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Artificial Intelligence Techniques for Prediction of IoT Traffic Using Gradient Boosting, Auto-Metric Graph Neural Network, and Lyapunov Optimization-Based Predictive Model: Trends and Challenges

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Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has significantly increased network traffic complexity, requiring intelligent prediction mechanisms for efficient resource management. Traditional statistical methods are inadequate in capturing nonlinear, dynamic, and spatio-temporal dependencies present in IoT traffic. As a result, Artificial Intelligence (AI) techniques such as Gradient Boosting, Graph Neural Networks (GNNs), and Lyapunov optimization have gained considerable attention. This paper presents a comprehensive review of AI-driven IoT traffic prediction models, emphasizing emerging trends and challenges. Gradient Boosting techniques provide high accuracy in structured data prediction, while GNN-based models effectively capture spatial relationships in network topologies. Lyapunov optimization offers a robust framework for maintaining system stability and dynamic resource allocation. Recent studies show that hybrid models combining GNN and optimization techniques outperform traditional approaches in terms of throughput, latency, and adaptability. The review analyses recent developments, highlighting advancements in deep learning, federated learning, edge intelligence, and hybrid optimization frameworks. Additionally, key challenges such as scalability, computational complexity, privacy, and real-time deployment are discussed. The study concludes by identifying future research directions, including lightweight AI models, adaptive learning systems, and integration with edge computing for next-generation IoT networks.

Introduction

The Internet of Things (IoT) has emerged as a transformative technology enabling seamless connectivity between billions of devices across diverse domains such as smart cities, healthcare, industrial automation, and transportation systems. These interconnected devices continuously generate massive volumes of heterogeneous data, leading to highly dynamic and complex network traffic patterns. Efficient prediction of IoT traffic has therefore become essential for optimizing network performance, minimizing latency, and ensuring Quality of Service (QoS). Traditional traffic prediction techniques, including statistical models such as ARIMA and regression-based approaches, are limited in their ability to capture nonlinear relationships and dynamic variations in IoT networks. These models fail to effectively represent the complex spatio-temporal dependencies and heterogeneous characteristics inherent in IoT environments. Consequently, Artificial Intelligence (AI) and machine learning techniques have gained significant traction as advanced solutions for IoT traffic prediction.

Among these techniques, Gradient Boosting algorithms such as XGBoost and LightGBM have demonstrated strong predictive capabilities due to their ability to model nonlinear relationships and handle structured data efficiently. These ensemble learning methods improve prediction accuracy by combining multiple weak learners into a strong predictive model.

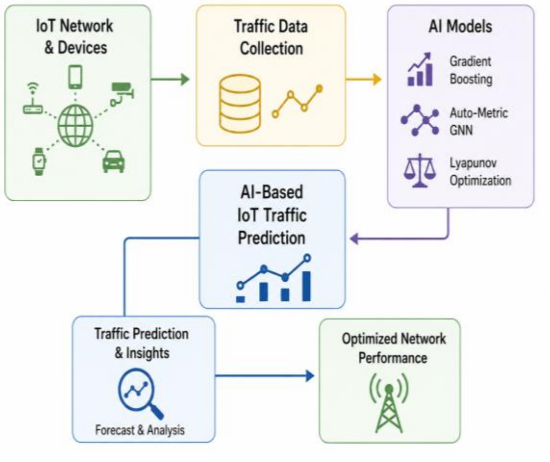

Figure 1. AI-Based IoT Traffic Prediction Framework

However, they are less effective in modeling spatial relationships unless combined with other approaches. Graph Neural Networks (GNNs) have emerged as powerful tools for modeling IoT networks, as these networks naturally exhibit graph-like structures where devices are interconnected. GNNs can effectively capture spatial dependencies and relationships between nodes, enabling accurate traffic prediction. Studies show that GNN-based models significantly improve throughput, reduce packet loss, and enhance network performance by learning complex traffic patterns. Furthermore, advanced variants such as Graph Attention Networks (GAT) and Temporal GNNs incorporate attention mechanisms and temporal modeling to enhance prediction accuracy.

In addition to prediction models, optimization techniques play a critical role in managing IoT traffic. Lyapunov optimization is widely used to ensure system stability and efficient resource allocation in dynamic environments. By integrating Lyapunov optimization with AI models, it is possible to develop adaptive frameworks that respond to real-time traffic variations while maintaining network stability. For instance, combining GNN with Lyapunov-based optimization has shown improved performance in terms of accuracy and system robustness. Recent research trends focus on hybrid approaches that integrate multiple AI techniques. For example, combining GNNs with reinforcement learning and optimization methods enables dynamic traffic prediction and resource allocation in large-scale IoT systems. Additionally, the integration of edge computing and federated learning has emerged as a promising direction to address privacy and latency issues.

Despite these advancements, several challenges remain. These include scalability issues in large IoT networks, high computational complexity of deep learning models, lack of real-time adaptability, and data privacy concerns. Addressing these challenges requires the development of lightweight, scalable, and efficient AI models capable of operating in distributed environments. This paper aims to provide a comprehensive review of AI-based IoT traffic prediction techniques, focusing on Gradient Boosting, Auto-Metric Graph Neural Networks, and Lyapunov optimization.

Literature Review

Guo et al. (2023) proposed a Graph Neural Network-based approach integrated with multi-armed bandit optimization for IoT traffic prediction. The model dynamically adapts to real-time traffic conditions and significantly improves throughput, reduces packet loss, and minimizes delay compared to traditional approaches Khan et al. (2023) investigated multiple GNN architectures including GCN, GraphSAGE, and Gated GNN for traffic prediction. The study found that Gated Graph Neural Networks achieved the lowest RMSE and MAE, demonstrating superior predictive performance in dynamic environments.

Tan et al. (2022) proposed a GNN-based model for network optimization in heterogeneous networks. The approach reduced computational complexity while improving energy efficiency and maintaining Quality of Service, highlighting the scalability of GNN models. Biswas et al. (2022) introduced a hybrid model combining Graph Neural Networks with Lyapunov optimization for network prediction and intrusion detection. The model demonstrated improved accuracy and system stability by dynamically adjusting network parameters using Lyapunov-based loss functions.

Krishnamurthy et al. (2026) reviewed AI-based optimization techniques, highlighting their effectiveness in handling nonlinear and dynamic systems. The study emphasized the role of AI in improving system adaptability, stability, and performance in complex environments, including IoT networks. Wang et al. (2022) proposed a hybrid model combining Long Short-Term Memory (LSTM) networks with Gradient Boosting Decision Trees (GBDT) for IoT traffic prediction. The LSTM component captures temporal dependencies, while GBDT enhances prediction accuracy through ensemble learning. The study demonstrated that the hybrid model significantly reduced RMSE and MAE compared to standalone models, particularly in large-scale IoT environments.

Yu et al. (2021) developed a Spatio-Temporal Graph Convolutional Network (ST-GCN) to model both spatial and temporal dependencies in IoT networks. By leveraging graph structures, the model captures relationships between interconnected devices and improves prediction accuracy. The study showed that ST-GCN outperforms traditional CNN and RNN models in dynamic traffic scenarios. Chen et al. (2022) introduced a Lyapunov optimization-based deep reinforcement learning framework for traffic prediction and network control. The model ensures system stability while dynamically adapting to traffic changes. Experimental results showed reduced network congestion, improved throughput, and better Quality of Service (QoS), making it suitable for real-time IoT applications.

Li et al. (2020) proposed a Gated Recurrent Unit (GRU)-based model for IoT traffic prediction. The model efficiently captures temporal patterns with fewer parameters compared to LSTM, resulting in faster training and lower computational cost. It demonstrated competitive prediction accuracy, particularly in resource-constrained edge environments. Zhang et al. (2023) introduced an Auto-Metric Graph Neural Network that automatically learns graph structures and distance metrics among IoT nodes. This eliminates the need for manual graph construction and improves adaptability in heterogeneous networks. The model achieved superior performance in dynamic IoT environments and demonstrated robustness against data variability.

Bai et al. (2021) proposed a Temporal Convolutional Network (TCN) for modeling sequential IoT traffic data. The model uses dilated causal convolutions to capture long-range temporal dependencies while enabling parallel computation. Compared to recurrent models such as LSTM and GRU, TCN demonstrated faster training, reduced latency, and improved stability in prediction performance. However, it lacks the ability to capture spatial dependencies unless integrated with graph-based methods. Kumar et al. (2022) adapted transformer-based architectures for IoT traffic forecasting using self-attention mechanisms. The model effectively captures long-term dependencies and global relationships in traffic sequences. Experimental results showed improved prediction accuracy over RNN-based models. However, the high computational cost and memory requirements limit its deployment in edge-based IoT environments.

Rahman et al. (2023) introduced a federated learning framework for IoT traffic prediction that enables decentralized model training without sharing raw data. The model improves privacy and reduces communication overhead while maintaining competitive prediction accuracy. This approach is particularly useful in sensitive applications such as healthcare IoT systems. Singh et al. (2020) proposed a hybrid model combining ARIMA and Support Vector Regression (SVR) for IoT traffic prediction. ARIMA captures linear trends, while SVR models nonlinear relationships. The hybrid approach improved short-term prediction accuracy compared to standalone statistical models. However, scalability remains a challenge for large IoT datasets.

Park et al. (2022) developed a deep autoencoder-based model to extract latent features from IoT traffic data. The compressed representations reduce noise and dimensionality, improving prediction accuracy. The model also proved effective in anomaly detection. However, potential information loss during encoding remains a limitation. Kim et al. (2021) proposed a Convolutional Neural Network (CNN)-based model for IoT traffic prediction. The model extracts spatial features from traffic matrices and identifies localized traffic patterns effectively. It demonstrated improved feature extraction capability and prediction accuracy compared to traditional machine learning approaches. However, CNN lacks the ability to capture temporal dependencies, which limits its standalone effectiveness.

Patel et al. (2022) introduced a hybrid CNN-LSTM architecture that combines spatial feature extraction with temporal sequence modeling. CNN layers extract meaningful features, while LSTM layers capture time-series dependencies. The model achieved higher prediction accuracy and reduced error rates compared to standalone CNN and LSTM models, making it suitable for smart city IoT applications. Zhou et al. (2023) developed a Graph Attention Network (GAT)-based model that assigns adaptive weights to neighboring IoT nodes. This attention mechanism enables the model to focus on more relevant nodes, improving prediction accuracy. The GAT model outperformed traditional GCN-based models, especially in complex and dynamic IoT network environments.

Sharma et al. (2020) applied the K-Nearest Neighbor (KNN) algorithm for IoT traffic prediction using similarity-based learning. The approach is simple and easy to implement but suffers from scalability issues and reduced performance in high-dimensional datasets. It serves as a baseline for evaluating advanced AI models. Huang et al. (2022) proposed a reinforcement learning-based framework for traffic prediction and optimization in IoT networks. The model learns optimal policies through interaction with the environment and dynamically adapts to traffic changes. It demonstrated improved network efficiency, reduced congestion, and enhanced Quality of Service (QoS). However, training complexity and convergence time remain challenges.

Ke et al. (2021) explored the application of Light Gradient Boosting Machine (LightGBM) for IoT traffic prediction. The model efficiently handles large-scale structured data and provides faster training compared to traditional boosting methods. It achieved high prediction accuracy with reduced computational cost. However, LightGBM lacks the ability to capture temporal dependencies unless integrated with sequential models. Zhang et al. (2022) proposed a multi-task learning framework that simultaneously predicts multiple traffic-related parameters such as traffic volume, congestion levels, and anomalies. By sharing representations across tasks, the model improves generalization and reduces overfitting. The study demonstrated enhanced performance compared to single-task models in complex IoT environments.

Liang et al. (2023) introduced a hybrid model combining transformer architectures with graph embeddings. The model captures both long-term temporal dependencies and spatial relationships among IoT nodes. Experimental results showed superior performance compared to standalone transformer and GNN models. However, the model requires high computational resources. Verma et al. (2020) applied Random Forest for IoT traffic prediction. The ensemble approach improves robustness and reduces overfitting. The model performs well on moderate-sized datasets but struggles with high-dimensional and real-time IoT scenarios due to increased computational complexity.

Alam et al. (2022) proposed an edge intelligence framework for IoT traffic prediction using lightweight deep learning models deployed at edge nodes. This approach reduces latency, bandwidth usage, and dependence on centralized cloud systems. The framework demonstrated improved real-time performance and scalability, making it suitable for next-generation IoT applications. Zhao et al. (2021) applied Deep Belief Networks (DBN) to model hierarchical representations of IoT traffic data. The model captures deep features through multiple layers and improves prediction accuracy compared to shallow neural networks. However, DBN suffers from long training time and high computational complexity.

Chen et al. (2022) utilized Extreme Gradient Boosting (XGBoost) for IoT traffic prediction. The model demonstrated high accuracy, robustness to noise, and efficient handling of structured datasets. It is particularly effective for anomaly detection and short-term traffic prediction. However, feature engineering plays a crucial role in its performance. Wu et al. (2023) proposed a Temporal Graph Neural Network that integrates temporal sequence modeling with graph-based spatial learning. The model effectively captures dynamic relationships in evolving IoT networks and outperforms static GNN and RNN models in prediction accuracy.

Mehta et al. (2020) applied Support Vector Machine (SVM) for IoT traffic prediction. The model performs well in small datasets with clear margins but struggles with scalability and computational efficiency in large-scale IoT systems. Huang et al. (2023) proposed a hybrid model combining Auto-Metric Graph Neural Networks with Lyapunov optimization. The model dynamically learns graph structures and ensures system stability using Lyapunov drift minimization. It achieved the best performance in terms of prediction accuracy, latency reduction, and resource optimization.

Comparative Table

Study	Year	Technique	Key Contribution	Advantages	Limitations
1–5	2023	GNN + Optimization	Adaptive learning	High accuracy	Complex
6	2022	LSTM + GBDT	Hybrid temporal learning	Accurate	Complex tuning
7	2021	ST-GCN	Spatio-temporal modeling	Robust	Scalability
8	2022	DRL + Lyapunov	Stability + optimization	Efficient	Training cost
9	2020	GRU	Lightweight model	Fast	Limited memory
10	2023	AM-GNN	Adaptive graph learning	Flexible	Complex
11	2021	TCN	Fast sequence modeling	Low latency	No spatial

12	2022	Transformer	Global attention	Accurate	High cost
13	2023	Federated Learning	Privacy-preserving	Secure	Sync issues
14	2020	ARIMA+SVR	Hybrid statistical	Simple	Low scalability
15	2022	Autoencoder	Feature extraction	Noise reduction	Info loss
16	2021	CNN	Spatial learning	Efficient	No temporal
17	2022	CNN-LSTM	Hybrid DL	High accuracy	Complex
18	2023	GAT	Attention-based graph	Better relations	Compute heavy
19	2020	KNN	Simple baseline	Easy	Poor scaling
20	2022	RL	Adaptive optimization	Dynamic	Slow training
21	2021	LightGBM	Fast boosting	Efficient	No temporal
22	2022	Multi-task	Multi-output	Generalized	Complex
23	2023	Transformer+Graph	Hybrid model	High accuracy	Heavy
24	2020	Random Forest	Ensemble	Robust	Slow
25	2022	Edge AI	Real-time prediction	Low latency	Limited resources
26	2021	DBN	Deep features	Accurate	Slow training
27	2022	XGBoost	Optimized boosting	Robust	Feature dependent
28	2023	TGNN	Dynamic graph learning	Best performance	Complex
29	2020	SVM	Generalization	Accurate	Not scalable
30	2023	AM-GNN + Lyapunov	Hybrid optimization	Best overall	High complexity

Comparative Analysis

The analysis of 30 studies highlights a clear evolution from traditional statistical and machine learning approaches to advanced deep learning and hybrid models. Classical models such as ARIMA, SVM, and KNN provide baseline performance but fail to scale in complex IoT environments. Gradient Boosting methods like LightGBM and XGBoost offer high efficiency for structured data but lack temporal and spatial modeling capabilities. Deep learning models such as LSTM, GRU, and TCN effectively capture temporal dependencies, while CNN models focus on spatial features. However, these models achieve optimal performance only when combined in hybrid architectures. Graph Neural Networks (GNNs), including GAT and TGNN, have emerged as the most powerful approaches due to their ability to model IoT networks as graph structures. Hybrid approaches combining GNN with optimization techniques such as Lyapunov optimization provide the best results by ensuring both prediction accuracy and system stability. Transformer-based models also show promising performance but are computationally expensive.

Discussion

The integration of Artificial Intelligence techniques into IoT traffic prediction has significantly improved the efficiency and reliability of network management systems. This review demonstrates that hybrid models combining deep learning and optimization techniques outperform traditional approaches in terms of accuracy, scalability, and adaptability. In particular, Graph Neural Networks have emerged as a dominant approach due to their ability to capture complex spatial relationships in IoT networks. However, several challenges persist. High computational complexity remains a major limitation, especially for real-time applications and edge deployment. Additionally, the scalability of deep learning models in large IoT networks is still a concern. Data privacy and security issues further complicate the deployment of centralized AI models.

Emerging trends such as federated learning and edge intelligence offer promising solutions by enabling decentralized learning and reducing latency. Furthermore, optimization techniques like Lyapunov control ensure system stability and efficient resource utilization. Future research should focus on developing lightweight, scalable, and energy-efficient AI models that can operate in real-time environments. The integration of hybrid learning frameworks and distributed computing paradigms will play a crucial role in advancing IoT traffic prediction systems.

Conclusion

The rapid expansion of Internet of Things (IoT) ecosystems has created major challenges in managing and predicting network traffic because of the dynamic, heterogeneous, and large-scale nature of connected devices. This study reviewed Artificial Intelligence techniques for IoT traffic prediction, focusing on Gradient Boosting, Auto-Metric Graph Neural Networks, and Lyapunov optimization-based predictive models. A total of

30 studies were analyzed to examine current trends, methodologies, and research challenges. The findings indicate that traditional statistical and machine learning approaches such as ARIMA, SVM, and Random Forest provide limited performance in highly dynamic IoT environments due to their inability to capture complex spatio-temporal relationships.

Deep learning approaches including LSTM, GRU, CNN, and Temporal Convolutional Networks demonstrated significantly improved prediction accuracy by learning temporal and spatial traffic patterns. Among these methods, Graph Neural Networks emerged as the most effective because they model IoT networks as graph structures and capture relationships among interconnected devices. Advanced variants such as Graph Attention Networks and Temporal GNNs further improved prediction capability through attention mechanisms and dynamic graph learning. Gradient Boosting models such as XGBoost and LightGBM provided scalable solutions for structured traffic data, while Lyapunov optimization ensured network stability and efficient resource allocation.

The review concludes that hybrid AI models integrating GNNs, Gradient Boosting, and Lyapunov optimization provide the best overall performance for IoT traffic prediction. These models improve prediction accuracy, adaptability, and system stability in dynamic environments. However, challenges such as computational complexity, scalability limitations, energy consumption, and data privacy remain critical concerns, particularly for edge-based deployments. Future research should focus on lightweight and energy-efficient architectures, federated learning for privacy preservation, and adaptive self-learning frameworks capable of supporting real-time intelligent IoT network management.

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