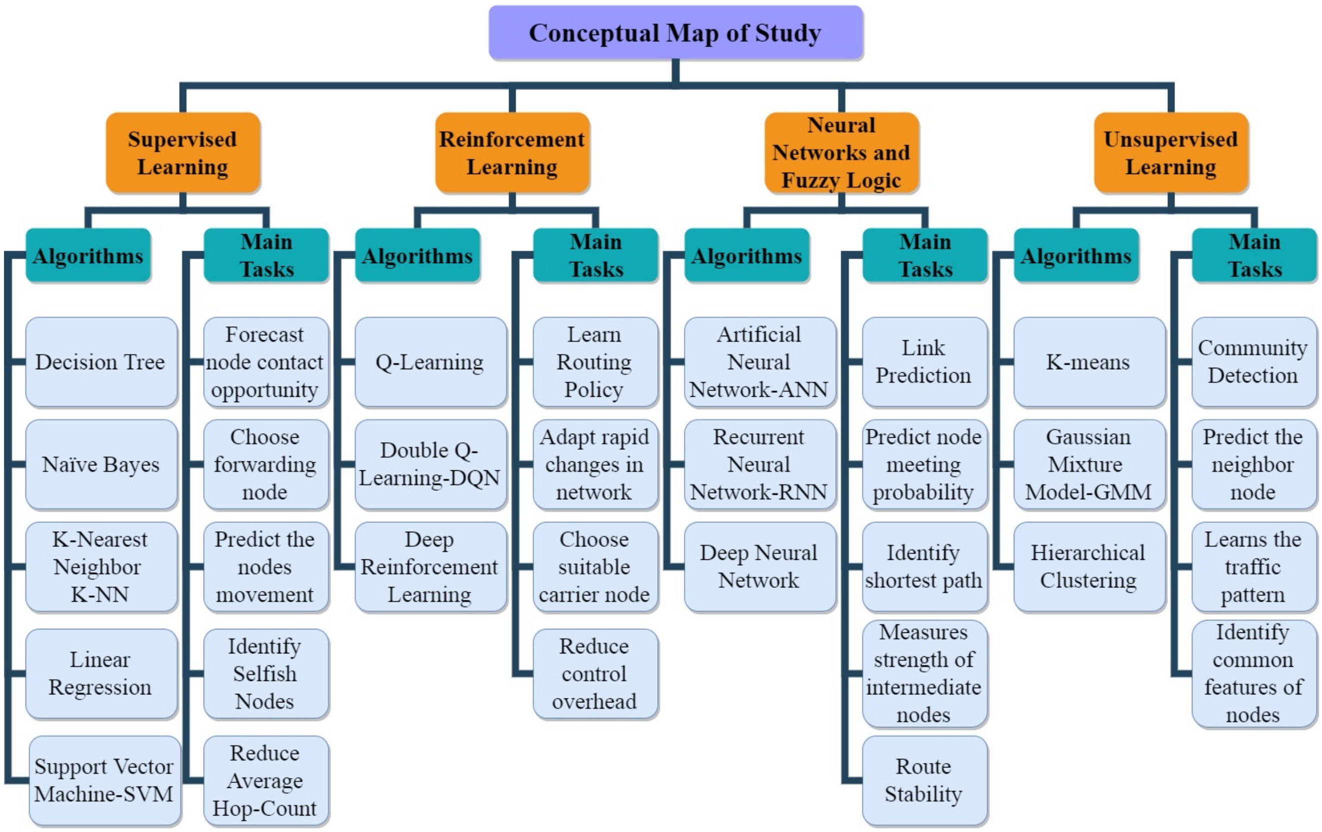

Figure 1: Machine Learning in Opportunistic Networks

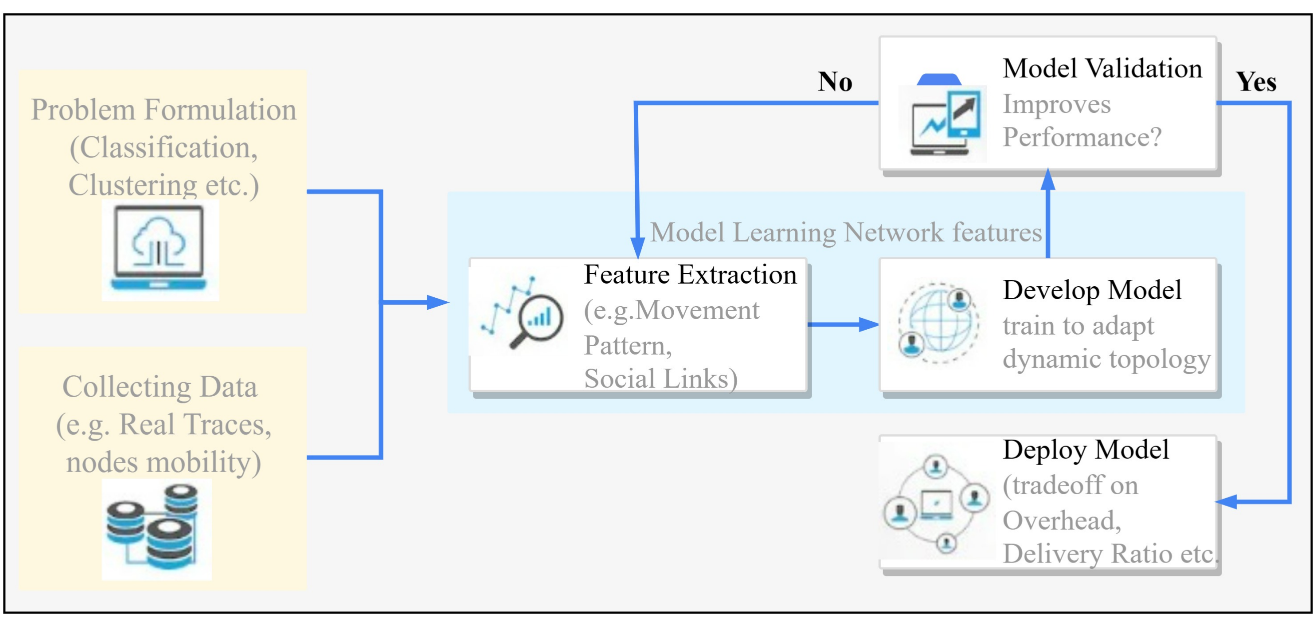

Figure 2: Workflow of Machine Learning in Opportunistic Networks

composition of problem formulation helps to understand the conventional ML Approach to improve the performance of Opportunistic Networks.

Data Collection: ML tasks usually depend upon the characteristics of the data. ML framework utilizes to explore potential correlations between the input and output data without human intervention [2] [145]. Data collection is a crucial step in Opportunistic Networks since networks scenario varies from one-time duration to the other. There are mainly two types of datasets, namely Real trace and Mobility models. The real trace dataset is generated from the real-world experiment, whereas Mobility models mimic the real scenario and movement of mobile nodes.

Feature Extraction: Massive datasets have many features that require the processing of many computing resources. Consequently, this phase intends to decrease the number of features in a dataset by producing distinct features from the existing ones (and then abandoning the original features). Feature extraction is selecting and combining significant features that effectively reduce the volume of data needed to process [136]. In Opportunistic Networks, revealing features such as the number of encounters with nodes, social strength of nodes, community detection, and finding selfish nodes is essential. These feature helps to improve the performance of networks.

Develop Model: It is the method of feeding an ML techniques with data to recognise and learn relevant characteristics of Networks. The process of developing an ML model involves using an ML techniques with training data to adapt the dynamic behaviour of Opportunistic Networks [149]. In the development phase of ML models, it is suitable that the trained model works well on unseen and new data. In order to disguise such data from the available data, proper data splitting is required. (Often mentioned as the train-test split).

Model Validation: After the development of a model, it is evaluated to verify whether the desired performance has been achieved. This phase also determines whether the optimization is obliged to enhance performance [149] [99]. The relevant network scenarios are then supplied into the model to measure the performance. Usually, the performance measures for Opportunistic Networks are in terms of Delivery Probability, Overhead, Average Latency, Average Hop Count, Energy Consumption, etc.

Deploy Model: In this phase ML model is deployed in the specific network scenario to evaluate with the test datasets [149]. The test set is a collection of network circumstances utilised to measure the model's performance using the performance metric mentioned in the above phase. This phase is the method where a trained model is assessed with a testing dataset.

4.2. Supervised Learning in Opportunistic Routing Protocols

In supervised learning, the main task is to learn the target values used to predict class values. It is the process of developing a model that can predict the unknown values (testing environment or output variables) using the known values (historical data or input variables). Supervised learning is divided into two categories: classification and regression. This section discusses the classification techniques used in Opportunistic Networks [189].

4.2.1. Decision Tree-based protocols

We have analysed routing protocols in Opportunistic networks that utilise decision tree algorithms for routing decisions. These protocols employ decision tree models to classify nodes or predict optimal routes based on various attributes, enhancing routing efficiency and adaptability in dynamic network environments.

+C [137]: The multi-copy routing algorithms transmit multiple copies of a message to increase the delivery probability and reduce the delivery delay. However, at the same time, it increases the network overhead. The principal goal of the proposed work is to decrease the network overhead without decreasing the delivery probability by applying ML techniques. The algorithm is divided into three phases: In the first phase, the message-forwarding data is collected from all the nodes. In the following phase, the collected data is used as a training set to build the Decision Tree for classification. In the last phase, network nodes use the classifier to predict whether the neighboring node is a suitable forwarder. So, instead of forwarding copies of a message to all neighboring nodes, the classifier restricts the number of copies by predicting a better node to deliver the message. The performance evaluation for the proposed approach is done using different real-world mobility traces and datasets in ONE simulator [90]. The proposed approach reduces the network overhead of two regular DTN routing algorithms, namely Epidemic [182] and Spray and Wait [174], by integrating ML classifiers.

CAML [185]: The paper proposed the cascade learning-based ML approach for routing, which is named as Cascaded ML-based routing protocol (CAML) for Opportunistic IoTs (OppIoTs). Cascade learning is an ML-based ensemble technique used in class imbalance problems. In this approach, each classifier passes its knowledge to other classifiers. The CAML builds upon the idea of MLProph [157] algorithm, which calculates ML probability for sending a message to the neighbor. In CAML, logistic regression as an additional classifier is used to calculate the probability of message delivery. The cascade classifier is built using Logistic Regression, Random Forest, Support Vector Machine, and MLP Neural Network. Each classifier trains sequentially and passes the input to other classifiers. The simulation result shows that the CAML outperforms MLProph [157], KNNR [160], HBPR [49], ProPHET [107] in terms of delivery probability, overhead ratio, and average hop count.

4.2.2. Naive Bayes and Bayesian Learning-based protocols

We have reviewed routing protocols in Opportunistic Networks leveraging Naive Bayes and Bayesian learning techniques for routing decision-making. These protocols enhance route selection and network performance in uncertain and dynamic communication scenarios by probabilistically modelling node behaviours and network conditions.

FSF [171]: The proposed Friendship and Selfishness Forwarding (FSF) algorithm takes the forwarding decision based on two aspects: First, it measures friendship strength between the nodes using ML techniques. Second, it identifies selfish nodes that do not receive the message despite having a strong friendship with the destination node. ML's Naïve Bayes Classifier approach measures the friendship strength between two nodes. It considers attributes like the frequency of meetings, contact duration, and the number of calls and messages. There are two types of selfish node behaviour for selfish nodes: selfish in a few situations, e.g., resource constraint, and others who behave selfishly all the time. A reputation-based selfishness detection mechanism is used to assess the selfishness of the nodes. The simulations are performed in the ONE simulator [90] using real datasets, and results show that the FSF algorithm performs better than the Epidemic [182], ProPHET [107], BubbleRap [74] in terms of delivery ratio, average cost, and average efficiency.

Q-Routing [53]: This paper proposed the framework of the ML-based DTN routing algorithm. The main focus of the proposed technique is to improve space networking, where the end-to-end path may not exist. It applies bayesian learning and reinforcement learning ML techniques with the combination of well-known Contact Graph Routing (CGR) algorithm [11] for DTN. CGR takes the routing decision based on the last meeting of the nodes and contact times. The reinforcement learning-based Q-routing algorithm estimates the delivery time for end-to-end transmission using the reward table or Q-table. The learner chooses the neighboring node for packet delivery, which minimizes the delivery time. The Bayesian technique calculates the most favorable outcome called the posterior or MAP hypothesis. The proposed method uses previous contacts of nodes to determine the probability of reliability in the future for the same contact opportunities. The probability depends on contact start and stop times, data rates, distance, and the number of meetings. The open-source discrete event simulator OMNET++ [183] is used, and the simulation results show that ML-based protocol outperforms ProPHET [107] and CGR [11].

BACE [16]: In this paper, the Bayesian Network (BN) based algorithm, namely BACE, is proposed to estimate nodes' contact probability in DTN. The two nodes' contact probability prediction depends on the average contact time, contact frequency, and average contact interval. Two real datasets, i.e., Cambridge [154] and Reality [54], are analyzed to understand the distribution of contact probability. BACE can obtain this statistic and gives an accurate forecast of nodes' encounters for the future. BACE consists of the graphical structure connecting variables, a set of variables, and local conditional probability distribution used to calculate contact probability. The ONE Simulator [90] is used to compare the BACE with the existing approach, namely the ProPHET [107] routing algorithm and the Power-law distribution method [39]. The experimental results show that BACE gives the highest predictive accuracy and an increased delivery ratio for all four datasets.

MBN [118]: In real life, most vehicles have repetitive movement patterns but are time-based. Due to this, a single prediction model cannot predict accurately. The paper proposed the Multi-period Bayesian (MBN) Network to generate multiple prediction models to predict the repetitive movement of a vehicle. The Bayesian network contains a set of probabilities, variables, and a graphical structure that connects variables to improve the routing decision. Dynamic Multiple Level Classification (DMLC) is used to classify the nodes and optimize the classification through a dynamic parameter. The routing algorithm comprises five phases: node classification, attribute selection, structure learning, forwarding technique, and inference strategy. MBN is compared with Epidemic [182] and ProPHET [107] routing algorithms through the ONE simulator [90]. The experimental results show that the MBN improves delivery probability with less forwarding overhead.

FSF [172]: This paper proposed a novel technique to classify the friendship strength between nodes. Friendship and Acquaintanceship Forwarding (FSF) uses a Naïve Bayes algorithm to find social strength between destination and intermediate relay nodes. FSF only forwards a message to those nodes that are friends or acquaintances. Different parameters are considered to determine friendship strength between nodes, like contact time, duration, contact time, and frequency. This algorithm also considers the critical issue of the socially selfish nodes, which are not participating in the message relaying between nodes. The algorithm identifies a node as socially selfish using existing detection and reputation-based mechanisms and does not transmit a message to that node. In the detection system, components are installed in every node responsible for identifying selfish neighbour nodes based on past behaviour. The simulation is performed in the ONE simulator [90], and the results show that the proposed algorithm increases the delivery ratio compared to Epidemic [182], ProPHET [107], and BubbleRap [74].

K2-GA [196]: In this paper, the authors have proposed Bayesian Network (BN) based routing algorithm named K2-GA to build the prediction model. The prime focus of K2-GA is to predict the mobility patterns of nodes in the Vehicular Delay Tolerant Network (VDTN) scenarios. VDTN is a particular type of DTN network that considers vehicles as nodes. More attributes of nodes are considered to improve the BN model's prediction accuracy. These attributes are supposed to expose the node's movement pattern by which the number of message copies can be decreased in the network. The proposed K2-GN algorithm combines the K2 algorithm [36] with a genetic algorithm to determine optimal BN structure efficiently. The simulation results obtained using ONE simulator [90] show that K2-GA achieves a competent delivery ratio with a minor overhead ratio.

RFCSec [86]: The authors have proposed Random Forest Classifier based protocol named RFCSec for reliable and safe routing for OppIoT. The proposed protocol is divided into two phases: Training and Testing. In the training phase, the protocol is trained on real data traces whereas, in the testing phase, the protocol classifies optimal forwarding nodes based on their prior behaviour in the network. This phase identifies malicious nodes and encourages participation of other nodes in forwarding which has a low message drop rate, higher buffer capacity, stable forwarding behaviour and high probability of message delivery. The simulation performed in ONE simulator [90] shows that RFCSec protocol is a considerably reliable and secure protocol as compared to RLProph [159], MLProph [157] and CAMP [190] Protocols.

4.2.3. Diverse Learning-based Protocols

We have examined routing protocols in Opportunistic Networks that employ diverse learning such as SVM, regression, KNN and other algorithms for routing optimisation. By analysing historical data and network parameters, these protocols predict optimal routes and adjust routing decisions to improve communication efficiency and reliability in Opportunistic Networks.

UMCRP & GMCRP [138]: The significant issue related to DTN-enabled VANETs is identifying the best node and time to forward the message. This paper proposed the timeliness-aware trajectory data mining method to predict the future position of nodes. The dynamic VANET topologies are maintained by developing a sparse graph model using predicted time information of nodes. Based on this, two routing algorithms are developed: a timeliness-aware data mining algorithm and a sparse time-space model. The timeliness-aware data mining algorithm uses association rule mining to predict the location of moving nodes because the current state of moving nodes is affected by the previous state. Using this predicted result of node movement, it can generate a time-space graph and determine the path with minimum link overhead on the sparse graph model. The simulation results show that the proposed algorithm provides a highly reliable route and cost-efficient connectivity.

KNNR [160]: For selecting the appropriate intermediate node, the past behavior of nodes needs to be understood. The K-nearest neighbor-based protocol named KNNR is proposed to select a suitable carrier node for a message based on the nodes' state. A node's state information includes buffer space, time-out ratio, the distance between a neighbour node to the destination node, hop count, speed of neighbour node, and meeting probability. The KNNR protocol has two classes: class-0 and class-1. In the application phase, when a node encounters a neighbor node, if the node classifies it in class-1, then a message is transferred. If it belongs to class-0, then the message is not transferred. The KNNR is compared with Epidemic [182], HBPR [49], and ProPHET [107], and simulation results show that the KNNR outperforms these protocols in terms of delivery probability, overhead ratio, average latency, and hop count.

We have also surveyed related works in supervised learning approaches. Among these, RF-BBFT [126] is a random forest-based multimedia big data routing protocol for social OppIoTs. By considering metrics like direct bonding, node popularity, and power consumption, RF-BBFT achieves superior performance in successful transmissions, average latency, and buffer time compared to existing techniques, outperforming BBFT and MLProph. iPRoPHET [176] presents an improved PRoPHET-based multi-copy routing algorithm for OppIoTs networks, utilizing a Random Forest classifier to categorize nodes as reliable or non-reliable forwarders. By leveraging contextual information and delivery probability, iPRoPHET enhances delivery probability and reduces hop count and overhead ratio, albeit with slightly increased average buffer time, showcasing superior performance in multi-copy routing for IoT communication.

ML-Fresh [64] is a novel framework designed to address challenges faced by Opportunistic Networks, such as blind data forwarding and performance degradation due to increasing data sizes. ML-Fresh aims to establish optimal communication paths between participating nodes by leveraging ML techniques, including pattern prediction, decision tree prediction, and the Adamic-radar method. Combo-Pre [102] is a combination link prediction method designed to enhance routing protocol efficiency in Opportunistic Networks. By leveraging periodic pattern mining, decision tree methods, and the Adamic-Adar method, Combo-Pre predicts various contact patterns among node pairs more accurately than existing single-method approaches. Experimental results demonstrate that Combo-Pre outperforms state-of-the-art link prediction methods in terms of routing cost reduction and delivery rate. The paper [7] focuses on enhancing the traditional PRoPHET protocol in Opportunistic Networks. By leveraging association rule mining, a ML technique, the proposed ARBP routing protocol aims to improve message delivery, reduce overhead, minimize dropped messages, and lower latency. This approach utilises historical data from PRoPHET and applies association rules to identify optimal encountering nodes for efficient message delivery.

The Comparative Analysis of Supervised Learning in Opportunistic Networks is presented in Table 4.

4.3. Reinforcement Learning in Opportunistic Routing Protocols

The reinforcement learning algorithm is an ML approach concerned with taking suitable action by an agent that maximizes the reward in a particular environment. The agent decides to maximize its reward and minimize the penalty by learning the environment/situation. This model keeps learning and maximizes performance. The reinforcement learning algorithm is the preferred choice where the environment is known but does not have an analytical solution. The reinforcement learning model can sustain the changes for a more extended period [189].

4.3.1. Q-Learning-based Protocols

We have explored protocols that utilize Q-learning, a fundamental reinforcement learning algorithm, to determine optimal action-selection policies in various environments.

QLAODV [194]: This paper proposed the QLAODV (Q-learning AODV) protocol for VANET. QLAODV is a distributed reinforcement learning-based routing protocol capable of adapting to frequent path changes and works well in a highly dynamic network environment. In QLAODV, each node maintains a table of Q-values by exploring environment states and each possible action. For forwarding, the message nodes choose the next hop with the highest Q-value. If the message reaches the destination node with the selected action, it makes the reward 1; otherwise, 0. The learning rate parameter α shows how quickly learning happens, and the discount factor controls the values of future rewards. For maintaining the Q-table, every node frequently exchanges the hello packets with neighbor nodes to exchange link in-

Table 4
Comparative Analysis of Supervised Learning in Opportunistic Networks

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
2014	+C [137]	Supervised Learning: Decision Tree-J48	Classifier is used to predict good forwarder node	Reduce the network overhead	Epidemic [182] , Spray and Wait [174]	Bus Movement (Seattle buses)	ONE Simulator [90]
2017	UMCRP & GMCRP [138]	Trajectory Data Mining	Uses trajectories mining for frequent movement of nodes	Predict the future position of vehicle	ULCP-Union of Least Cost Path (ULCP) [73]	Time Evolving Network	Custom
2017	FSF Friendship & Selfishness Forwarding [171]	Supervised Learning: Naïve Bayes	Measures friendship strength and identify selfish users	Increase delivery and reduce average cost	Epidemic [182], PRoPHET [107], BubbleRap [74]	Infocom05 [154], Cambridge [154]	ONE Simulator [90]
2018	Q-routing [53]	Supervised Learning: Bayesian Learning, Reinforcement Learning	Reward table/Q-table is used to choose neighbor node for transmission	Finds future contact opportunity using past contacts of nodes	ProPHET [107], CGR [11]	Custom Mobility Model	OMNET++ [183]
2017	KNNR [160]	Supervised Learning: K-nearest Neighbour	Learning nodes activities using K-NN	Used to select suitable carrier nodes	Epidemic [182], HBPR [49], PRoPHET [107]	Map based movement model [90], Reality [54]	ONE Simulator [90]
2018	BACE [16]	Supervised Learning: Bayesian Learning	Bayesian network is used to measure contact probability	Forecast the nodes encounter using contact history	PRoPHET [107]	Cambridge [154], and Reality [54]	ONE Simulator [90]
2018	MBN [118]	Supervised Learning: Naive Bayes	Predict vehicle movement pattern using Bayesian network	Improves the delivery ratio with minor overhead	Epidemic [182], Prophet [107]	Seattle Public Transport System	ONE Simulator [90]
2019	FSF Friendship & Acquaint-anceship Forwarding [172]	Supervised Learning: Naive Bayes	Routing decision is based on social ties between nodes	Identify the selfish nodes which improves delivery ratio	Epidemic [182], PRoPHET [107], BubbleRap [74]	Cambridge [154], NCCU [181], Sassy [23], Reality [54]	ONE Simulator [90]
2019	CAML [185]	Supervised Learning: Logistic Regression, SVM, Neural Network, Random Forest	Compute contact Probability to make forwarding decision using cascade learning	Performs better than MLProph and ML-based routing protocol	MLProph [157], KNNR [160], HBPR [49], PRoPHET [107]	Map based Movement Model [90]	ONE Simulator [90]
2020	K2-GA [196]	Supervised Learning: Bayesian Learning	K2 [36] and genetic algorithm is used to predict mobility pattern	Improves routing performance by predicting vehicle's position	Epidemic [182], PRoPHET [107]	Real Mobility Traces of Buses [94]	ONE Simulator [90]
2020	RFCSec [86]	Supervised Learning: Bayesian Learning	Random forest classifier based protocol is used to find malicious nodes	Encourages nodes with good forwarding behaviour to participate in transmission	MLProph [157], RLProph [159] CAML [185]	MalGenome [212]	ONE Simulator [90]

formation. The paper performed an exhaustive simulation with different mobility models and showed significant improvement in performance than AODV [132], AODV-HPDF [105] and Neighborhood Route Diffusion (NRD) [139].

ARBR [58]: Adaptive Reinforcement based Routing (ARBR) uses a collaborative reinforcement learning (CLR) technique in which a group of nodes makes a forwarding decision using a cost function when each node contacts another node. CLR technique handles a complex time-varying problem where global knowledge of the system is unknown. This approach considers the feedback of user behavior and network conditions like buffer occupancy, congestion, and node mobility statistics to measure the quality-metric function. The quality-metric function is used to decide for each active message. The proposed model considers the states, transitions, actions, and reinforcements for DTN routing to make a forwarding decision. Each node maintains the network information for a fixed time window and the rate of change in connectivity used for the transfer from consecutive windows. ARBR is a multi-copy routing scheme that uses a community-based mobility model. ARBR shows significant performance improvement in the parameters like delivery ratio and average delivery delay compared to Epidemic [182], SARP [57].

DTRB [146]: Delay Tolerant Reinforcement-Based (DTRB) protocol is a Multi-Agent reinforcement learning to find the best route and forward the messages based on reward. The reward is calculated by an algorithm based on distances between the nodes, which are the function of time from the last meetings. DTBR is a flooding-based routing approach and uses a gossip algorithm to measure the latest information exchange. In DTRB, nodes exchange the knowledge using broadcast "ControlMessage," which is sent at regular intervals. It contains two types of information: the distance table and the generated rewards by message exchange. The fundamental assumption is that the nodes that recently transfer gossip about the destination are more likely to deliver the message and consequently receive the rewards. Every node maintains a reward table, and rewards are recalculated when the node again receives a "ControlMessage." The learning rate shows how quickly the Q-value changes with a change in topology, and a discount factor controls the value of the future reward. The simulation result shows DTBR performs well for the dense network and achieves a better delivery ratio and low network overhead than the well-known ProPHET [107] algorithm.

SaRE-MANET [61]: Recently, Opportunistic Networks protocols use social ties to improve performance but are not applicable in a harsh network like a battlefield. The paper proposed the SaRE-MANET (Situation-aware Robot Enhanced Mobile Ad-hoc Networks) protocol that observes multi-robot mobility in a harsh environment using reinforcement learning. The main objectives of SARE-MANET are: 1) Developing a framework for MANET routing that effectively handles multi-robot movement. 2) Designing a reinforcement learning-based routing protocol that manages multi-robot path planning and handles the complex environment. The Q-learning is used to learn optimal routing by using the frequency of encounters between robots, the movement of robots, and the current probability of a robot transmitting the message to the destination—the protocol tested for both unicast and multicast routing. The simulation and experiments show the effectiveness of the proposed protocol compared to BubbleRap [74], OLSR [38], and Simbet [46].

FQLRP [51]: The proposed Fuzzy logic-based Q-Learning Routing Protocol (FQLRP) uses fuzzy logic with Q-learning for efficient routing in Opportunistic Networks. The proposed approach finds the optimal forwarding node by considering various network parameters such as buffer occupancy, the number of hops to deliver the message to a destination, node speed, bandwidth, etc. The Q-learning considers the network parameters and state transition to predict the most suitable forwarding node based on reward. The node with the highest reward is qualified as the next forwarding node. In a reward-based mechanism, the FQLRP considers some fuzzy parameters: the node's energy and movement. Fuzzy logic uses these parameters to measure reward that helps to select the next forwarding node. The simulation performed using the SPMBM [90] model and the Infocom [154] dataset shows that FQLRP improves the performance in terms of delivery ratio, overhead ratio, average delay, and under varying TTL.

RLProph [159]: In this paper, the authors attempt to completely automate the OppIoT routing with the help of the Policy Iteration algorithm that increases the likelihood of message delivery. Furthermore, the proposed RLProph protocol models the OppIoT as a Markov Decision Process (MDP) that considers network states, rewards, actions, and transition possibilities. To develop MDP in OppIoT, one must first define a state that describes the nodes' characteristics and behavior. The reward function is formed to promote the behaviour of nodes. Actions define all the activities performed by the nodes, such as relay, forward, discard messages, etc. Finally, the state transition probability function defines the likelihood of shifting from one state to another. Based on state transition probability, the RLProph can determine the ideal state for the message transmission and wants the nodes to be in that state. The proposed approach can optimize the routing process by discovering optimal policy through MDP. The simulation result obtain using ONE simulator [90] shows that RLProph performs better than Epidemic [182], ProPHET [107], HBPR [49], KNNR [160] on a various performance metrics.

QBOR [81]: Underwater Acoustic Sensor Networks (UASNs) have drawn considerable attention in past years due to their exploration and monitoring capabilities. It has been utilised in several fields, resulting in a tremendous rise in the types and amounts of data. UASNs must periodically transfer the data to the data center efficiently and reliably. The proposed Q-learning-Based Opportunistic Routing (QBOR) protocol provides real-time data upload to onsite architecture. QBOR protocol follows the mechanism of opportunistic routing protocol, where data transmission happens via neighbours and intermediate nodes. In the Initial Phase, the sensor devices collect the information from the monitoring channel. After that, QBOR is utilized to find the optimal forwarding node. For the reward function, the residual energy and packet delivery probability are considered in routing to achieve higher energy efficiency and Packet Delivery Ratio (PDR). The simulation result shows QBOR significantly improves PDR, energy consumption, and average delay performance.

RLOR [205]: Due to limited energy and low bandwidth of sensor nodes, the UASNs suffer from high delay and bit error rates. Developing a reliable and robust routing protocol for such a dynamic network is essential. The authors have proposed a Reinforcement Learning-based Opportunistic Routing (RLOR) protocol that combines the advantages of reinforcement learning with opportunistic routing. The RLOR protocol follows a distributed approach that considers the node's current status to choose appropriate relay nodes. The node's state information helps the RLOR protocol dynamically optimize the routing path, improving energy efficiency and data transmission reliability in real-time. The data delivery rate decreases in the sparse area due to the scarcity of nodes. RLOR proposes a new recovery mechanism to enable the void node that selects a recovery node to bypass the sparse/void region. The void node is the node that belongs to a sparse area. The recovery mechanism uses reinforcement learning to enable void nodes to identify the appropriate recovery relay nodes to recover the transmission path. The result shows that the RLOR protocol achieves significant performance in terms of data delivery, end-to-end delay, and energy efficiency.

4.3.2. Diverse Learning-based Protocols

We have surveyed protocols employing advanced reinforcement learning techniques such as Double Q-learning and Deep Reinforcement Learning, offering innovative solutions for diverse networking challenges.

DQLR [201]: The performance of DTN can be improved using reinforcement learning of ML. However, choosing a suitable forwarding node is still an open issue that needs to be solved. The appropriate forwarding node improves the performance of networks. Q-Learning behaves poorly in a few environments due to a considerable overestimation of the action values. This paper proposed the Double Q-learning Routing (DQLR) that solves the overestimation problem and selects the appropriate forwarding node distributedly. Instead of maintaining a single Q-value like Q-Learning, Double Q-Learning maintains two Q-values to avoid overestimation. DQLR learns the pattern of intermediate nodes related to the destination and develops the optimized routing policy to improve the performance. The intermediate nodes get a higher reward if it takes fewer hops to forward a message to its destination. DQLR is a greedy technique that selects the forwarding node with the highest reward value. The simulation performed in ONE simulator [90] using mobility models and real datasets shows the improvement in the delivery ratio with low overhead compared to ProPHET [107] and Q-learning protocols [146].

Our survey extends to encompass prior works utilizing reinforcement learning paradigms to fine-tune routing mechanisms within Opportunistic Networks contexts. DQNSec [85] is a routing approach for securing OppIoT networks against sinkholes, hello floods, and distributed denial of service (DDoS) attacks. It leverages Deep Q-Learning (DQL) to ensure the network's security. DQNSec models OppIoT as a Markov Decision Process (MDP) to address security challenges effectively. By incorporating the actor-critic approach of DQL, DQNSec outperforms other ML-based routing protocols. DQNSec enhances network security and resilience in dynamic and adversarial OppIoT environments. DeepMPR [89] is a multicast routing technique designed using multi-agent DRL. Unlike traditional multi-point relaying (MPR) selection algorithms, DeepMPR eliminates the need for MPR announcement messages and outperforms MPR selection. The proposed approach showcases its effectiveness in reducing network overhead and enhancing reliability in opportunistic routing scenarios. The article [110] addresses the opportunistic UAV-assisted data transmission challenge in wireless sensor networks. The study jointly optimizes UAV scheduling and power control to maximize network data transmission over time. Formulating the problem as a MDP, the authors employ DRL, specifically Deep Q-Network (DQN) and Deep Deterministic Policy Gradient (DDPG), to obtain optimal solutions.

Several studies have explored the application of reinforcement learning techniques in optimizing routing [186] [45], congestion control mechanisms [166], energy efficiency [112] and latency [158] in Opportunistic Networks. These approaches leverage reinforcement learning algorithms to dynamically adapt routing decisions based on network conditions. By utilizing reinforcement learning, these methods aim to improve Opportunistic Networks' overall performance and reliability, offering adaptive and efficient routing solutions in dynamic and challenging environments.

The Comparative Analysis of Reinforcement Learning in Opportunistic Networks is presented in Table 5.

4.4. Neural Networks and Fuzzy Logic in Opportunistic Routing Protocols

Neural Networks (NN) and Fuzzy Logic are part of the soft computing area. NN focuses on forming the human brain like hardware imitating the primary functions, Whereas the Fuzzy Logic systems focus on software that imitates symbolic and fuzzy rationalising. NN learns from data similar to the biological neural network, while Fuzzy logic decides on ambiguous and raw data. Neural Networks and Fuzzy Logic are primarily divided into two categories 1) Modelling several characteristics of the human brain, such as learning, reasoning, structure, and perception, etc. 2) Modelling the artificial systems and associated data, such as clustering, recognition, parameter estimation, function approximation. In this paper, two types of neural networks are presented: Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) [189].

4.4.1. Artificial Neural Network-based Protocols

We have reviewed protocols leveraging ANN to make routing decisions in Opportunistic Networks, capitalising on the parallel processing capabilities and learning mechanisms inspired by the human brain.

iRPROPR [27]: In the Opportunistic Networks, if the nodes can predict the future location of neighboring nodes, they can use this information to choose suitable nodes that carry the message to the destination. The proposed approach is used to predict the location of nodes by investigating continuous numeric coordinates using ANN. The ANN uses Fast Artificial Neural Network (FANN) to design and test the model. FANN is an open-source programming library used to develop multilayer feedforward ANNs. The iRPROPR al-

Table 5
Comparative Analysis of Reinforcement Learning in Opportunistic Networks.

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
2010	QLAODV [194]	Reinforcement Learning	Node maintains Q-table and capable of adapting frequent changes	Improves performance than traditional approach	AODV [132], AODV-HPDF [105] and NRD [139]	Freeway Model, Manhattan Model [15]	NS-2 [60]
2010	ARBR [58]	Reinforcement Learning	Uses states, transitions, actions and reward to make forwarding decision	Provides good stability, delivery ratio and average delay	Epidemic [182], SARP [57],	Community based Mobility Model	DTNSim [175]
2013	DTRB [146]	Reinforcement Learning	Nodes maintains Q- table and Q-value updates with change in topology	Performs well for dense network and reduce overhead ratio	ProPHET [107]	Random Way Point [21], UDEL [93]	OMNET++ [183]
2018	SARE-MANET [61]	Reinforcement Learning	Observes the movement of multi-robot in a complex environment	Improves performance by learning optimal routing strategy	BubbleRap [74], OSLR [38], SimBet [46]	UAS test site	Real Experiment
2019	DQLR [201]	Reinforcement Learning	Double Q-learning is used to select the forwarding node	Uses the path with minimum no. of hops to reach destination	ProPHET [107], Q-Learning Protocol [146]	Map based Movement Model [90], Infocom06 [154]	ONE Simulator [90]
2020	FQLRP [51]	Reinforcement Learning	Determines reward function using energy distribution amongst nodes	Helps to identify most suitable carrier node	Epidemic [182]	Infocom [154], Map based movement model [90]	ONE Simulator [90]
2020	RLProph [159]	Reinforcement Learning	Optimize routing process by using markov decision process (MDP)	Helps to identify most suitable carrier node	Epidemic [182], ProPHET [107], HBPR [49], KNNR [160]	Cambridge [154], Map based movement model [90]	ONE Simulator [90]
2021	QBOR [81]	Reinforcement Learning	Uses reinforcement learning-based distributed approach to select forwarding nodes	Optimizes routing path, improves reliability of data transmission	MURAO [72], EE-DBR [52], Flooding [4], VAPR [127], RDBF [103]	Random Way point [21]	Custom
2021	RLOR [205]	Reinforcement Learning	Q-learning incorporates with the traditional Opportunistic algorithms	Improves network performance and energy utilization	DBR [199], HHVBF [124], QELAR [71], GEDAR [41]	UASNs Scenario	Custom

gorithm is used to train the ANN, and the ANN is used as a routing protocol after testing. In the ANN, seven input neurons, two output neurons, one hidden layer, and fifteen hidden neurons were chosen as architecture. The ANN predicts location by determining which neighboring nodes are closest to the destination. For that, the ANN takes two previous times and locations as input along with the current time and predicts x and y coordinates. After the experimental results, the paper concluded that even with the change in the number of nodes, contact duration, and mobility model, the ANN can still predict a node's future location with high accuracy.

MLProph [157]: This paper proposes novel ML techniques based on an opportunistic routing protocol named MLProph. It uses a neural network and decision tree algorithms to train the model based on factors like hop count, buffer capacity, node energy, number of successful delivery, and popularity parameters. The MLProph algorithm is divided into two parts: Training and Real Simulation. A dataset was generated for neighbor nodes by simulating the training phase. These generated data are used to train above mentioned models. The Real Simulation phase first captures the ProPHET [107] probability and calculates the probability value P_m called ML probability using ML models. The message is forwarded to the neighbor node if $P_m > K * P_r$ where K is a normalization factor, and P_r is ProPHET [107] probability. The neural network and decision tree models are trained and deployed using the Weka ML library. Compared with the well-known ProPHET [107] algorithm, the simulation result shows that MLProph outperforms in terms of overhead, hop count, delivery probability, and dropped messages.

IWDNN [98]: It is required to have an intelligent dynamic strategy to choose the optimal forwarding node to improve routing performance in Opportunistic Networks. This paper proposes an Intelligent Water Drop Neural Network-IWDNN routing protocol that utilises Intelligent Water Drop (IWD) Algorithm [155] with Neural Networks. The protocol uses a nature-inspired algorithm to optimize weights rather than the standard back-propagation algorithm. The nature-inspired algorithm is stable and robust to dynamic changes in Opportunistic Networks. The IWD algorithm minimizes the error by calculating the optimal weight for neural networks. IWDNN outperforms other protocols that follow a related ideology, such as MLPROPH [157], KNNR [160], ProPHET [107], CROP [68], IICAR [18] The result shows a significant improvement in terms of delivery ratio, latency, overhead ratio, and message drop.

4.4.2. Recurrent Neural Network-based Protocols

We have analysed protocols that employ RNN to handle temporal dependencies and sequential data, offering robust solutions for routing in dynamic and time-varying Opportunistic Network environments.

RNN-LP [29]: The link prediction can help to predict the future links between the nodes; this information helps to make an effective message-forwarding decision. The paper proposed the recurrent neural network link prediction (RNN-LP) framework for link prediction. It uses historical information about the node's link that affects the connection state in the next moment. The protocol generates the vector consisting of node information and the node's historical connection information using the time series method, t. The recurrent neural network in sequence modeling obtains hidden features from the vector sequence data. Using this model predicts the node pair connection state at the next moment. The performance of RNN-LP is measured under different realistic parameters and with traditional similarity indices. The experimental result shows that the proposed approach gives better link prediction for the Cambridge [154] and MIT datasets [54].

DLDF [190]: The extensive use of mobile and its trajectory data makes it possible to use deep learning in the mobile social network to design a forwarding algorithm. By using the strong feature learning ability of deep learning, the paper proposed a data forwarding algorithm named DLDF (Deep Learning-based Data Forwarding) to find a fixed path between source and destination. DLDF designs an RNN-recurrent neural network using LSTM (Long Short-Term Memory) to predict the encounter probability between the nodes. It takes several time intervals as input for nodes meeting for a given time window and delivers the output of the next meeting probability between nodes in the next time window. Based on this, it composed a fixed path with high probability links that transmit the data between source and destination. The simulation result includes delivery ratio, delay, overhead, hop count, and a path set cardinality for performance metrics. Compared with the existing algorithms like Epidemic [182], Spray and Wait [174], and SEBAR [101] algorithms, the proposed approach significantly increases the delivery ratio and reduces network overhead.

4.4.3. Fuzzy Logic-based Protocols

We have examined protocols utilising Fuzzy Logic, a computational paradigm inspired by human decision-making processes, to handle uncertainty and imprecision in Opportunistic Networks routing, enhancing adaptability and efficiency.

HMM [118]: This paper proposes a routing protocol for an Opportunistic Networks which learns the data traffic pattern and extracts data semantics. It uses Hidden Markov Model (HMM) and Fuzzy Logic to learn the traffic pattern generated in the Opportunistic Networks. The algorithm uses data traffic information passed amongst routing nodes and database servers. It uses the HMM-based semantic reasoning model to estimate the information related to node location, speed, and resources which helps to identify a particular node. For simulation, the proposed approach is integrated with two well-known algorithms, namely Epidemic [182] and ProPHET [107], which are flooding-based and prediction-based routing protocols, respectively. The result shows that intelligence-based routing protocol gives higher data delivery, minimizes overhead ratio, and improves latency.

FDQLR [197]: This paper proposes a Fuzzy logic-based Double Q-Learning Routing (FDQLR) protocol to identify an optimal route for message forwarding. The approach finds the most suitable neighbour node in the routing process. A fuzzy reward mechanism adapts the fuzzy logic that evaluates the network characteristics. The characteristics such as contact interval, node movement, and speed are converted into the fuzzy reward of the Double Q-Learning. The Hot Zone mechanism identifies the strength of the neighbour nodes based on recent contact with the destination node. Whereas, Drop mechanism is proposed to restrict the message copies in the network without degrading the delivery ratio. The effectiveness of FDQLR is examined using ONE simulator [90] with two movement models, namely, the RioBuses dataset [94] and the Map-Based Movement model [90]. The result shows that FDQLR archives a better delivery ratio and low overhead as compared to ProPHET [107], Q-Learning Protocol [146], and DQLR [201].

RLFGRP [91]: This paper proposes Reinforcement Learning-based Fuzzy Geocast Routing Protocol (RLFGRP) for Opportunistic Networks. The fuzzy controller uses reward value, Q-value, and available buffer space as input parameters to determine the likelihood of neighbour nodes being selected as forwarding nodes for the message toward the destination. RLFGRP is designed to follow the feedback mechanism where the model learns and adjusts automatically for the routing process. Whenever a source node wants to send a message to a destination node, the source node first discovers the Q-value assigned to its neighbour nodes. The neighbour node with the highest Q-values receives the message and delivers it to the destination. The simulation results determined using ONE Simulator [90] show that RLFGRP outperforms FCSG [92] and FQLRP [51] protocols in terms of delivery ratio, overhead ratio, and average latency.

4.4.4. Diverse Learning-based Protocols

We have encompassed diverse protocols leveraging innovative techniques such as Genetic Algorithms, Deep Belief Networks, and Deep Learning, showcasing novel approaches to routing optimisation and adaptation in Opportunistic Networks.

CDBN [162]: This paper proposes a link prediction approach using a deep learning framework for Opportunistic Sensor Networks (OSN). It is used to capture the change in topology and optimize the performance of the routing algorithm using a Conditional Deep Belief Network (CDBN). This method models the time series of past time and finds a similarity index that denotes the dynamic behavior of OSN. CDBN applies the multilayer Conditional Restricted Boltzmann Machine (CRBM) to model the time series. It extracts the essential characteristics of the dynamic network using the node's contact information. After completing the training phase of the link prediction model, it is used in the testing dataset to verify the model's accuracy. The CDBN considers two problems: firstly, the link prediction approach used in the social network is different for OSN. Second, the appropriate learning rate is needed to train the model. A high or low learning rate leads to instability in the model. The Infocom [154] and MIT datasets [54] were used in the experiment. It shows the effectiveness of predicting links of CDBN over the prediction techniques like Adamic-Adar (AA), common neighbor (CN), resource allocation (RA), Katz, and local path (LP) [191].

GASER [96]: This paper uses a genetic algorithm with other methods to select the best path for forwarding the message to the destination. For the sparse mobile Ad-hoc Network, the paper proposed the genetic algorithm-based secure and energy-aware routing (GASER) protocol. It selects the best path in terms of the shortest path between the source and destination and residual energy. The selected path includes nodes with higher message forwarding possibility to a destination than other network nodes. GASER securely identifies the grey/black hole attack to avoid the packet dropping from specific nodes. The GA method identifies three groups for message forwarding, and this process continues until the message reaches the destination group. The proposed algorithm saves the energy of nodes, reduces the computation power, and is secure compared to Epidemic [182], ProPHET [107], and Spay and Wait [174] protocols.

IRWR-DBN [106]: The proposed link prediction approach called IRWR-DBN is used to predict the likelihood of future links between nodes. The network information, such as mobility model, network topology, intermittent connections, and node attributes, are used to estimate future links. The approach first reconstructs the Markov probability transition matrix using neighbours of nodes and finds similarity index Improved Random Walk with Restart (IRWR). Second, it divides networks into snapshots and builds a sample set using the IRWR index. Finally, a deep belief network-based predictive model is constructed to extract the time-domain characteristics from the sample set. The model helps to achieve superior link prediction performance. The experimental result performed on Cambridge and Reality dataset shows that IRWR-DBN is more stable and accurate than the similarity-based index (CN, AA, LP, Katz, TLP) [191].

Our review includes relavant studies using Neural Network to refine Opportunistic Networks routing. ML-BBFT [125] is a ML-based approach proposed for enhancing forwarding techniques in social OppIoT networks. The technique leverages bonding-based forwarding and ML techniques to optimize data transmission within these dynamic networks. Game Theory-based Energy Efficient Routing (GTEER) [164] introduces a routing protocol based on game theory principles to improve energy efficiency in Opportunistic Networks. The proposed protocol optimizes next-hop selection based on context information and energy considerations by framing routing decisions as a cooperative game. Ant-Router [161] is an efficient routing protocol inspired by ant colony optimization for social Opportunistic Networks. The Ant Router protocol utilizes ant routing strategies to dynamically adapt to changing network conditions, enhancing routing efficiency in social opportunistic environments. Lastly, BRNN-LP [113] is a Bayesian Recurrent Neural Network-based Link Prediction protocol. This method predicts future links in dynamic networks, aiding in more efficient routing and resource allocation.

We have also surveyed relevant studies using fuzzy logic in Opportunistic Networks. EEFLPOR [122] is an Energy-Efficient Fuzzy Logic Prediction-based Opportunistic Routing protocol for wireless sensor networks. By integrating a fuzzy-based prediction method with current and future node parameters, EEFLPOR optimises relay node selection to enhance network lifetime and throughput. FCSG [92] is a Fuzzy-based Check-and-Spray Geocast routing protocol for Opportunistic Networks. FCSG improves the delivery ratio compared to existing geocaching protocols using a fuzzy controller and a Check-and-Spray mechanism. In [42], two fuzzy logic-based systems, INSS1 and INSS2, are proposed for IoT node selection in Opportunistic Networks. These systems consider parameters like node distance to task, remaining energy, buffer occupancy, and inter-contact time to select optimal IoT nodes. In [43], an integrated intelligent system for IoT device selection and placement in Opportunistic Networks is presented. This system combines fuzzy logic and genetic algorithms to optimise IoT device selection and placement, addressing intermittent connectivity challenges and enhancing network performance.

Table 6
Comparative Analysis of Neural Network and Fuzzy Logic in Opportunistic Networks.

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
2014	iRPROPR based ANN [27]	Artificial Neural Network	Model is train using previous time and location of nodes	High accuracy in predicting nodes future location	MANET Location Prediction using ML Algorithm [28]	Random Waypoint [21], Reference Point Group [70], Gauss-Markov model [104]	NS-2 [60]
2015	HMM based Epidemic and ProPHET [118]	Hidden Markov Model, and Fuzzy Logic	Adapts the traffic pattern and extract data semantics	Reduces overhead and increases delivery ratio	Epidemic [182], ProPHET [107]	Custom Mobility Model	ONE Simulator [90]
2016	MLProph [157]	Supervised Learning: Decision Tree, Neural Network	Compute ML Probability to take forwarding decision	Performs better than PROPHET	ProPHET [107]	Bus Movement and Working Day Movement [55]	ONE Simulator [90]
2017	CDBN [162]	Deep Learning	Extract the characteristic of dynamic network using deep belief network	Gives better link prediction accuracy	Similar indices like CN, AA, LP, Katz, TLP [191]	Infocom05 [154], Reality [54]	Custom
2019	RNN-LP [29]	Recurrent Neural Network	Uses time series method to predict next connection state	It helps to make efficient forwarding decision	Similar indices like CN, AA, RA, LP, Katz [191]	Cambridge [154], Reality [54]	Custom
2019	DLDF [190]	Deep Learning, Recurrent Neural Network	RNN structure is used to predict nodes meeting probability	Used to find fixed path for forwarding	Epidemic [182], Spray and Wait [174], SEBAR [101]	ONE year GPS traces [26]	Custom
2019	GASER [96]	Genetic Algorithm	GA based secure and energy aware routing protocol	Identify destination node group and select shortest path	Epidemic [182], Spray and Wait [174], Prophet [107]	Random Way Point [21]	Custom
2020	IRWR-DBN [106]	Deep Belief Network	Link prediction model is constructed using Deep Belief Network	Extracts time-domain characteristics for better link prediction	Similar indices like CN, AA, LP, Katz, TLP [191]	Cambridge [154], Reality [54]	Custom
2020	IWDNN [98]	Neural Network	IWD [155] algorithm with Neural network is used to find forwarding node	Optimized next hop selection strategy that improves performance	MLPROPH [157], KNNR [160], ProPHET [107], CROP [68], IICAR [18]	Map based movement model [90]	ONE Simulator [90]
2021	FDQLR [197]	Fuzzy Logic based Double Q-learning	Fuzzy logic based Double Q-learning is used to find optimal route	Improves buffer management and message forwarding	ProPHET [107], Q-Learning Protocol [146], DQLR [201]	Rio Bus Dataset [94], Map based movement model [90]	ONE Simulator [90]
2021	RLFGRP [91]	Fuzzy Logic with Q-learning	Fuzzy controller uses Q-value to find suitable path	Selects best forwarder node for message passing	FCSG [92], FQLRP [51]	Haggle [94]	ONE Simulator [90]

The Comparative Analysis of Neural Networks and Fuzzy Logic in Opportunistic Networks is presented in Table 6.

4.5. Unsupervised Learning in Opportunistic Routing Protocol

Unsupervised Learning is to infer patterns from the dataset where only input data is available without labeled data or output variables. So, specific techniques are mainly used for discovering the unknown structure of the data. Unsupervised Learning is mainly grouped into clustering and association problems. Clustering methods divide the dataset into different groups based on similar characteristics. Association mining learns the rules of the frequently occurring event together from a dataset [189].

4.5.1. K-means Algorithm-based Protocols

We have explored protocols leveraging the K-means algorithm, a popular clustering technique, to partition data into clusters based on similarity, facilitating efficient routing decisions in Opportunistic Networks.

TL-QL [209]: In this paper, the authors investigate the use of ML techniques to improve the load balancing, spectrum allocation, and energy-saving perspectives in the opportunistic mobile broadband network for various dynamic scenarios. The k-means algorithm divides the cell into clusters that improve spectrum reuse and interference mitigation. The k-means algorithm is incorporated with Q-learning for transfer learning and resource allocation for cell selection. The clustered Q-learning improves transfer learning by increasing cell overlapping. The experiment performed in the Ljubljana city scenario shows significant improvement in resource allocation at high traffic levels in the various area of a cell. Furthermore, it improves energy-saving, load, and spectrum optimization, enhancing network capacity.

KRop [156]: KRop routing protocol applies an unsupervised learning method of ML. It uses the k-means clustering algorithm to train protocol using the network features and make the decision to select the next hop. The KRop protocol trained using four-node features available buffer space, encountered nodes, distance with the destination node, successfully delivered the message by the node. After feature identification, the protocol generates the clusters using k-means. It consists of three phases.1) Initializing cluster 2) Cluster assignment 3) Cluster movement. After completion of this process k different clusters created with neighboring nodes. The evaluation function is used to decide on selecting the best cluster. Once the best cluster identifies the message is passed to each node belonging to that cluster. In this scenario, to limit the number of messages, the Spray and Wait [174] protocol is used for message passing. In the future, this work can consolidate with energy consumption and security issues.

IBR-DTN [167]: In this paper, an ML classifier is applied to predict the neighbor node that is most likely to deliver the message to the destination. The classifier utilized historical information on the node's movement. e.g., People moving towards the office use the same route every day. The three renowned ML classifiers, namely Naïve Bayes, Decision Tree, and K-Nearest Neighbor, were used to learn this pattern. The classifiers accommodate the diversity of conditions like entering or leaving a node, heavy traffic, region, and time, and work dynamically. The proposed approach, IBR-DTN, also uses k-means clustering algorithms to determine the region where nodes visit frequently. It helps make an efficient forwarding decision based on grouping similar nodes. The empirical result shows that IBR-DTN can predict the network traffic and determine suitable neighbor nodes to transfer the message to a destination successfully.

Clustering Approach [129]: The article proposed the unsupervised ML-based approach to improve routing in the Opportunistic Networks of vehicles. The method detects the community between nodes (vehicles) for effective opportunistic communication. The proposed hierarchical routing algorithm combines three strategies: metric of detecting Opportunistic Networks' geographical sectors, metric of building communication community from Spatio-Temporal data with a time constraint, and metric of node's local encounter. These metrics are used to make a message-forwarding decision. In the testing phase, when two nodes encounter, they exchange messages based on previously extracted knowledge of finding the local community. Comparing the proposed approach with Epidemic [182] shows a significant improvement in the number of messages delivered. In the future, researchers focused on comparing the proposed approach with the existing social-based method Bubble-Rap [74].

4.5.2. Density-based Clustering Protocols

We have studied protocols utilising density-based clustering algorithms such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to identify clusters of nodes with high density, enabling effective routing in regions of varying network density.

OPSCAN [56]: This paper presents an algorithm named Opportunistic Spatial Clustering of Applications with Noise (OPSCAN) to cluster the nodes based on the geographic location. The proposed algorithm applies Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to find clusters and distinguish noise from the dataset. The clusters are generated using a density-based clustering algorithm that determines geographic areas with more similarity between nodes and higher density. The nodes belonging to low-density areas are marked as noise. These nodes can be utilized as carrier nodes due to their higher mobility. OPSCAN can recognize the arbitrary shape cluster that provides better identification of clusters. Given the simulation results, OPSCAN outperforms DBSCAN [59] and ST-DBSCAN [24] and efficiently creates clusters. The OPSCAN algorithm is evaluated on Microsoft Research GeoLife dataset [210].

V2V cooperative approach [192]: In this paper, the authors propose a framework to identify hazardous spots on roads. The framework combines mobile sensing and vehicle-to-vehicle (V2V) Opportunistic Networks. Hidden Markov Model (HMM) based data processing is proposed to correct faults in identifying hazardous spot detection. The Viterbi algorithm [133] helps vehicles to make periodic decisions concerning the state of the road using sensing data. The proposed system consists of three processes: hazardous spot identification using mobile sensing. Second is HMM-based data processing, and finally, V2V collaborative data processing. The buses, cars, and taxis are equipped with sensor devices with computational resources or smartphones that can be used for mobile sensing. The result shows that the proposed approach can enhance the accuracy of detecting hazardous spots for vehicles in the community that avoid accidents.

4.5.3. Diverse Learning-based Protocols

We have covered diverse protocols employing innovative techniques such as Gaussian Mixture Models, Hierarchical Clustering, and other unconventional approaches to address routing challenges in Opportunistic Networks.

GMMR [184]: OppIoTs network is very similar to the Opportunistic Networks. So, the identical routing design can apply to both networks. The OppIOT network is part of the Internet of Things network where device connectivity is infrequent, and routing is a highly complex problem. This paper proposed the ML-enabled routing protocol, GMMR, which uses Gaussian Mixture Models. GMMR consolidates the benefit of context-free and context-aware protocols. GMM-based soft clustering approach is suited for a given network, so GMM is preferred over k-means that follow hard clustering. GMMR protocol works in two phases: GMMR training and GMMR routing. In the training phase, it collects feature data, trains GMM using that data, and assigns each node a cluster label. In the routing phase, first, it identifies the destination cluster of a message and sends the message to nodes belonging to that cluster. Finally, a message is sent to the destination node encountered. The GMM algorithm can be replaced with density-based spatial clustering or agglomerative hierarchical clustering for more extensive analysis.

We have surveyed several notable contributions in unsupervised learning within Opportunistic Networks. Density-Based Spatial Clustering of Applications with Noise (DOIDS) [204] is an intrusion detection scheme for opportunistic routing in Underwater Wireless Sensor Networks (UWSNs). DOIDS uses the DBSCAN clustering algorithm to identify potential malicious nodes by analyzing energy consumption, forwarding behavior, and link quality. DOIDS enhances detection accuracy (up to 15% improvement in various scenarios) while minimizing false positives and addressing security concerns in large-scale UWSNs. DBSCAN-R [135] is a context-aware routing protocol for Opportunistic Networks, leveraging the DBSCAN clustering algorithm. By utilizing four dynamic network parameters as features for clustering, DBSCAN-R outperforms benchmark algorithms such as Epidemic [182], ProPHET [107], and MaxProp [25] routing in terms of delivery success rate, average hop count, overhead ratio, and messages dropped, thereby demonstrating its effectiveness in automating routing decisions in OppNets.

The Hierarchical Learning-based Sectionalized Routing paradigm for pervasive communication and Resource efficiency (HiLSeR) [19] is a scheme for opportunistic routing in IoT networks. By utilizing hierarchical learning for topology sectionalization and routing decisions, HiLSeR combines controlled flooding and opportunistic sector-based transmission. HiLSeR achieved an average successful delivery rate of 0.911, outperforming existing protocols by up to 88.33%. It demonstrates HiLSeR's enhanced performance and sustainability in IoT network communication. The Opportunistic Fuzzy Clustering Routing (OFCR) [6] protocol proposes to enhance routing decisions in intermittent IoT networks. OFCR employs a three-tiered intelligent fuzzy clustering paradigm to represent node characteristics and their associations better. OFCR shows improved performance and consistency across various simulation parameters.

The Comparative Analysis of Unsupervised Learning in Opportunistic Networks is presented in Table 7.

5. Real-world Implementation and Validation of ML Techniques in Opportunistic Networks

We analysed the practical deployment and validation of ML techniques within Opportunistic Networks. It showcases impact across diverse application domains such as UAVs, entertainment, health and wellbeing, and sensor data collection. Additionally, it addresses significant challenges, including the lack of user incentivisation mechanisms and the absence of viable business models for service providers. We addressed the potential role of ML techniques in mitigating these challenges.

5.1. Deployment Scenarios and ML Impact

Opportunistic Networks have various applications, such as UAV networks, entertainment delivery, health monitoring, and sensor data collection, where ML techniques play a crucial role [22] [119] [47]. We have described how ML facilitate such real deployments.

5.1.1. UAV Networks

ML techniques are critical in optimising UAV flight paths and energy consumption, enabling efficient data exchange between UAVs and ground stations in real-world applications such as surveillance missions or disaster response operations.

To optimise UAV flight paths, ML techniques analyse historical flight data, environmental factors, and mission objectives. These algorithms ensure efficient navigation and optimise fuel consumption by continuously learning and adapting to dynamic environments [14]. ML enables UAVs to adaptively navigate in dynamic environments, responding to changing conditions such as weather patterns, airspace restrictions, or unexpected obstacles [110]. This adaptability is crucial for real deployments where mission parameters may change rapidly, ensuring safe and efficient data collection or delivery. ML techniques facilitate efficient data exchange between UAVs and ground stations by optimising communication protocols and transmission strategies. By analysing network conditions and data traffic patterns, ML techniques assure timely and reliable data delivery, even in challenging environments with limited bandwidth or intermittent connectivity.

5.1.2. Entertainment Applications

ML-powered recommendation systems revolutionise entertainment consumption by delivering personalised multimedia content opportunistically, even in bandwidth-constrained environments [69].

Table 7
Comparative Analysis of Unsupervised Learning in Opportunistic Networks.

Year	Protocol	Category	Functionality	Advantages	Compared to	Dataset	Validation Tool
2015	TL-QL [209]	Unsupervised and Reinforcement Learning: K-means, Q-Learning	k-means is integrated with Q-learning for spectrum, load and energy optimization	Improves spectrum reuse and interference mitigation	Transfer Learning [208]	Ljubljana scenario	Custom
2018	kRop [156]	Unsupervised Learning: K-means	k-means is used to cluster the nodes based on common feature	Select the best cluster based on destination	PRoPHET [107], ProWait [48], HBPR [49]	Map based Movement Model [90]	ONE Simulator [90]
2018	GMMR [184]	Unsupervised Learning: Gaussian Mixture Model	Gaussian Mixture Models helps to create clusters	Gives soft clustering approach so preferred over k-means	KNNR [160], HBPR [49], MLPROPH [157], PROPHET [107]	Map based Movement Model [90]	ONE Simulator [90]
2018	IBR-DTN [167]	Supervised and Unsupervised Learning: Naïve Bayes, Decision Tree, K-NN, K-means	ML classifier predicts the neighbor node based on historical information	Able to predict network traffic pattern, reduces the network overhead	Epidemic [182], Prophet [107]	Zebranet [83]	CORE [5]
2019	Clustering Approach [129]	Unsupervised Learning: K-means	Community based routing using unsupervised learning	Makes the message forwarding decision based on community	Bubble Rap [74]	Map based Movement Model [90]	ONE Simulator [90]
2020	OPSCAN [56]	Unsupervised Learning: Density based Clustering	Destiny-based clustering identifies the arbitrary-shaped cluster in network	Used to predict the mobility of nodes in high and low density areas	DBSCAN [59], ST-DBSCAN [24]	Microsoft Research GeoLife Dataset [210]	Custom
2020	V2V cooperative approach [192]	Unsupervised Learning: Density based Clustering	HMM based algorithm represents spatial relationship between the road condition	Efficiently detects the hazardous spots on roads	EM and Viterbi Algorithm [133]	working car project [128]	MATLAB [1]

ML techniques analyse user preferences based on historical viewing behaviour, ratings, and feedback to generate personalised recommendations. By continuously learning from user interactions, these algorithms adapt to evolving preferences and ensure relevant content delivery in real time [109]. ML-based recommendation systems consider network conditions such as bandwidth availability, latency, and congestion levels to optimise content delivery. By dynamically adjusting streaming bitrates or prefetching content segments, these systems ensure seamless playback and minimise buffering interruptions to enhance user experience. ML considers contextual factors such as device type, location, and time of day to tailor content recommendations. By understanding user context, these algorithms deliver relevant content that aligns with users' preferences and viewing habits, fostering engagement and satisfaction.

5.1.3. Health and Wellbeing Monitoring

ML processes opportunistically collected sensor data to detect anomalies and predict health-related events, enabling personalized interventions and enhancing healthcare outcomes [78].

ML techniques analyze sensor data streams from wearable devices or medical sensors to detect deviations from standard physiological patterns [116]. These algorithms trigger timely interventions or alerts by identifying anomalies indicative of health risks or emergencies, improving patient safety and outcomes. ML techniques forecasts future health events based on historical data and contextual information. By predicting potential health issues in advance, these algorithms enable proactive interventions and personalized treatment strategies, optimizing healthcare delivery and resource allocation. ML-driven health monitoring systems deliver personalized interventions tailored to individual patient needs and preferences. By analyzing patient data and treatment outcomes, these systems recommend targeted interventions such as medication adjustments, lifestyle changes, or remote consultations, empowering patients to manage their health proactively [173].

5.1.4. Sensor Data Collection

ML techniques optimise data collection using Opportunistic Networks by dynamically adapting transmission strategies based on network availability and user demand.

ML techniques analyse real-time sensor data and network conditions to adjust transmission strategies dynamically. These algorithms ensure efficient data collection while minimising energy consumption and network congestion by prioritising critical data packets, optimising routing paths, and adjusting transmission power. ML-driven sensor networks are scalable and resilient to environmental changes and network disruptions. By leveraging adaptive algorithms and decentralised decision-making, these networks can autonomously reconfigure themselves to maintain connectivity and data integrity in challenging conditions, ensuring reliable data collection in real-world deployments [63]. ML techniques optimise resource allocation in sensor networks by balancing data collection requirements, energy constraints, and user demand. By intelligently scheduling data transmissions, allocating bandwidth and energy resources, and optimising data aggregation, security and privacy of user's data maximise the efficiency and effectiveness of sensor data collection in various application scenarios [50] [142].

ML techniques enable real deployments and real-life applications across diverse domains. By leveraging advanced algorithms and data-driven insights, ML-powered systems optimise performance, enhance user experience, and improve the performance of Opportunistic Networks.

5.2. Leveraging ML to enhance the adoption of Opportunistic Networks

Opportunistic Networks face significant challenges in incentivizing user participation and establishing sustainable business models for service providers. There is a possibility of broad adoption of Opportunistic Networks by providing solutions to these issues using ML techniques.

5.2.1. Lack of User Incentivization Mechanisms

Users in Opportunistic Networks need more incentives to actively participate in data sharing or resource provisioning due to concerns regarding privacy, resource consumption, or perceived benefits. ML techniques personalise incentives based on user preferences, behavior, and contextual factors [117] [76]. By analysing historical data and user interactions, ML techniques provide incentives to align with users' interests and motivations, increasing engagement and participation. ML techniques adapt incentive mechanisms over time by learning from user responses and feedback. It dynamically adjusts incentives based on the effectiveness of previous strategies, maximising user participation while minimising resource consumption and costs. ML techniques analyse user interactions and preferences to recommend relevant content or services, thereby fostering user engagement and participation. By leveraging similarity metrics and user feedback, algorithms enhance the relevance and effectiveness of incentives, increasing user satisfaction and retention.

5.2.2. Lack of Business Models for Service Providers

Service providers face challenges monetising Opportunistic Networks due to the absence of traditional revenue models and uncertainty regarding service quality and availability [180]. ML techniques optimise resource allocation, service provisioning, and pricing strategies in Opportunistic Networks. By analysing historical usage patterns, network conditions, and user preferences, ML techniques can dynamically allocate resources and adjust pricing to maximise revenue while ensuring service quality and availability [187]. Predictive analytics models forecast user demand and network conditions, enabling service providers to anticipate market trends and adjust their offerings accordingly. Leveraging ML techniques such as time series analysis and regression, predictive analytics help service providers make informed pricing and capacity planning decisions. It maximises profitability and competitiveness in the market. Game theoretic approaches model the interactions between users and service providers as strategic games where participants aim to maximise utility. By applying game theoretic concepts, ML techniques can design incentive mechanisms that foster collaboration and value creation in Opportunistic Networks ecosystems. These mechanisms incentivise cooperative behaviour among users and service providers, leading to mutually beneficial outcomes and sustainable business models.

By personalizing incentives, optimizing resource allocation, and facilitating stakeholder collaboration, ML techniques enable the development of viable and sustainable ecosystems where users are motivated to participate actively, and service providers can monetize their offerings effectively.

5.3. Validating ML-based Solutions in Real-world with Field Trials and Pilot Projects

Field trials and pilot projects serve as critical components in the validation process of ML solutions within Opportunistic Networks. Integrating ML into real-world deployments of Opportunistic Networks is an evolving research domain. Although challenges are associated with implementing ML at scale in Opportunistic Networks, ongoing research explores its potential across diverse contexts. The pilot projects for remote health monitoring offer substantial demonstrations of Opportunistic Networks' real-world deployment [78]. Concurrently, other research focuses on applications like opportunistic mobile crowd-sourcing and social networks that leverage opportunistic principles in real-world experiments [144] [84]. These real-world deployments provide invaluable insights into the usability, acceptance, and performance of ML techniques under practical constraints.

Field trials and pilot projects allow researchers and practitioners to evaluate the performance of ML techniques in scenarios that closely resemble the intended deployment context, considering factors such as network conditions, user behaviours, and environmental variables [83]. Field trials provide an opportunity to assess the usability of ML-driven solutions in real-world settings, focusing on factors such as user interaction, interface design, and user experience. Pilot projects enable researchers to evaluate the acceptance and adoption of ML-driven solutions among end-users, stakeholders, and other relevant parties [77]. By soliciting feedback, conducting surveys, and analyzing user engagement metrics, researchers can gauge users' perceived value, utility, and willingness to embrace ML-powered technologies in their everyday activities [9].

Field trials provide an opportunity to assess the performance of ML-driven solutions in real-world conditions, considering factors such as reliability, scalability, and efficiency. Researchers can measure key performance indicators, such as data throughput, latency, and resource utilization, to evaluate the effectiveness of ML techniques in achieving their intended objectives. By observing how ML techniques perform under real-world constraints such as limited resources, network disruptions, and user variability, researchers can identify potential bottlenecks, vulnerabilities, and areas for optimization, informing iterative development cycles and guiding future research directions.

6. Identification of Research Challenges and Future Directions

This section discusses the open issues in the field of Opportunistic Networks that can be solved using ML techniques. From the literature review, we found that the researchers have proposed many solutions in the last decade, but still, there is scope for improvement that was discussed. This section helps and motivates new researchers to work in this up-growing field of networking. Despite the numerous proposed approaches and improvements achieved in the field of Opportunistic Networks, many open issues need to be solved. This section identifies the problems that should be handled by optimised routing in Opportunistic Networks. Fig. 3 shows research challenges and future directions in the area of Opportunistic Networks.

6.1. Link Prediction

The analysis of social networks recently received significant consideration amongst researchers because of its ample applicability in obtaining social behaviour, Link prediction, and the likelihood of having a connection between two nodes in the network that are not directly connected. ML techniques like time series analysis and graph neural networks hold promise in accurately predicting link formation based on historical encounter data and network topology [29], [162]. Link prediction is utilised to identify the probability of future links between nodes with the help of available network knowledge, such as node attributes and network topology [106]. In Opportunistic Networks, if the routing protocol can predict the node contact pattern, it is used to choose an appropriate neighbour for forwarding the message. By accurately predicting the node's position in the future, we can increase the delivery ratio and reduce the network overhead. So, can an ML-based routing protocol predict the best forwarder node for a given destination using Link Prediction?

6.2. Mobility Models

The mobility model presents rules of node mobility and the way of node movement in Opportunistic Networks. In the real scenario, the node's movement is not random. Moving from one place to another has a regular hourly, daily, or weekly pattern. The average duration of contact, frequencies of meetings, and other parameters help reveal human movement and patterns of habits. Few existing protocols use ML algorithms like reinforcement learning and neural networks to learn and adapt to node movement patterns based on historical data [106] [159] [89]. By exploiting these features, we can predict the future encounter of nodes. Can the routing algorithm efficiently adapt the moving pattern of nodes using ML techniques?

6.3. Community Detection

The social network of humans is advantageous to making data-forwarding decisions. Community Detection is used to learn the features of networks by analysing their composition. It helps to exhibit and understand the social community structure, contact pattern, node movement, and other network behaviours. ML-based community detection algorithms based on network features like node attributes and connection patterns are employed to identify groups of nodes with frequent interactions [64] [211]. By revealing the relevant characteristics of nodes, communication in the social network helps to trace regular contact patterns between the nodes. So, how can the routing algorithm's performance be improved using community detection?

6.4. Traffic Generation

Network traffic is the volume of data generated across a network over some time. It is the number of packets and payloads produced by the actual nodes. The packet generation speed and the number of nodes in the network can affect performance. ML techniques like traffic forecasting models are employed to predict future traffic patterns based on historical data and network conditions [168] [163] [150]. In Opportunistic networks, the number of encounters between nodes increases the message passing, eventually increasing traffic. If message generation is at a rapid rate, it increases congestion, and nodes drop the messages. So, how does the routing protocol handle the dynamic behaviour in the case of a dense and sparse network?

6.5. Security/Privacy

It is essential to provide security and privacy at the intermediate nodes while transmitting the message from source to destination. It requires a trust management framework while all the network nodes are not truthful. Machine learning techniques like anomaly detection and intrusion prevention systems are used to identify and isolate malicious nodes attempting to disrupt network operations or compromise data integrity [50] [142]. The framework should offer privacy

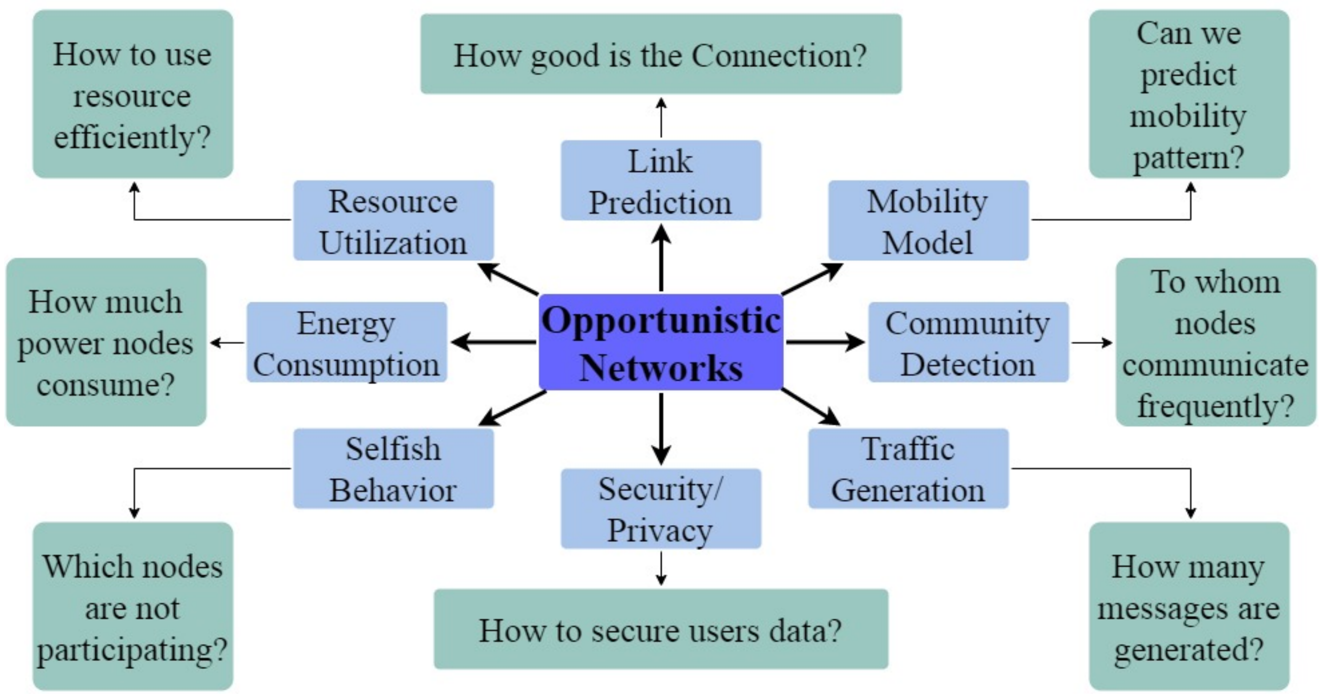

Figure 3: Research Challenges and Future Directions in Opportunistic Networks

protection, data confidentiality, and data integrity. Due to an inefficient security framework, the malicious node does not participate in the message-passing process, ultimately affecting network performance. Several routing protocols consider the presence of malicious nodes present in the network. So, how to secure user data if such nodes are present?

6.6. Selfish Behavior

The nodes not participating in forwarding the message are called selfish nodes. The nodes do not want to participate for several reasons, such as malicious data from the other nodes, low resources (e.g., buffer size, battery, bandwidth), or not being interested in helping the communities. The presence of such selfish nodes in Opportunistic Networks may degrade the entire transmission system. ML algorithms learn and adapt to node behaviour, offering rewards for participation and penalties for non-cooperation. Additionally, reputation systems based on historical interactions are implemented to identify and isolate selfish nodes, preventing them from disrupting network operations [171] [172]. Recognising the selfish nodes and strengthening their participation in the network is profoundly needed, so how do we identify them and make them participate in the forwarding mechanism?

6.7. Energy Consumption

Energy consumption determines the amount of energy the network uses to perform tasks such as message transmission, reception, data collection, etc. In the real scenario, nodes always suffer from the scarcity of power/battery. The energy-efficient model is a required design for the effective use of power/battery. ML algorithms like decision trees and reinforcement learning are used to predict node energy levels and adapt routing strategies accordingly [112] [92] [17]. Since energy efficiency is a prominent issue, the routing protocols must consider this performance parameter alongside other conventional metrics. So, how to design an energy-efficient routing protocol?

6.8. Resource Utilisation

Opportunistic Networks comprise several homogeneous and heterogeneous resources. There is a significant problem in scheduling and efficient usage of resources due to the dynamic behaviour of Opportunistic Networks. ML techniques employed to optimise resource utilisation based on real-time network conditions and node capabilities [34] [176] [45]. The optimal use of resources reduces the likelihood of packet drop and improves delivery ratio, average latency, and other parameters. Predicting the node's workload and resource requirements is even more challenging in a highly dense scenario. So, how to use resources efficiently for various network scenarios?

7. Conclusion

This paper summarizes the evolution of ML technique-based approaches in Opportunistic Networks and other Adhoc Networks. The article explored the relevant ML approach and analyzed its performance and impact on Opportunistic Networks. We have compared the methodology, simulation tool, dataset, and advantages of the current algorithm with traditional methods. The comparative analysis of different approaches provides researchers insight into choosing an appropriate technique based on application. Furthermore, the numerous open issues and opportunities for future research discussed in the paper encourage the research community to contribute to the Opportunistic Networks field.

CRediT authorship contribution statement

Jay Gandhi: Conceptualization of this study, Methodology, Software. **Zunnun Narmawala:** Data curation, Writing - Original draft preparation.

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