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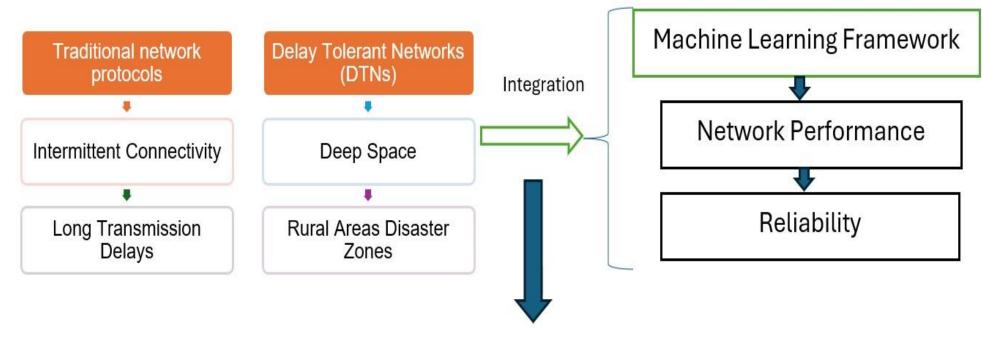
Abstract

Proposed research aims to present overview of integrating Machine Learning (ML) in High-Rate Delay Tolerant Networking (HDTN) to enhance communication in environments with intermittent connectivity. For this, a thorough investigation is demonstrated on various ML strategies applied to optimize routing, improve data reliability, and manage network resources effectively. Besides, proposed analysis emphasizes ML's impact on network performance in challenging scenarios like space communications and disaster zones. Comparative results demonstrate that ML-enhanced DTNs significantly outperform traditional routing methods, achieving higher throughput and lower error rates. In addition, this research explores ML's potential to dynamically respond to network changes, increasing resilience and efficiency in communications.

DTN enables the use of multiple paths and providers to efficiently deliver data from deep space to Earth



Problem Statement



Required Innovative Solution

Problems for machine learning integration



Real Time Communications Conference and Expo at Illinois Tech

IEEE International Conference

IEEE RTC 2024 - October 8-10, 2024 - IIT, Chicago, IL, USA

Review of Machine Learning Applications in High Delay Tolerant Networks

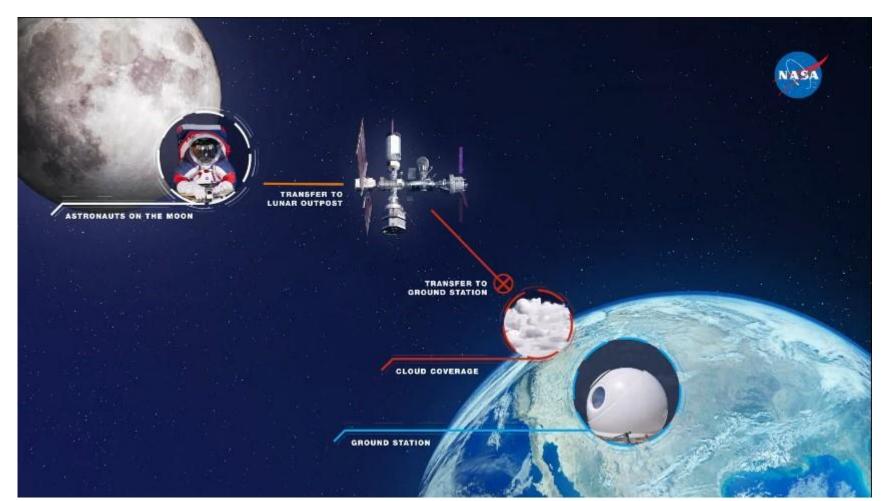
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Background and Method of Approach

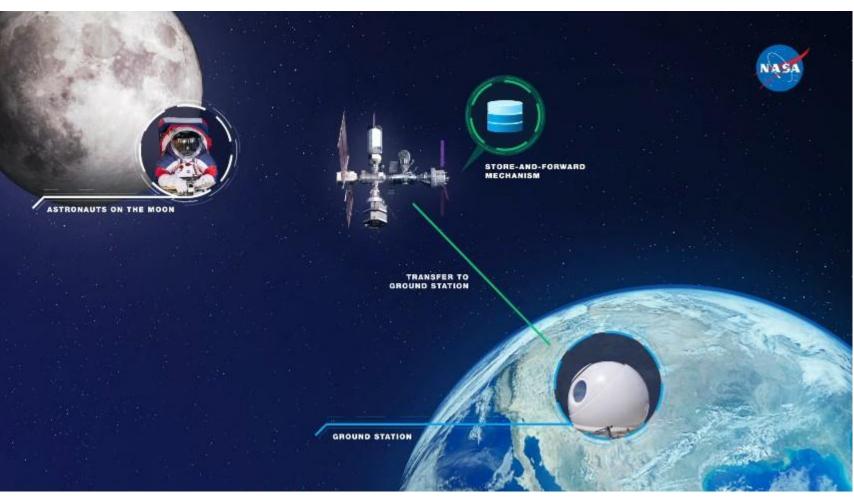
V Delay Tolerant Networks (DTNs) enable communication in environments with intermittent connectivity or long delays.

✓ Traditional network protocols are inadequate for scenarios like deep space communications, rural areas, disaster-stricken zones, space networks.

Machine Learning (ML) enhances DTN adaptability and efficiency, offering solutions to challenges like long delays, limited bandwidth, and unpredictable topologies. Key contributions from Whitbeck et al. and NASA's Glenn Research Center have set the groundwork for ML in DTNs for store and forward mechanism and high speed data transfer indicated in Figure 4 and Figure 5.



Communication challenges in space networks



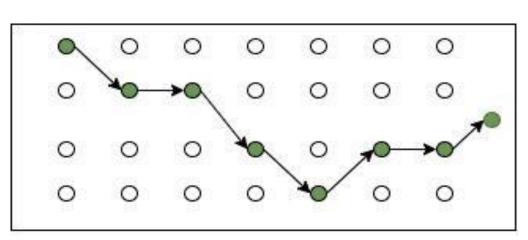
Store-and-Forward mechanism in HDTN



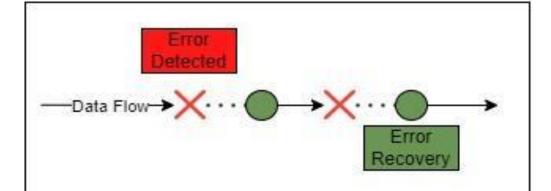
High-speed data transfer in space networks



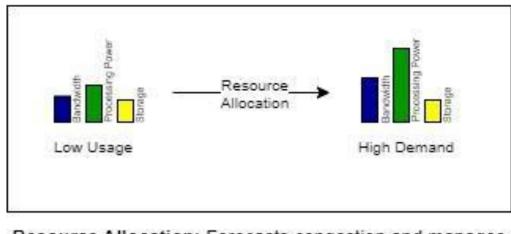
Analysis of ML strategies in three key areas :



Routing Optimization: Predicts best routes using ML classifiers.



Error Handling: Improves error correction with MLenhanced fountain codes.



Resource Allocation: Forecasts congestion and manages bandwidth dynamically.

Case study analysis: Investigation was performed on practical implementations, including NASA's HDTN Project for Space Communications and ML applications for routing optimization in DTNs.

Comparative analysis: Proposed investigation compares the performance of DTNs with and without ML enhancements, focusing on data delivery rates, error rates, and system resilience.

Exploration of various ML techniques: Various ML methods were investigated such as decision trees, Bayesian classifiers, neural networks, and reinforcement learning in HDTN contexts.

Evaluation of ML impact on network adaptability: Assessments were conducted on how ML enables networks to anticipate and respond to changes in network conditions.

Analysis of security implications: Significant challenges and potential solutions are explored for securing ML-enhanced DTNs.

Investigation of scalability issues: Various ML models can be adapted for large-scale HDTN deployments which is another outcome from this comprehensive review.

Consideration of real-time processing requirements: This research investigated the development of lightweight ML models for timely decision-making in HDTN environments.

Identification of challenges and future directions: Scalability, realtime processing, and security concerns are identified as key challenges in ML-enhanced DTNs for which effective integration method will be proposed in future.

threats.





Results

Scalability and Complexity: As HDTN systems expand, particularly for interplanetary Internet, scalability of ML models is a key challenge. Efficient models must balance resource constraints, such as limited bandwidth and computational power.

Real-time Processing: Real-time decision-making is vital for critical applications like space missions and emergency response. Lightweight ML models and edge computing help reduce latency and

Scalability Challenges

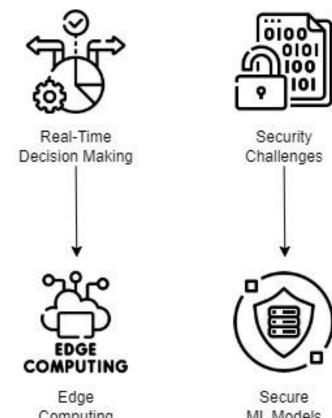
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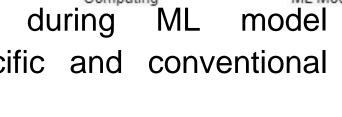
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make fast decisions despite delays. Security Concerns: ML-driven DTNs need robust encryption and 200 real-time threat detection to prevent

tampering and cyberattacks. Adaptive and Decentralized ML: Adaptive ML models scale based on network resources, while decentralized methods like federated learning are ideal for fragmented DTI Adaptive

Security-By-Design: Integrating security development ensures resilience to AI-specific and conventional







Conclusion

Integrating machine learning (ML) into High-Rate Delay Tolerant Networking (HDTN) enhances network management in high-latency, disruptive environments, turning challenging scenarios into viable communication channels. ML allows dynamic adaptation, optimizing data flow and addressing failures, which is vital for space communications and disaster response.

Future Research Directions: Focus on real-time optimization using lightweight neural networks and edge computing for efficient processing. Develop secure, tamper-resistant ML models for realtime threat detection. Ensure ML integrates with current network management systems. Collaboration across fields like machine learning, cybersecurity, and network engineering is crucial.

Broader Impact: ML-enhanced DTNs can boost global connectivity, environmental monitoring, and crisis communication. Interdisciplinary collaboration is key to addressing complex challenges at the intersection of networking and AI, enabling more adaptive and secure communication networks.

References

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