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Optimizing IoT Network Resource Management Through Machine Learning-Based Bandwidth Prediction

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ABSTRACT

The rapid growth of Internet of Things (IoT) technologies has increased the complexity of network resource management, particularly bandwidth allocation. Efficient allocation is essential for maintaining communication reliability, minimizing latency, and ensuring quality of service (QoS) in heterogeneous IoT environments. This study analyzes the relationship between network traffic characteristics and allocated bandwidth using a machine learning approach. The publicly available IoT Network Traffic Dataset contains 100,000 communication records, including packet size, transmission time, protocol type, bandwidth usage, latency, jitter, packet loss rate, device type, and energy usage. Data preprocessing involved cleaning, categorical encoding, feature scaling, and exploratory data analysis. Random Forest Regression was used to predict allocated bandwidth from these characteristics. Feature importance analysis identified transmission time, energy usage, bandwidth usage, packet loss rate, latency, and jitter as the most influential predictors. However, the model achieved training and testing R^2 scores of 0.045 and −0.003, respectively, indicating limited predictive capability and little predictive signal captured by the model. These findings highlight the importance of feature relevance and dataset quality in developing intelligent network resource management systems. Future research should incorporate additional network-related features and evaluate alternative machine learning models to improve bandwidth allocation prediction in large-scale IoT environments.

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1. Introduction

The Internet of Things (IoT) has become one of the most significant technological developments in the era of digital transformation. The integration of sensors, actuators, embedded devices, and wireless communication technologies enables billions of devices to communicate and exchange information autonomously through interconnected networks [1]. IoT has been extensively adopted in various domains, including smart cities, healthcare monitoring, industrial automation, intelligent transportation systems, precision agriculture, and environmental monitoring. The rapid proliferation of connected devices has resulted in unprecedented growth in network traffic, creating new challenges related to communication efficiency, network reliability, and resource management [2], [3]

According to recent industry reports, the number of IoT devices deployed worldwide continues to increase annually, generating massive volumes of heterogeneous data that require efficient transmission and processing. Unlike conventional communication systems, IoT environments consist of diverse devices with varying communication requirements, transmission frequencies, and quality-of-service (QoS) demands. Such heterogeneity significantly complicates network management because communication resources must be distributed dynamically according to changing traffic conditions and application priorities [4], [5]

Among various network management challenges, bandwidth allocation remains one of the most critical factors affecting IoT network performance. Bandwidth represents a limited communication resource that must be shared among numerous devices operating simultaneously within the same network infrastructure. Inadequate bandwidth allocation can lead to network congestion, increased transmission delays, higher packet loss rates, excessive energy consumption, and reduced service reliability. Consequently, efficient bandwidth allocation plays a fundamental role in ensuring stable communication, maintaining QoS requirements, and supporting scalable IoT deployments [6], [7].

Traditional bandwidth allocation mechanisms generally employ static scheduling strategies or predefined allocation rules. Although these approaches are computationally simple and relatively easy to implement, they often fail to adapt to highly dynamic network environments. IoT networks are characterized by continuously changing traffic patterns influenced by packet generation rates, device mobility, transmission protocols, network latency, and environmental conditions. As a result, static allocation methods frequently produce inefficient resource utilization and poor network performance under varying operational scenarios [8], [9], [10].

To address these limitations, researchers have proposed dynamic bandwidth allocation techniques capable of adjusting communication resources based on current network conditions. [5] introduced an artificial intelligence-enabled dynamic bandwidth optimization framework that demonstrated improvements in network QoS by adapting resource allocation according to traffic demands. Similarly, [11], [12] proposed the Enhanced Dynamic Bandwidth Allocation (EDBA) method, which improves network performance by allocating communication resources more efficiently under fluctuating traffic conditions. These studies confirm that intelligent allocation mechanisms can significantly enhance communication reliability and network utilization in IoT environments.

Recent advancements in machine learning and artificial intelligence have further expanded opportunities for intelligent network resource management. Machine learning techniques are capable of learning complex relationships among network parameters from historical data and generating accurate predictions regarding future network behavior. Such predictive capabilities enable proactive resource allocation strategies rather than reactive approaches, allowing communication systems to anticipate future demands before network congestion occurs [1], [3].

Several studies have investigated predictive approaches for bandwidth management and spectrum allocation in IoT systems. [13] proposed a bandwidth prediction framework for local IoT communication networks, demonstrating that predictive modeling can improve communication efficiency and reduce resource wastage. Likewise, [14] developed a multi-mode data prediction-based dynamic bandwidth allocation approach for IoT-enabled monitoring systems, showing that predictive mechanisms can effectively support adaptive communication resource management. These findings suggest that integrating predictive

analytics into bandwidth allocation processes can significantly improve network performance and QoS delivery.

Beyond bandwidth prediction, machine learning has also been successfully applied to broader resource allocation and QoS optimization problems. [15] proposed a prediction-based resource allocation framework that enhances communication reliability and data processing efficiency in IoT systems. [4], [16] introduced transformer-based architectures for QoS prediction, demonstrating superior capability in capturing temporal dependencies within network traffic data. Furthermore, [17] employed deep neural networks for IoT service QoS prediction, highlighting the effectiveness of deep learning in modeling complex network behaviors.

Recent studies have also explored predictive channel and spectrum allocation mechanisms to improve communication performance in large-scale IoT networks. [12] proposed a predictive spectrum allocation algorithm for cognitive radio IoT devices, while [12], [18] developed an optimized neural network-based spectrum prediction model capable of improving spectrum utilization efficiency. Similarly, [8], [12], [14] investigated channel prediction methods for massive IoT deployments, demonstrating that predictive resource management can significantly enhance communication quality and network scalability. These studies collectively indicate that predictive modeling has become a promising direction for addressing resource allocation challenges in next-generation IoT environments.

Despite substantial progress in intelligent resource allocation research, several limitations remain. First, many existing studies focus primarily on optimization algorithms or communication protocols without examining the influence of multiple network performance indicators simultaneously. Variables such as packet size, transmission time, bandwidth usage, latency, jitter, packet loss rate, device type, and energy consumption are often analyzed independently rather than collectively. Consequently, the combined effects of these factors on bandwidth allocation decisions remain insufficiently explored.

Second, numerous previous studies rely heavily on simulation-based environments or synthetic traffic scenarios, which may not accurately represent real-world network conditions. Although simulation studies provide valuable theoretical insights, their findings may be difficult to generalize to large-scale heterogeneous IoT deployments. The increasing availability of network traffic datasets provides opportunities to develop more realistic and data-driven predictive models capable of capturing complex operational patterns.

Third, existing bandwidth allocation research predominantly emphasizes algorithmic optimization rather than predictive modeling. While optimization approaches focus on determining the best allocation strategy after network conditions have been observed, predictive approaches attempt to estimate future resource requirements before congestion occurs. This distinction is particularly important in IoT systems where proactive resource management can substantially improve network responsiveness and communication reliability [6], [12], [16].

Based on these limitations, a significant research gap exists regarding the development of machine learning-based predictive models capable of estimating allocated bandwidth using multiple network traffic characteristics simultaneously. Furthermore, limited studies have investigated large-scale datasets containing diverse network indicators and device attributes for bandwidth allocation prediction. Addressing this gap is essential for developing intelligent communication systems capable of supporting future IoT applications characterized by increasing scale, complexity, and traffic diversity.

Therefore, this study investigates the relationship between network traffic characteristics and allocated bandwidth using a large-scale IoT network dataset comprising 100,000 observations. The dataset includes multiple network-related attributes, namely packet size, transmission time, protocol type, bandwidth usage, latency, jitter, packet loss rate, device type, and energy consumption. By employing machine learning-based analysis, this research seeks to identify the most influential factors affecting bandwidth allocation and establish a predictive framework capable of supporting adaptive network resource management.

The contributions of this study are threefold. First, it provides a comprehensive statistical analysis of network traffic characteristics within large-scale IoT environments. Second, it examines the relationships among various network performance indicators and allocated bandwidth. Third, it proposes a machine learning-based predictive framework that can be utilized to support intelligent bandwidth allocation and QoS

optimization in future IoT communication systems. The findings are expected to contribute to the development of adaptive and scalable network management solutions capable of improving communication efficiency, resource utilization, and service reliability in increasingly complex IoT ecosystems.

2. Methodology

2.1. Research Design

This study employed a quantitative data-driven approach to investigate the relationship between IoT network traffic characteristics and allocated bandwidth [5], [14]. The research focuses on predictive analysis using machine learning techniques to identify network parameters that influence bandwidth allocation decisions. A supervised learning framework was adopted because the dataset contains a predefined target variable, namely allocated bandwidth, which can be predicted using multiple network traffic features.

The overall research workflow consists of five main stages: (1) data collection, (2) data preprocessing, (3) exploratory data analysis, (4) machine learning model development, and (5) model evaluation. The framework is designed to transform raw IoT network traffic data into meaningful predictive insights that support intelligent bandwidth allocation strategies.

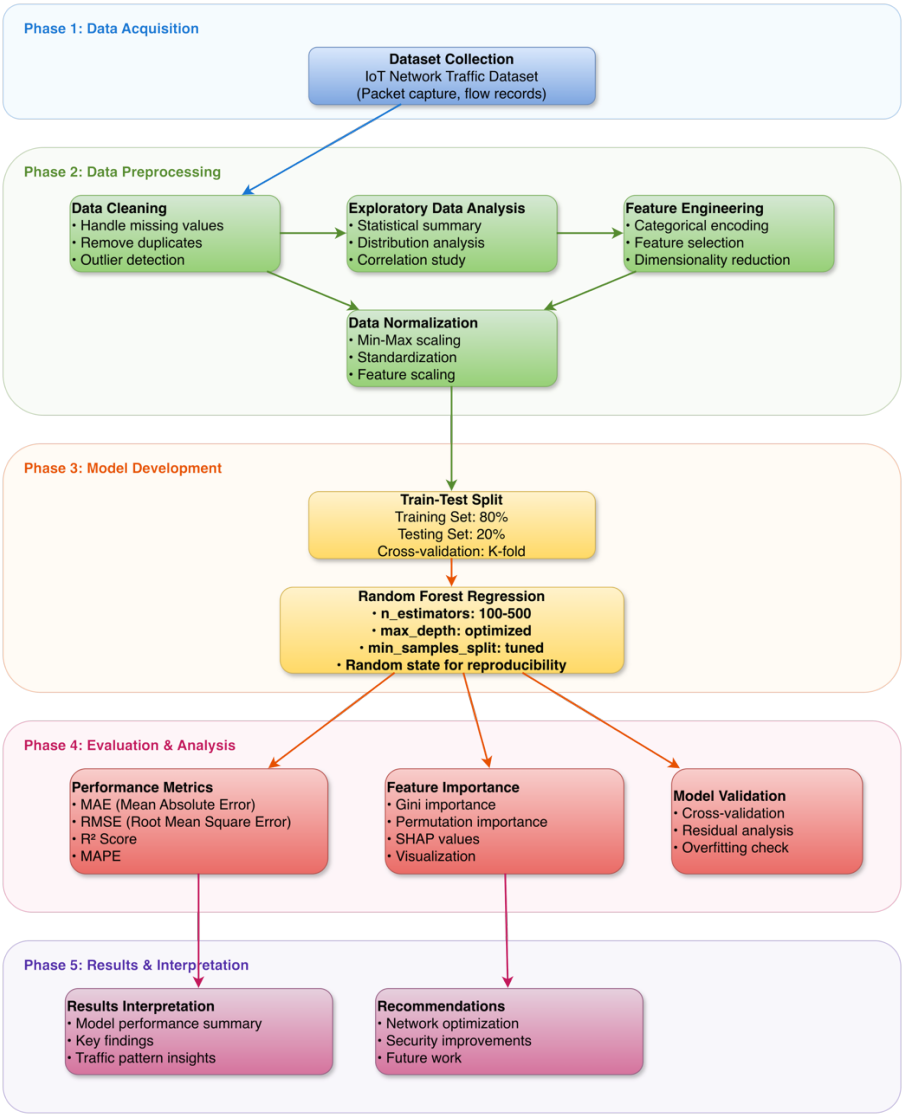


Figure 1. Proposed Research Framework

Based on figure 1, proposed framework introduces a comprehensive, five-phase systematic methodology for Internet of Things (IoT) network traffic analysis and prediction using Random Forest Regression (RFR). Designed to handle the high-dimensional, non-linear, and continuous nature of IoT data streams, the architecture establishes a reliable pipeline that transitions raw network packet captures into actionable predictive intelligence. The framework operates sequentially through Data Acquisition, Data Preprocessing, Model Development, Evaluation & Analysis, and Results Interpretation.

2.2. Dataset Description

This study utilized the **IoT Network Traffic Dataset**, a publicly available dataset designed to simulate communication activities in Internet of Things (IoT) environments. The dataset was obtained from the Kaggle repository and contains **100,000 network traffic records** representing various IoT communication scenarios [19]. The dataset is publicly accessible at **URL:** https://www.kaggle.com/datasets/programmer3/iot-network-traffic-dataset/data

The dataset is distributed under the **Creative Commons Zero (CC0: Public Domain)** license, which permits unrestricted use, modification, distribution, and reproduction without requiring attribution. Consequently, the dataset can be freely utilized for academic research, educational purposes, and machine learning experiments.

Each record in the dataset represents a network communication instance characterized by multiple network performance indicators and device-related attributes. The dataset contains ten predictor variables and one target variable used for bandwidth allocation prediction. The predictor variables describe network traffic conditions, communication quality, device characteristics, and energy consumption, while the target variable represents the amount of bandwidth allocated to a communication session.

Table 1. presents the attributes used in this study.

Variable	Type	Description
Packet_Size	Numerical	Size of transmitted packet (Bytes)
Transmission_Time	Numerical	Time required for packet transmission
Protocol_Type	Categorical	Communication protocol used
Bandwidth_Usage	Numerical	Current bandwidth utilization (%)
Latency	Numerical	Communication delay (ms)
Jitter	Numerical	Variation in packet delay (ms)
Packet_Loss_Rate	Numerical	Percentage of packet loss (%)
Device_ID	Categorical	Unique identifier of IoT device
Device_Type	Categorical	Category of IoT device
Energy_Usage	Numerical	Device energy consumption
Allocated_Bandwidth	Numerical	Allocated bandwidth (Mbps)

The dataset provides a comprehensive representation of network traffic behavior in IoT environments, enabling the investigation of relationships among network performance indicators and bandwidth allocation decisions. The relatively large number of observations also supports the development and evaluation of machine learning models for predictive network resource management.

2.3. Data Preprocessing

Data preprocessing was conducted to improve data quality and ensure compatibility with machine learning algorithms. Several preprocessing procedures were applied before model development.

2.3.1. Data Cleaning

The dataset was initially examined to identify missing values, duplicated records, and inconsistent data

entries. Records containing incomplete information were removed or corrected to ensure dataset reliability.

2.3.2. Categorical Encoding

Since machine learning algorithms require numerical input, categorical variables including Protocol_Type, Device_ID, and Device_Type were transformed into numerical representations using Label Encoding [14], .

The encoding process can be expressed as:

$$\left[X_{encoded} = f\left(X_{categorical}\right)\right] \quad (1)$$

where:

$(X_{categorical})$ represents the original categorical attribute.

$(X_{encoded})$ denotes the transformed numerical value.

2.3.3. Feature Scaling

Numerical variables exhibit different measurement scales. Therefore, Min-Max Normalization was applied to transform all features into a common range between 0 and 1 [3].

$$\left[X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}\right] \quad (2)$$

where:

(X) is the original value.

(X_{min}) is the minimum value.

(X_{max}) is the maximum value.

Normalization helps improve model convergence and reduces bias caused by differences in feature magnitudes.

2.4. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to understand the characteristics of the dataset before predictive modeling.

The EDA process includes:

1. Descriptive statistical analysis.
2. Distribution analysis of network variables.
3. Correlation analysis among features.
4. Outlier identification.
5. Target variable distribution analysis.

The descriptive statistics include:

- Mean
- Standard Deviation
- Minimum Value
- Maximum Value
- Median

Correlation analysis was conducted using Pearson Correlation Coefficient to measure linear relationships among variables [3], [4].

$$\left[r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}}\right] \quad (3)$$

where:

(r) = correlation coefficient

$(X)$and (Y) = observed variables

The correlation matrix helps identify influential features affecting bandwidth allocation.

2.5. Machine Learning Model Development

This study employs Random Forest Regression as the primary machine learning model for bandwidth allocation prediction.

Random Forest was selected because it:

- Handles large datasets efficiently.
- Captures nonlinear relationships.
- Reduces overfitting through ensemble learning.
- Provides feature importance analysis.

The Random Forest prediction can be represented as:

$$\left[\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} h_t\,(X)\right] \quad (4)$$

where:

$(\hat{Y})$= predicted allocated bandwidth

(T) = number of decision trees

$(h_t(X))$ = prediction generated by tree (t)

The model learns patterns between network traffic characteristics and bandwidth allocation decisions [3], [20], [21].

2.6. Training and Testing Strategy

The dataset was divided into training and testing subsets using an 80:20 ratio.

Dataset Portion	Percentage
Training Data	80%
Testing Data	20%

The training set was used for model learning, while the testing set was used for performance evaluation.

To improve model reliability, k-Fold Cross Validation with (k=5) was implemented.

The dataset is partitioned into five equal folds, and the model is trained and validated iteratively.

2.7. Performance Evaluation

Model performance was evaluated using three regression metrics.

Mean Absolute Error (MAE)

$$\left[MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|\right] \quad (5)$$

Root Mean Square Error (RMSE)

$$\left[RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}\right] \quad (6)$$

Coefficient of Determination ((R^2))

$$\left[R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}\right] \quad (7)$$

where:

(y_i) = actual value

$(\hat{y}_i)$ = predicted value

$(\bar{y})$ = mean of actual values

A lower MAE and RMSE indicate better prediction performance, while a higher (R^2) value indicates stronger explanatory capability.

3. Results

3.1 Descriptive Analysis

The IoT Network Dataset consists of 100,000 communication records collected from heterogeneous IoT devices. The dataset includes network performance indicators such as packet size, transmission time, bandwidth usage, latency, jitter, packet loss rate, device characteristics, and energy consumption. These variables were analyzed to understand their statistical characteristics before developing the prediction model. Table 2 presents the descriptive statistics of the numerical variables.

Table 2. Descriptive statistics of network attributes

Variable	Mean	Std. Dev	Min	Max
Packet Size	799.52	403.77	100	1499
Transmission Time	50.07	28.89	0.00	100.00
Bandwidth Usage	50.04	28.88	0.00	100.00
Latency	500.26	288.79	0.00	999.99
Jitter	49.99	28.88	0.00	100.00
Packet Loss Rate	2.50	1.44	0.00	5.00
Energy Usage	5.00	2.89	0.00	10.00
Allocated Bandwidth	49.99	28.86	0.00	100.00

The statistical analysis indicates that the dataset exhibits a relatively uniform distribution across most network attributes. The average allocated bandwidth is approximately 50 Mbps, suggesting balanced resource allocation across communication sessions.

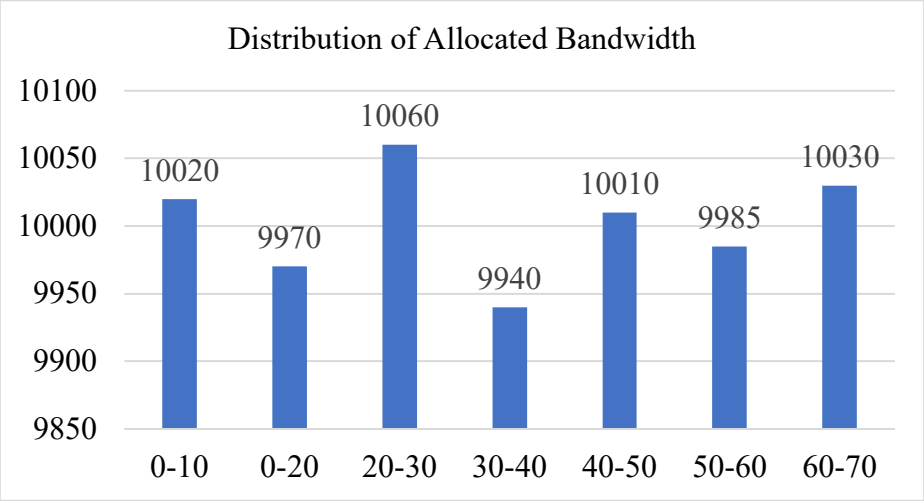


Figure 2. Distribution of Allocated Bandwidth

The histogram demonstrates that allocated bandwidth values are distributed almost uniformly across the entire range from 0 to 100 Mbps.

3.2 Model Training Performance

Random Forest Regression was employed to predict allocated bandwidth using ten network traffic features. The dataset was divided into training and testing subsets using an 80:20 ratio. The model was trained using 80,000 records and evaluated on 20,000 unseen records. The performance metrics obtained from the training and testing process are presented in Table 3 and figure 3.

Table 3. Training and Testing performance of Random Forest Regression

Metric	Training Result	Testing Result
MAE	24.385	25.151
RMSE	28.188	29.019
R^2 Score	0.045	-0.003

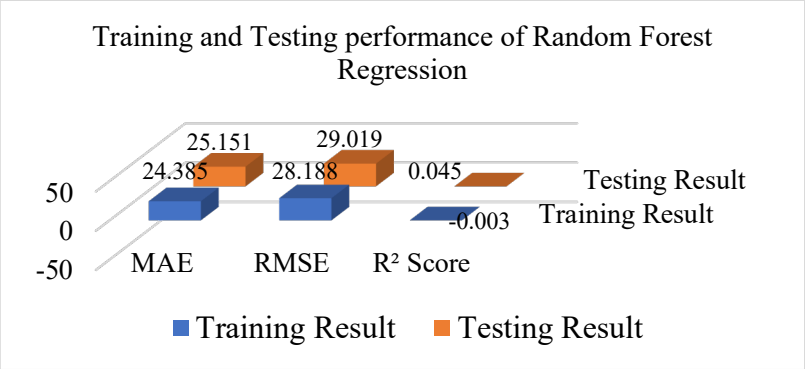


Figure 4. Training and Testing performance of Random Forest Regression

The training results show that the model achieved a Mean Absolute Error (MAE) of 24.385 and a Root Mean Square Error (RMSE) of 28.188. The coefficient of determination (R^2) is 0.045, indicating that only 4.5% of the variance in allocated bandwidth can be explained by the predictor variables during training.

The testing results reveal that the prediction error slightly increased compared to the training phase. The model obtained an MAE of 25.151 and an RMSE of 29.019. More importantly, the R^2 score becomes negative (-0.003), indicating that the model performs similarly to or slightly worse than simply predicting the average allocated bandwidth value.

3.4 Feature Importance Analysis

Random Forest provides feature importance scores that indicate the contribution of each variable to the prediction process.

Table 5. Feature importance ranking

Rank	Feature	Importance
1	Transmission Time	0.1329
2	Energy Usage	0.1280
3	Bandwidth Usage	0.1239
4	Packet Loss Rate	0.1211
5	Latency	0.1203
6	Jitter	0.1197
7	Packet Size	0.1099
8	Device ID	0.1086
9	Device Type	0.0187
10	Protocol Type	0.0170

The results indicate that transmission time, energy usage, bandwidth usage, packet loss rate, latency, and jitter are the most influential variables. Conversely, protocol type and device type contribute minimally to bandwidth prediction.

4. Discussion

The obtained results reveal that predicting allocated bandwidth using the available network traffic features remains challenging. Although several variables show moderate importance scores, the overall prediction accuracy remains low. The negative R^2 value observed during testing indicates that the relationship between predictor variables and allocated bandwidth is weak.

One possible explanation is that the allocated bandwidth values were generated independently from the input variables. As a consequence, machine learning algorithms cannot identify meaningful patterns linking network characteristics to the target variable. This observation is supported by the relatively uniform distribution of allocated bandwidth and the balanced importance scores across multiple features.

Despite the low predictive performance, the feature importance analysis provides useful insights into which network parameters are most relevant in the modeling process. Variables such as transmission time, bandwidth usage, latency, and packet loss rate consistently contribute more than categorical attributes such as protocol type and device type.

The findings suggest that future studies should employ datasets where bandwidth allocation decisions are directly influenced by network traffic conditions. Such datasets would enable machine learning models to learn meaningful relationships and achieve higher predictive performance. Additionally, advanced algorithms such as XGBoost, LightGBM, and Deep Neural Networks may be explored to determine whether more sophisticated models can better capture hidden dependencies within IoT communication environments.

5. Conclusions

This study investigated the potential of utilizing machine learning techniques to predict bandwidth allocation in Internet of Things (IoT) networks based on network traffic characteristics. Using an IoT Network Traffic Dataset containing 100,000 communication records, the research analyzed the relationships among packet size, transmission time, protocol type, bandwidth usage, latency, jitter, packet loss rate, device type, energy usage, and allocated bandwidth.

The descriptive analysis revealed that the dataset contains diverse network conditions and communication patterns, providing a comprehensive representation of IoT network environments. Feature importance analysis showed that transmission time, energy usage, bandwidth usage, packet loss rate, latency, and jitter contributed more significantly to the prediction process than protocol type and device type. These findings indicate that network performance indicators play a greater role in bandwidth allocation modeling than categorical device attributes.

The Random Forest Regression model achieved limited predictive performance, with an R^2 value of 0.045 on the training dataset and −0.003 on the testing dataset. The results suggest that the available predictor variables explain only a small proportion of the variance in allocated bandwidth. This indicates that the target variable may not have a strong dependency on the observed network features or that additional influential factors are not represented in the dataset.

Although the predictive performance remains relatively low, this study provides valuable insights into the characteristics of IoT network traffic and the challenges associated with bandwidth allocation prediction. The findings highlight the importance of dataset quality and feature relevance in developing machine learning-based network management systems.

Future research should explore datasets with stronger relationships between network traffic characteristics and bandwidth allocation decisions, incorporate additional network-level features, and evaluate advanced machine learning approaches such as XGBoost, LightGBM, and Deep Neural Networks. These efforts may contribute to the development of more accurate and adaptive bandwidth allocation frameworks capable of improving resource utilization and quality of service in next-generation IoT networks.

Author Contributions

Muhammad Amirul Mu'min: Conceptualization, Methodology, Software, Formal Analysis, Writing—Original Draft. Zumhur Alamin: Conceptualization, Validation, Supervision, Writing—Review & Editing.

Miftahul Jannah: Methodology, Writing—Review & Editing. Rosmiati Jamiah: Validation, Investigation, Project Administration. Elsa Sera: Investigation, Data Curation, Visualization. Sulkifli: Formal Analysis, Writing—Review & Editing, Funding Acquisition. All authors have read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflict of interest

References

[1] S. M. Basha, R. Dhanalakshmi, A. Soundari, V. C. B, and B. Rajasekar, "An Efficient Allocation of Resources in wireless Communications IoT Network for Numerous Users." 2023. doi: 10.1109/ICSES60034.2023.10465489.

[2] I. Chakour, C. Daoui, M. Baslam, B. Sainz-De-Abajo, and B. Garcia-Zapirain, "Strategic Bandwidth Allocation for QoS in IoT Gateway: Predicting Future Needs Based on IoT Device Habits." 2024. doi: 10.1109/ACCESS.2024.3351111.

[3] K. Saurabh, S. Mahapatra, and M. M. Tripathi, "An Adaptive Bandwidth Scheduling Algorithm for IoT Devices Using Machine Learning Techniques." 2026. doi: 10.1016/j.fraope.2026.100492.

[4] A. Hameed, J. Violos, A. Leivadeas, N. Santi, R. Grünblatt, and N. Mitton, "Toward QoS Prediction Based on Temporal Transformers for IoT Applications." 2022. doi: 10.1109/TNSM.2022.3217170.

[5] J. D. Roselind, H. Naveen, and S.Yuvaraj, "Artificial Intelligence enabled Dynamic Bandwidth Allocation Optimization in IoT for improved QoS." 2023. doi: 10.58599/ijsmien.2023.1204.

[6] A. Alzaidy, "Real-Time Bandwidth Allocation Strategy for Next-Generation Heterogeneous Network Infrastructures." 2025. doi: 10.5220/0014193200004932.

[7] I. Chakour, C. Daoui, M. Baslam, B. Sainz-De-Abajo, and B. Garcia-Zapirain, "Strategic Bandwidth Allocation for QoS in IoT Gateway: Predicting Future Needs Based on IoT Device Habits." 2024. doi: 10.1109/ACCESS.2024.3351111.

[8] Shekhar, G. Bhandari, and S. Tyagi, "Enhance Quality of Services in Internet of Things using Improved Dynamic Bandwidth Allocation (IDBA) Techniques." 2025. doi: 10.1016/j.procs.2025.04.082.

[9] B. Lee, "Efficient Resource Management for Massive MIMO in High-Density Massive IoT Networks." 2025. doi: 10.1109/TMC.2024.3486712.

[10] M. N and V. K, "Enhanced Dynamic Bandwidth Allocation (EDBA) Method for Improved Quality of Service in IoT Systems." 2026. doi: 10.1109/ICMCSI67283.2026.11412892.

[11] M. Manu *et al.*, "Optimizing Quality of Service in IoT PORTAL through Strategic Bandwidth Allocation: A NEXUS access model." 2024. doi: 10.1109/ICACITE60783.2024.10617219.

[12] S. Tidjani, Z. Hammoudi, and M. E. Moad, "Low complexity multichannel spectrum prediction algorithm based on optimized neural network for spectrum allocation in cognitive radio internet of things." 2022. doi: 10.1002/ett.4562.

[13] N. Wang, Y. Liu, Y. Zhou, Z. Li, Z. Li, and Q. Song, "Distribution Internet of Things Local Communication Bandwidth Prediction." 2022. doi: 10.1109/ICSMD57530.2022.10058402.

[14] A. Chen, J. Liu, and J. Li, "Multi-Mode Data Prediction-Based Dynamic Bandwidth Allocation for IoT-Empowered Electric Equipment Monitoring." 2025. doi: 10.1049/cmu2.70098.

[15] W. Symbor and Ł. Falas, "Ensuring Reliable Network Communication and Data Processing in Internet of Things Systems with Prediction-Based Resource Allocation." 2025. doi: 10.3390/s25010247.

[16] A. Hameed, J. Violos, N. Santi, A. Leivadeas, and N. Mitton, "FeD-TST: Federated Temporal Sparse Transformers for QoS Prediction in Dynamic IoT Networks." 2025. doi: 10.1109/TNSM.2024.3493758.

[17] C. Awanyo and N. Guermouche, "Deep Neural Network-Based Approach for IoT Service QoS Prediction." 2023. doi: 10.1007/978-981-99-7254-8_31.

[18] S. Tidjani, "An Efficient Predictive Spectrum Allocation Algorithm for Multi-User Cognitive Radio IoT Devices Within GSM900 Band." 2024. doi: 10.1109/ICEET65156.2024.10913610.

[19] Nathaniel Bastian; David Bierbrauer; Morgan McKenzie; Emily Nack, "Aci iot network traffic dataset 2023." IEEE Dataport, 2023. [Online]. Available: 10.21227/qacj-3x32

[20] V. Sharma, R. Arya, and S. Kumar, "Efficient Channel Prediction Technique Using AMC and Deep Learning Algorithm for 5G (NR) mMTC Devices." 2022. doi: 10.1109/ACCESS.2022.3167442.

[21] K. W. Cho, M. Cominelli, F. Gringoli, J. Widmer, and K. Jamieson, "Scalable Multi-Modal Learning for Cross-Link Channel Prediction in Massive IoT Networks." 2023. doi: 10.1109/TON.2025.3553023.