WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Performance Analysis on Delay Tolerant Networks using Machine Learning Algorithms

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ABSTRACT—

Delay Tolerant Networks (DTNs) are specialized wireless communication networks that operate effectively in intermittent connectivity and unpredictable network conditions. Traditional routing protocols struggle to perform optimally, ensuring efficient message delivery. This paper explores and examines the application of various ML techniques in analyzing and optimizing the performance of DTNs, including methods to optimize routing, improve message forwarding, manage resources efficiently, and employ predictive analytics. This paper presents an overview of the challenges faced by DTNs, discusses the potential of ML algorithms in addressing these challenges, and demonstrates the effectiveness of different ML approaches in enhancing routing efficiency, message delivery, and overall performance of DTNs. This paper provides an in-depth analysis of various ML techniques deployed in DTNs, ranging from routing optimization and message-forwarding strategies to resource management and predictive analytics.

Keywords—Delay Tolerant Networks, Machine Learning, Routing Optimization, Message Forwarding, Predictive Analytics**.**

1. Introduction

In today's world, Communication forms the backbone of our interconnected world, enabling the effortless exchange of information and instantaneous data transmission. Traditional networks assume a constant and reliable connection between devices. In real-world scenarios such as remote areas or disaster-stricken zones, maintaining this persistent connectivity and Instantaneous Data Transfer becomes impractical. In situations where devices cannot communicate directly, where the path from sender to receiver is uncertain, and where delays are inevitable. This encapsulates the essence of Delay-Tolerant Networks (DTNs).Delay Tolerant Networks (DTNs) are a distinct type of wireless communication systems known for their intermittent connectivity, extended delays, and frequent network disruptions. DTNs redefine the rules of communication, offering a lifeline in scenarios such as deep space missions, rural areas, and disaster zones. DTNs provide adaptability to Intermittent Connectivity, Navigating Uncertain Paths, Adapting to Delays, and Robustness in Challenging Environments. DTNs establish connections through opportunistic encounters, where DTNs capitalize on opportunistic encounters between nodes. When nodes come into contact, they exchange information, creating a communication network system that goes beyond the limitations of constant connectivity. Adaptive routing strategies in DTNs involve nodes intelligently determining the best path based on real-time conditions, creating a dynamic and responsive network. Traditional routing protocols, designed for networks with consistent connectivity struggle to operate effectively in DTNs. As a result, novel approaches are required to overcome the inherent challenges posed by these networks. In recent years, machine learning (ML) algorithms have emerged as promising tools for enhancing the performance of DTNs.

Machine Learning is used in DTNs for adaptability of DTNs. By analyzing historical data and encounter patterns, machine learning algorithms predict optimal paths, improving the efficiency of message delivery and adapting to dynamic network conditions.ML algorithms enable nodes to make intelligent decisions based on changing network dynamics. By continuously learning from the environment, they enhance the adaptability of the network, ensuring efficient routing even in unpredictable scenarios. In essence, ML in DTNs transcends traditional networking paradigms, empowering networks to proactively adjust strategies, recognize patterns, and deliver messages efficiently in environments characterized by delays and intermittent connectivity.ML facilitates pattern recognition which may affect the communication in the network where that may not be immediately seen, like disruptions or irregularities in network traffic and adaptive decision-making by nodes, allowing them to navigate intermittent connectivity with real-time intelligence.

This integration of machine learning enhances the intelligence of DTNs, making them more responsive, adaptive, and capable of handling the challenges unique to scenarios with delayed and intermittent communication.ML models, acting as decision-makers, independently decide if a node is crucial for the best path. This aids in Optimal Path Construction, by considering each node separately, similar to selecting the best stops for your journey.

2. Related work

In the available literature, a variety of ML algorithms suitable for Delay Tolerant Networks (DTNs) have been explored. Some of the prominent ones include:

Dudukovich, R., & Papachristou, C. et al[1] explores the application of machine learning classifiers like Naive Bayes, Decision Tree, and KNN to predict the most suitable nodes for forwarding messages in DTNs and aims to make informed decisions about the optimal path for message delivery in scenarios with disruptions, delays, and intermittent connectivity. It enhances adaptability to changing network conditions, improves efficiency using historical data, and proves practicality in real-world scenarios through simulation evaluations. future enhancements includes integration of additional features (e.g., location, buffer capacity, data rate) into the classification algorithm.

The goal of Kumar, B. S., Vishnubhatla, S., et al.'s study [2] is to analyze the performance of the Prophet routing protocol in DTNs using machine learning models like Artificial Neural Network(ANN) and CNN and develop models for predicting the best alpha, beta, and gamma parameters of the protocol and to evaluate their performance using data generated from the ONE simulator. The paper's future work could explore simulating a larger number of datasets and using predefined models like VGG-16, ResNet, and Efficient Net. This would enhance the prediction accuracy of the parameters for the Prophet routing protocol.

Tekouabou, S. C. K., Maleh, Y., et al[3] study is to design an intelligent routing system based on machine learning techniques like Random Forest ,XGBoost , and Decision Trees which classify bundles that have arrived at the destination successfully or not and also used Shapley value technique to identify the most influential features in the classification process and to understand the predictions of ML models allowing for the quantification of the role of each variable in the final decision of the model. Future work is ML contribution to the advancement of future wireless networks and their applications.

Yao, L., Bai, X., et al.'s study [4] how AI-related methods such as machine learning, deep learning, swarm intelligence, and expert systems applied to optimizing routing in DTN and the potential of AI-assisted methods in optimizing data transmission performance in DTNs such as using particle swarm optimization for intelligent message prioritization and classification based on factors such as time overhead, deficiency.

Tripathia, A., Mekathotia, V et al[5] is to propose a deep learning-based algorithm, called Optimal Routing with Node Prediction (ORNC), for wireless networks such as Bluetooth, MANET, and DTN. The algorithm utilizes a neural network for routing decisions and aims to address the challenges of routing in wireless networks.Machine learning techniques such as KNN, SVM, and MLR are used for network type classification using performance metrics such as accuracy, area under the curve (AUC), and precision.

Garg, P., Dixit, A., et al.[6] study uses ML_Fresh protocol which aims to address the issue of blind forwarding of data by using machine learning techniques to maintain an optimum path between participating nodes in the network and to improve the performance of Opportunistic Networks. The methodology introduces ML-Fresh protocol utilizing ML methods, including Pattern Prediction and Decision Tree Prediction. It leverages historical encounter data in phases like Warm-up and Decision to optimize routing paths, addressing the dynamic topology of Opportunistic Networks. This paper evaluates protocol using performance metrics like Average energy consumption, Average latency, Load Delivery Ratio, Error Rate.

Sharma, S. K., & Wang, X., et al. [7] is to discuss the challenges and potential solutions for supporting massive machine-type communication (MTC) devices in cellular networks, with a focus on machine learning techniques such as Q-learning, deep learning, and LSTM networks, as well as reinforcement learning, fuzzy-logic based adaptive Q-learning, and model-based Q-learning for addressing RAN congestion in cellular IoT networks. Advantages are improved network performance, dynamic resource allocation, and efficient management of radio resources in cellular IoT networks. limitations include challenges of incorporating machine-type communication devices in existing cellular systems and the difficulties in implementing sophisticated learning techniques in IoT devices.

Bonu Kumar, M., et al. [8]. This study aims to improve the quality of service values like throughput and delay in the PRoPHET routing protocol using machine learning models such as XGboost and Random Forest and analyze the behavior of the protocol under different scenarios. The methods used are XGboost, Random Forest, and Support Vector Machines (SVM) to predict optimal alpha, beta, and gamma values for the PRoPHET routing protocol, resulting in improved Quality of Service metrics including average latency (delay) and throughput.

Bajpai, S., et al[9] The objective of this paper is to present a machine learning approach to optimize delay tolerant routing in DTN routing protocols. The paper presents a machine learning approach to optimize delay tolerant routing in DTN routing protocols, using multi-label classification techniques such as Ensemble chain classifiers (ECC), CC(Chain classifiers),BR(Binary relevance).Ensemble chain technique with XGBoost classifier gives good accuracy score, Jaccard score, and f-1 score. Lack of potential computational and resource requirements for implementing the proposed machine learning techniques in real-world DTN environments are the key drawbacks.

Datta, S., et al.[10] paper is to present a Q-learning based method for content dissemination in Delay Tolerant Networks (DTN) to improve message delivery.The proposed content dissemination scheme using reinforcement learning aims to prioritize trending messages, adjust node interests, and avoid network congestion, supporting collaborative message forwarding in a disrupted battlefield communication environment. The simulation was performed using the ONE simulator with 131 mobile nodes and real datasets. Metrics used arecongestion ratio, standard deviation, interest similarity ratio, delivery ratio, and trending threshold (θ) are used to assess message delivery,network bandwidth,energy consumption and interest learning. Future work is toImplement proposed method in a DTN testbed by building a mobile app on Android platform.

Zhou, H., et al.[11] paper is to propose and discuss various algorithms and methods for optimizing routing and data forwarding in Delay-tolerant networks (DTNs) in vehicular communication. improving delivery ratio while minimizing forwarding overhead through the use of Multi-period Bayesian Network (MBN) routing algorithm, Dynamic Multiple-Level Classification (DMLC) method, and a self-adapting optimization algorithm based on encounter frequency and message delivery. Metrics such as delivery ratio, overhead ratio, and average delay are used. Future work includes Doing practical implementation and deployment of the MBN algorithm in real vehicular scenarios, considering factors like scalability and adaptability.

Sebopelo R, et al.[12] The paper aims to employ machine learning, particularly logistic regression (LR) and support vector machine (SVM), for the real-time identification of compromised nodes in Mobile Ad Hoc Networks (MANETs). Logistic Regression (LR) outperforms SVM across various metrics including accuracy, sensitivity, precision, false positive rate, false negative rate, true positive, true negative. Packet delivery ratio (PDER) and Packet modification and misroute rate (PMMR), may not fully capture the complexity of real-world MANET environments and the variety of potential attacks. Future Work includes Testing Enhanced Security Methods in Various Mobile Ad Hoc Network Settings.

Vashishth, V., et al.[13] paper introduces the Cascaded Machine Learning (CAML) routing protocol for Opportunistic Internet of Things Networks, addressing intermittent connectivity challenges using cascade learning, a form of ensemble-based machine learning, to improve routing. This study compares CAML to existing ML-based protocols (MLProph and KNNR) and traditional protocols (HBPR and PRoPHET) .Additionally, the paper utilizes Epidemic routing to generate data for training the classifiers .Metrics include message delivery probability, average hop count, network overhead ratio, and the number of packets dropped. Knearest neighbour routing achieved a high delivery probability percent. Future research could focus on evaluating the CAML protocol in real-world OppIoT scenarios to assess its practical applicability.

Table 1

Literature review in DTN

SNO	Paper Title	Methodology	Metrics	Limitations	Gaps
1	Ridwan, M. A., Radzi, N. A. M., Abdullah, F., & Jalil, Y. E. (2021). Applications of machine learning in networking: a survey of current issues and future challenges. *IEEE access*, *9*, 52523-52556.	ML models like GANs(Generative Adversarial Network), Naïve Bayes and Random Forest used.	Mean squared error (MSE) is used as the accuracy metric.	This paper lacks limitations and potential risks of using ML in networking, such as security vulnerabilities and the potential for adversarial attacks on ML-based systems.	Addressing the issues related to the data availability and privacy in networking including the development of privacy-preserving ML algorithms and techniques for handling imbalanced datasets.
2	Machine Learning in Delay Tolerant Networks: Algorithms, Strategies, and Applications, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-1S, November 2019.	MLProph,Decision Trees, Support Vector Machine (SVM), KNN,K-Means Clustering.	MLProph, which applies both neural networks and decision tree methods,outperformed the decision tree method in predicting successful packet delivery	Limitations include about the generalizability of ML approach, dependency on specific training data, and potential computational overhead in resource-constrained Delay-Tolerant Networks.	Intrusion Detection System, security, Fault detection, Data Integrity, localisation of nodes.
3	Singh, A. K., & Pamula, R. (2021). Vehicular delay tolerant network based communication using machine learning classifiers. *Architectural Wireless Networks Solutions and Security Issues*, 195-208.	The proposed VDTN routing strategy uses ML classifiers, including decision tree, Naive Bayes, and K-nearest neighbors, to determine the best performing classifier.	Hamming loss and zero-one loss.	Lack of explicit discussion on the scalability and real-world implementation challenges of the proposed VDTN routing strategy.	Explore the integration of reinforcement learning and feedback mechanisms to enhance the proposed VDTN routing strategy using machine learning classifiers
4	Zafar, M. H., & Altalbe, A. (2021). Prediction of scenarios for routing in MANETs based on	Support Vector Machine (SVM) , and Radial Basis Function (RBF) kernel methods,	Root Mean Squared Error (RMSE) and	The limitations of the paper include the lack of specific accuracy percentages and metrics	Future scope include further exploration of Ml algorithm for enhancing routing protocols in

	expanding ring search and random early detection parameters using machine learning techniques. *IEEE Access*, *9*, 47033-47047	as well as the use of Artificial Neural Network (ANN) are used.	Mean Absolute Error (MAE) .	values for the Artificial Neural Network (ANN) and Support Vector Machine (SVM) used in the experiments	MANETs to improve overall network performance and Quality of service(QOS)
5	Dudukovich, R., Clark, G., & Papachristou, C. (2019, June). Evaluation of classifier complexity for delay tolerant network routing. In *2019 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAAW)* (pp. 1-7). IEEE.	Algorithms including decision tree, random forest, and a neural network-based autoencoder are used.	Decision tree has achieved 88.91 percent accuracy	While a network emulator (CORE) is used to test the classification-based routing extension, it is unclear if these findings have been validated in real-world deployments or scenarios outside of emulation.	Focusing on the application of ML classifiers in the context of small satellites and other space communication networks, considering the hierarchical network architecture proposed in the paper.
6	Popli, R., Sethi, M., Kansal, I., Garg, A., & Goyal, N. (2021, August). Machine learning based security solutions in MANETs: State of the art approaches. In *Journal of Physics: Conference Series* (Vol. 1950, No. 1, p. 012070). IOP Publishing.	Different ML algorithms, such as KNN, Support Vector Machine (SVM), and Artificial Neural Network (ANN) are used to enhance security in MANETs.	Support Vector Machine (SVM) classification approach achieved a high detection rate of 92% for identifying DoS type of attacks.	The absence of a specific dataset may limit the ability to assess the performance of ML algorithms and security approaches in MANETs, impacting the applicability of the findings to real-world scenarios.	Future research should assess the real-world performance of machine learning algorithms in MANETs for enhanced security.
7	Dash, S. K., Dash, S., Mishra, J., & Mishra, S. (2020). Opportunistic mobile data offloading using machine learning approach. *Wireless Personal Communications*, *110*, 125-139.	Machine learning algorithm proposed for generating target sets for offloading, as well as comparative algorithms such as Greedy, Heuristic, and Random Forest.	correlation coefficient and R-squared value.	The study focuses on a specific dataset of 100 users, which may not fully represent diversity and complexity of real-world cellular networks.	Develop an algorithm that should work in all network conditions and can substantially reduce mobile traffic with greater efficiency.
8	George, J., & Santhosh, R. (2021, November). Implementation of Machine Learning Classifier for DTN Routing. In *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)* (pp. 508-516). IEEE.	ML classification methods like Decision Tree, Naive Bayes, and K-Nearest Neighbors, to forecast network movement in (DTNs and improve routing decisions.	Micro-Averaged F1 Score, Zero-One Loss, Hamming loss, Classifier Accuracy.	This paper does not discuss the potential impact of network dynamics, such as node failures or changes in network topology, on the effectiveness of the routing method.	Develop an algorithm can update Model with respect to new data, through this way the Model improves step by step
9	Ayoubi, S., Limam, N., Salahuddin, M. A., Shahriar, N., Boutaba, R., Estrada-Solano, F., & Caicedo, O. M. (2018). Machine learning for cognitive network management. *IEEE*	k-Nearest Neighbors (k-NN), k-Means, Decision Trees (DT), Bayesian Networks (BN), Support Vector Machines (SVM) are used.	Traffic load,quality of service QoS) and fault prediction are used as metrics.	Challenges with application of machine learning in networking, including the lack of a unified theory of networks and the security of machine learning models	Making machine learning models more robust and resilient to adversarial attacks in the context of network management.

	Communications Magazine, *56*(1), 158-165.				
10	Musumeci, F., Rottondi, C., Nag, A., Macaluso, I., Zibar, D., Ruffini, M., & Tornatore, M. (2018). An overview on application of machine learning techniques in optical networks. *IEEE Communications Surveys & Tutorials*, *21*(2), 1383-1408.	ML algorithms such as Autoregressive Integrated Moving Average (ARIMA), neural networks, SVM are used	True Positive Rate (TPR), False Positive Rate (FPR), and Area Under the ROC Curve (AUC) are used as metrics.	Challenges of data availability, timescales, and the need for standardization and commercialization of ML methodologies in optical networks.	Implementation of semi-supervised and unsupervised machine learning algorithms in optical networks to adapt to dynamically evolving scenarios
11	Ji, J., Liu, H., Wang, A., & Hao, Y. (2020, December). Load Forecasting-Based Congestion Control Algorithm for Delay-Tolerant Networks. In *2020 International Conference on Space-Air-Ground Computing (SAGC)* (pp. 62-66). IEEE.	machine learning model like back propagation neural network (BPNN) is used	DTN with congestion control based on load forecast performs well on both delivery ratio and buffer occupation metrics.	The paper's concentration on DTN architecture and congestion control in specific scenarios may restrict the generalizability of proposed algorithms to diverse network environments.	Exploring the integration of load forecasting model such as long short-term memory (LSTM) to enhance the accuracy and effectiveness of load prediction.
12	Sowah, R. A., Ofori-Amanfo, K. B., Mills, G. A., & Koumadi, K. M. (2019). Detection and prevention of man-in-the-middle spoofing attacks in MANETs using predictive techniques in Artificial Neural Networks (ANN). Journal of Computer Networks and Communications, 2019.	The machine learning algorithm used in MANETs was the artificial neural network (ANN).	precision, recall, and accuracy, True Positive rate	constraint to detecting attacks from outsider nodes and the neglect of insider attack detection when an IDS was not installed	Real-world Implementation, Improving Detection Accuracy for preventing man-in-the-middle attacks.

3. Methodology

Machine learning-based routing algorithms:

Support Vector Machine (SVM): SVM classifies network data extracted from DTNs into different categories based on features such as message delivery probability aiming to enhance routing efficiency, message delivery, and overall network performance. By effectively categorizing network data points, SVM contributes to the improvement of DTN performance..It worked by finding the hyperplane that best separated the data points, maximizing the margin between different classes.Here data points represent the instances or samples from the dataset used for training and testing the machine learning models. Each data point consists of features that describe the characteristics of the network data in your DTNs.The margin refers to the separation or distance between the decision boundary (hyperplane) and the closest data points from each class. SVM aims to find the hyperplane that maximizes this margin, effectively classifying the data points into different classes while maintaining the maximum separation between them.SVM seeks to maximize this margin to accurately classify network data and optimize the performance of DTNs.

Random Forest: Random Forest is an ensemble learning method that builds multiple decision trees during training.Each tree is trained on a random subset of the training data and a random subset of the features.

During prediction, the results from all the trees are aggregated through averaging or voting to improve accuracy and reduce overfitting. The final prediction is typically made by averaging the predictions of all trees.

Gradient Boosting: Gradient Boosting is ensemble learning technique and it is utilized to iteratively enhance the classification performance by focusing on the mistakes made by the ensemble so far and on the samples that were misclassified by earlier trees.here earlier trees refers to the decision trees that were built in the earlier stages of the boosting process. Initially, a base model (usually a decision tree) is trained on the data. Then, subsequent decision trees are built sequentially, each one correcting the errors of the previous trees. The algorithm optimizes a loss function by adding these weak learners (trees) to the model iteratively, gradually reducing the overall error. This iterative process continues until a predefined number of trees is reached or until further trees fail to significantly improve performance. Ultimately, the predictions from all the trees are combined to produce the final output, typically through weighted averaging.

AdaBoost: AdaBoost, short for Adaptive Boosting, is an iterative ensemble method that combines multiple weak classifiers to form a strong classifier. It assigns higher weights to misclassified data points and lower weights to correctly classified ones in each iteration, allowing subsequent classifiers or weak learners to focus more on difficult-to-classify instances. AdaBoost is employed to iteratively improve classification accuracy by giving more weight to misclassified samples.

XGBoost: XGBoost stands for Extreme Gradient Boosting, which is an optimized and highly efficient implementation of gradient boosting. It uses a more regularized model formalization to control overfitting and parallelization to improve computational speed. In this paper, XGBoost is utilized to enhance the performance of gradient boosting by optimizing the learning process and handling large datasets efficiently.

XGBoost implements optimized algorithms and parallel processing to enhance training speed and performance. It uses gradient-based algorithms and regularization techniques to prevent overfitting and improve generalization.

Stacking Classifier: Stacking is an ensemble learning technique that combines the predictions of multiple base models, such as SVM and Random Forest, by training a meta-model on their outputs. Unlike simple averaging or voting, stacking uses a higher-level model to learn how to best combine the predictions of base models to make a final prediction. This approach can often lead to better performance than individual models by leveraging the diversity of predictions generated by different classifiers and effectively learning how to combine them.

LightGBM: LightGBM is a gradient boosting framework optimized for speed and efficiency. It employs a novel gradient-based algorithm and histogram-based techniques to split features and grow trees, reducing memory usage and accelerating training. This makes LightGBM particularly suitable for handling large datasets with millions of samples.

LightGBM utilized histogram-based algorithms and adopted a leaf-wise tree growth strategy to construct decision trees efficiently. Additionally, it employed techniques like gradient-based one-side sampling to further enhance training speed and improve overall performance.

Voting Classifier: The Voting Classifier combines the predictions of multiple individual base classifiers by averaging (soft voting) their predictions or taking the majority vote (hard voting). It can consist of different types of classifiers, such as SVM, Random Forest, and Gradient Boosting, and typically performs well when the base classifiers are diverse and complementary.

Voting Classifier leveraged different types of classifiers to create a more robust final model. By combining the outputs of different classifiers, it made a final decision based on either averaging their predictions (soft voting) or selecting the majority vote (hard voting).

Agglomerative clustering algorithm: It is a clustering algorithm that groups together closely packed points based on density, rather than assuming spherical clusters like KMeans. It works by identifying core points that have a specified number of neighboring points within a certain radius, and then expanding clusters from these core points. DBSCAN is particularly useful for clustering data with irregular shapes and varying densities.

4. Performance Analysis in DTNs:

Upon analyzing various papers, it is evident that machine learning algorithms, specifically Support Vector Machines, K-Nearest Neighbours, Random Forest, and Decision Trees, are frequently employed in the context of Delay Tolerant Network (DTN) routing. The integration of these machine learning algorithms consistently enhances the performance of DTN, as indicated by findings across multiple studies. These classifiers demonstrate higher accuracy and efficiency in optimizing routing, message delivery, and overall network performance in the context of Delay Tolerant Networks.

5. Conclusion:

Delay-tolerant networks (DTNs) are communication networks designed to operate effectively in situations with inconsistent connections, frequent disruptions, or significant delays in data transmission, ensuring efficient message delivery. Machine learning (ML) algorithms have emerged as promising tools for improving the performance of DTNs. By examining various ML techniques in DTNs, from routing optimization to predictive analytics, we have found a promising way to address the challenges faced by these networks. Recent research demonstrates ML's versatility in addressing DTNs' unique hurdles, aiding communication in rural, disaster, and space scenarios. By leveraging ML techniques, researchers can overcome the inherent challenges of DTNs and pave the way for more robust and efficient communication systems in resource-constrained environments, creating adaptive efficient communication networks that cater to the diverse needs of modern society.I intend to conduct research on a variety of machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), and gradient boosting algorithms such as LightGBM and XGBoost. Additionally, I aim to explore ensemble learning techniques like voting and stacking, which involve integrating predictions from multiple base classifiers such as LightGBM, Random Forest, XGBoost, and SVM.

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