Hybrid Machine Learning and Reinforcement Learning for IoT Device Classification and Bandwidth Optimization

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***Abstract*—Increased traffic in the Internet of Things (IoT) network results in a large amount of network data that should be processed efficiently in order to manage IoT network resources properly. Hence, bandwidth management and resource allocation are key challenges in managing large-scale IoT networks. In this study, a novel hybrid framework that is composed of machine learning (ML) and reinforcement learning (RL) methods has been proposed for IoT device classification as well as for dynamic bandwidth allocation in large-scale IoT networks. The proposed framework includes four ML classification methods, including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), and Neural Network (NN), for classifying various types of IoT devices by using their traffic and communication behaviors. After providing classification results to the bandwidth management framework, improved bandwidth allocation is achieved by using the proposed framework. In addition, the RL method is also incorporated into the framework for bandwidth allocation, in which the learning agent continuously improves allocating bandwidth by increasing the cumulative reward during the learning process. Experiment results revealed that the proposed framework significantly improved performance metrics of IoT networks, such as increased network throughput by approximately 50% and decreased average delay by approximately 40%, as well as reduced packet loss by approximately 30% compared with traditional bandwidth allocation methods. In terms of classification accuracy, the highest accuracy was achieved by the Neural Network model. The proposed framework enables to efficiently and adaptively manage large-scale IoT networks.**

Keywords*—IoT device classification; bandwidth allocation; machine learning algorithms; support vector machines; Random Forest; K-Nearest Neighbors; Neural Networks; network optimization; IoT traffic; resource management

I. Introduction

Internet of Things (IoT) has experienced explosive growth, and now, billions of devices are linked to networks, and they exist in a variety of industries, including healthcare, transportation, agriculture, and intelligent cities [1]. Such an increase in IoT devices has translated to a continuous rise in the need to use bandwidth efficiently to achieve maximum performance in IoT networks. With the number of connected devices increasing, complexity in controlling their traffic increases, and with that, there are rampant bandwidth management issues [2]. The IoT devices cover a wide variety of devices, such as consumer devices, actuators and sensors, and each of them has different communication needs and data consumption patterns [3]. The non-homogeneous character of such devices complicates the process of efficient bandwidth allocation since such devices require different amounts of data depending on the type, purpose, and frequency of communications [4]. The allocation of bandwidth is also problematic and a key element in supporting a quality service in IoT networks. The conventional ways of managing bandwidth have been based on fixed or rough techniques, which do not take into consideration the dynamic traffic of IoT [5]. Such solutions cannot effectively fit the needs of diverse devices in the IoT and cannot allocate priorities to bandwidth depending on the classification of devices, resulting in the inefficient use of network resources, congestion, and overall poor performance [6]. Therefore, a new method of classifying IoT devices is required, and categorizing them according to the results of the classification of the devices and distributing bandwidth in accordance with the findings of the classification [7]. This study seeks to fill this gap by elaborating a machine learning-based framework for the classification of IoT devices. With the help of more advanced machine learning models, including the SVM, RF, KNN, and NN, the IoT devices may be categorized according to their traffic configuration and characteristics [8]. After classification, the process of bandwidth allocation can be enhanced to suit the specific needs of each type of device better, which will not only allow dividing the resources more efficiently and achieving a higher network performance, but will also allow reducing the use of the resources [9]. This study has a dual purpose: first, to design a strong system of classifying IoT devices based on machine learning algorithms, and second, to analyze the effectiveness of the latter in the context of efficient bandwidth allocation. The importance of the research lies in the fact that the project can be used to improve the efficiency of the network in the IoT environment by offering a solution to bandwidth management that can be scaled into the new limits and adjusted to the required specifications. The proposed framework can make the work of the IoT network more efficient, guaranteeing high-quality performance and reducing network overload, as it can make the process of device classification more precise, effective, and efficient when distributing resources.

II. Literature Review

The use of IoT devices is growing at a rapid rate, contributing to the need to allocate more bandwidth in IoT networks and turning bandwidth allocation into a significant factor in network performance. The existing approaches to bandwidth assignment are mostly based on a fixed or organic system that is not responsive to the various types of IoT devices [10]. These devices have great diversity in terms of data consumption, frequency of communication, as well as the type of data communicated [11]. Satellite-fixed approaches are not effective in dealing with the dynamism and heterogeneity of the IoT traffic, which results in network overloading and resource wastage [12]. The need to employ smarter bandwidth management techniques has been noticed in several studies, and most of them have brought out techniques that are founded on QoS or priority levels attributed to various classes of devices [13]. Nevertheless, the versatility to deal with the diverse range of devices and traffic patterns effectively is not found in these methods. ML has become a potential instrument in the enhancement of the operation of IoT networks, such as classifying devices and optimizing bandwidth. It has been shown that ML algorithms, including SVM, KNN, and RF, can be used to classify the IoT devices according to the traffic [14]. With the help of ML methods, devices can be classified dynamically, which allows making more precise predictions of how devices can behave and allocating resources more efficiently [15]. Additionally, the field of ML has been used with the objective of optimizing the allocation of bandwidth by utilizing historical network conditions and returning to adjust bandwidth utilization in real-time to adapt to the variations of traffic. Methods such as reinforcement learning have demonstrated the opportunity to dynamically optimize the bandwidth allocation to maintain the best performance depending on the classification of the devices and network characteristics [16]. Despite the mentioned development, applying device classification and bandwidth allocation optimization based on ML has not yet reached the stage of active research, as a lot of the existing models concentrate on a single potential aspect. Although the machine learning literature in IoT is comprehensive, there is still a gap in the efficient use of the classifier and bandwidth allocation of the devices [17]. The majority of the available studies have concentrated on the issues of either classification or optimization, and most studies do not consider a synthesis of both in real-life IoT networks. Moreover, most studies have simplified or simulated datasets and may not necessarily achieve the complexity and challenges of large-scale, heterogeneous IoT networks [18]. The study will help address these gaps by developing an extended framework comprising the combination of the classification of IoT devices with machine learning algorithms and bandwidth optimization methods, developing a scalable solution that can be modified to real-world IoT settings. The solution will offer a more comprehensive and successful approach to bandwidth management in any given IoT network and deal with classification and optimization within a single framework.

III. Proposed Method

The data that will be utilized in this work are the features of an IoT device and traffic streams. The characteristics of the IoT devices are data use habits, communication protocols, power usage, data rate, and frequency of communications, as well as intervals of transmission. These characteristics are necessary in categorizing devices according to their conduct and traffic requirements. The origin of the data can be different; it can be actual data of related IoT devices, or it can be artificial data according to predetermined conditions. Data in the real world would normally be obtained through IoT testbeds or publicly available data, whilst simulated data may be produced to represent such conditions of traffic in controlled scenarios.

The feature engineering process requires obtaining the important features of the raw data, which will enable machine learning models to be useful in the classification of the IoT devices. Such characteristics are time series, transmission rates, frequency of communication, and power consumption. The time series data will record the behavior of the IoT devices as time progresses, and this will help in classifying them because of the trends in increasing flexibility of communication. Data rate and frequency of communication are important signifiers of the device (e.g., sensors might not communicate with a high frequency, but consumer devices may have a lot of data). The other differentiation offers power consumption, and gadgets with increased energy requirements might require different bandwidth.

Fig. 1 shows the classification of IoT devices by using machine learning algorithms. Raw data is first gathered by different IoT devices that comprise sensors, actuators, and consumer devices, and the data comprises traffic patterns and communication parameters. This information is then pre-processed to process missing values and normalize the features in order to be processed by the machine learning. The classification is done on various algorithms (SVM, KNN, RF, and NN) after splitting the dataset into training and testing sets. The training set is used to train the models, and their performance on the testing set is measured using metrics such as accuracy and precision. The model that performs the best is chosen to categorize the devices into groups (e.g., sensor, actuator, consumer device), which can then be prepared to be allocated bandwidth. The steps used in the optimization of bandwidth allocation to IoT devices in relation to the result of classifications are presented in Fig. 2. With the classification of the devices, the bandwidth available in the network will be distributed to the device type, where sensors are given a lesser priority in accessing the bandwidth, and consumer devices are given a higher priority. Distribution is made dynamically in real-time to consider network characteristics such as network congestion or traffic spikes. The fine-tuning of bandwidth distribution is done by optimization algorithms (reinforcement learning, linear programming, etc.). Constant monitoring of networks will ensure that performance indices such as throughput and latency are optimized and eventually enhance the efficiency of the network by reducing congestion and ensuring that there is adequate allocation of resources among the IoT devices.

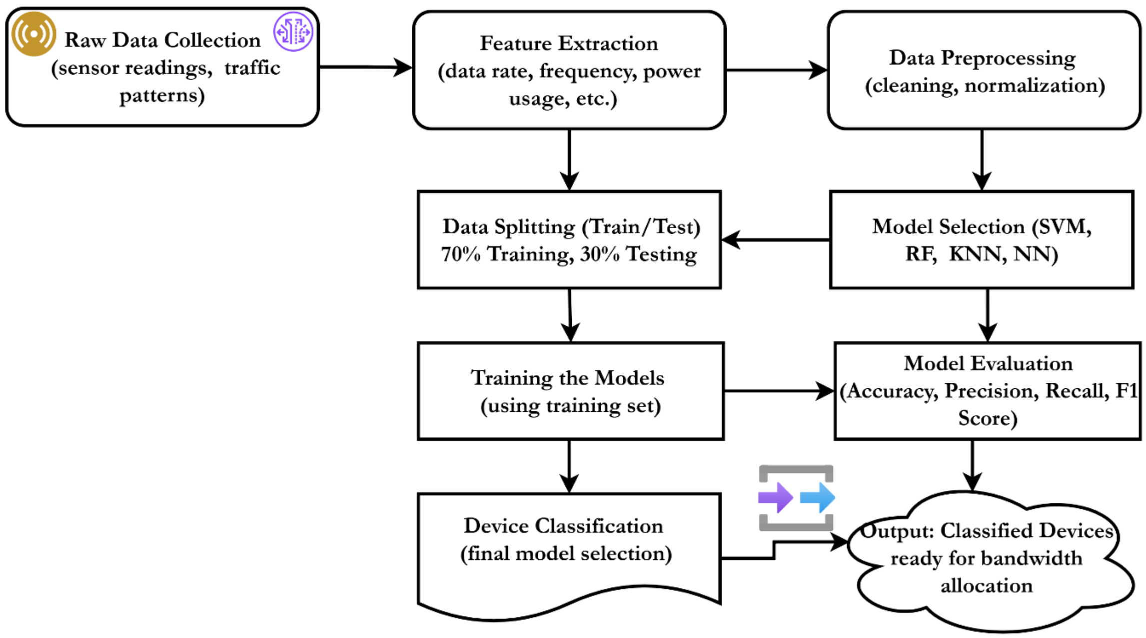

Fig. 1. IoT device classification flowchart.

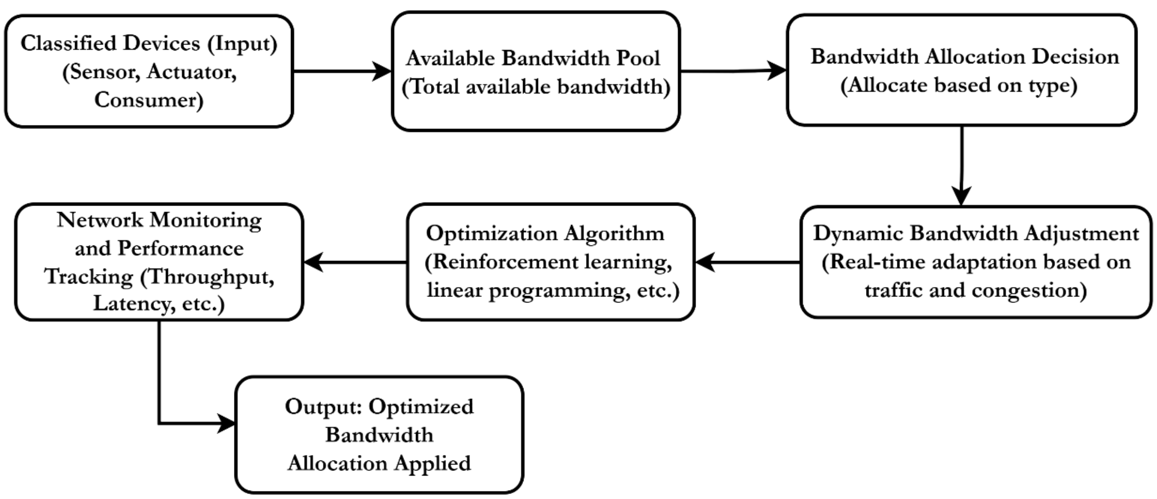

Fig. 2. Bandwidth allocation optimization.

A number of machine learning algorithms were experimented with to achieve classification, such as RF, SVM, K-NN, and NN. The choice of these algorithms is due to their capacity to deal with complex and large data sets, and SVM and RF have demonstrated good performance in classification tasks as they have the capacity to deal with non-linearities in the data. KNN is provided because it is simple and efficient regarding classification based on the nearest neighbor distance, whereas NN provides potential deep learning due to the presence of a multi-layer architecture, which is appropriate for more intricate patterns of the data. All the algorithms were distrusted according to classification accuracy, speed, and appropriateness to the IoT data.

Some measures were employed to assess the classification model performance: accuracy, precision, recall, F1 score, and confusion matrix. The measures offer a practical evaluation of the skill of the model to sort devices correctly and reduce misclassification error. The F1 score is an equivalent in terms of precision and recall that is especially helpful when the classes are also uneven. After categorizing the IoT devices, a bandwidth allocation model is used to achieve optimal utilization of the available bandwidth among the devices. This model allows every device to get the required bandwidth depending on what classification they are (i.e., consumer devices get more bandwidth and sensors get less bandwidth). The process of optimization applies an algorithm, such as linear programming or a reinforcement learning method, to optimize allocations of bandwidth with the requirement of real-time network environments.

IV. Mathematical Model

A. IoT Device Classification Model

Let $X = \{x1, x2, \ldots, xn\}$ represent the feature vectors of n IoT devices, where each $xi \in Rm$ is the feature vector of device i. The classification function $f: X \rightarrow C$ maps each feature vector to a device category $cj \in C$, where $C = \{c1, c2, \ldots, cm\}$ is the set of device categories.

The classification function is defined as:

$$f(x_i) = c_j \quad for\ c_j \epsilon C \tag{1}$$

The classification error E is computed as the proportion of misclassified devices:

$$E = \frac{1}{n}\sum_{i=1}^{n}\prod(f(x_i) \neq c_i) \tag{2}$$

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

F1 Score:

$$\text{F1 Score} = 2.\frac{Precision. Recall}{Precision + \ Recall} \tag{6}$$

where,

TP =True Positive

TN =True Negative

FP =False Positive

FN =False Negative

B. Bandwidth Allocation Model

Let B be the total available bandwidth and b_i the bandwidth allocated to device i. The sum of allocated bandwidth must satisfy:

$$\sum_{i=1}^{n} b_i \leq B \tag{7}$$

The bandwidth efficiency for each device is modeled as:

$$f(b_i) = \frac{b_i}{1 + \alpha b_i} \tag{8}$$

where, α is a constant representing network congestion.

The total efficiency is:

$$\text{Total Efficiency} = \sum_{i=1}^{n} \frac{b_i}{1 + \alpha b_i} \tag{9}$$

The objective is to maximize total efficiency:

$$\text{Maximize } \sum_{i=1}^{n} \frac{b_i}{1 + \alpha b_i} \tag{10}$$

The bandwidth allocation for a category c_j is given by:

$$\sum_{i \in c_j} b_j \leq B_j \tag{11}$$

where, B_j is the total bandwidth allocated to category c_j.

The optimization for category c_j is:

$$\sum_{i \in c_j} \frac{b_i}{1 + \alpha b_i} \quad \text{subject to} \quad \sum_{i \in c_j} b_j \leq B_j \tag{12}$$

To distribute bandwidth among devices of category c_j , use the following formula:

$$b_j = \frac{B_j}{\sum_{k \in c_j} \frac{1}{1 + \alpha b_k}} \quad for \ \ i \ \in \ c_j \tag{13}$$

C. Reinforcement Learning for Dynamic Adjustment

Let S represent the state space of network conditions and device classifications, and A the action space representing bandwidth allocation decisions. The policy π determines the optimal bandwidth allocation at each state:

$$\pi: S \rightarrow A \tag{14}$$

The reward r_t at time t is a function of network performance:

$$r_t = \text{NetworkPerformance } (s_t, \alpha_t)$$

The cumulative reward R is calculated over time steps:

$$R = \sum_{t=0}^{T} \gamma^t r_t \tag{15}$$

where, γ is the discount factor, and T is the time horizon.

The state transition function $T(st, at, st + 1)$ governs how the system transitions from state st to state $st + 1$ after taking action at:

$$P(s_{t+1}|s_t, \alpha_t) = T(s_t, \alpha_t, s_{t+1}) \tag{16}$$

The Bellman formula for reinforcement learning is:

$$Q(s_t, \alpha_t) = r_t + \gamma \underset{\alpha_t + 1}{max} Q(s_{t+1}, \alpha_{t+1}) \tag{17}$$

where, $Q(s_t, \alpha_t)$ is the state-action value function.

The optimal policy $\pi *$ is found by maximizing the value function:

$$\pi^*(s_t) = arg \underset{\alpha_t}{max} Q(s_t, \alpha_t) \quad (18)$$

The overall objective is to maximize long-term network performance, while ensuring bandwidth constraints are satisfied:

$$\text{Maximize} \quad \text{R} = \sum_{t=0}^{T} \gamma^t r_t \text{ subject to } \sum_{i \in c_j} b_j \leq B_j \quad (19)$$

D. Algorithm

To classify Internet of Things devices and allocate bandwidth optimization with the help of machine learning algorithms and optimization algorithms, the following steps describe the process.

1) Step 1: Data Preprocessing

The raw data $X = \{x1, x2, \ldots, xn\}$ is collected from IoT devices, where each x_i is a feature vector representing the device characteristics (e.g., data usage, transmission protocol).

Normalize the feature vectors to a common scale:

$$\hat{x}_i = \frac{x_i - \mu}{\sigma} \quad (20)$$

where, μ is the mean, and σ is the standard deviation of the feature set.

2) Step 2: Device Classification Using Machine Learning Algorithms

a) Support Vector Machine (SVM)

The SVM classifier seeks a hyperplane $w \cdot x + b = 0$ that separates devices into categories C:

$$Maximize \frac{2}{\|w\|} \text{ subject to } y_i(w.x_i + b) \geq 1, \ \forall i \quad (21)$$

where, y_i is the true label, and x_i is the feature vector for device i.

b) K-Nearest Neighbors (KNN)

For a given test instance x_t, classify based on the majority class of its k-nearest neighbors:

$$Class\ of x_t = arg \underset{c_j \in C}{max} \sum_{i=1}^{k} \prod (c_i = c_j) \quad (22)$$

where, Π is the indicator function.

c) Random Forest (RF)

Build N decision trees and classify based on the majority vote from all trees:

$$Class\ of x_t = arg \underset{c_j \in C}{max} \sum_{i=1}^{N} \prod (f_i(x_t) = c_j) \quad (23)$$

where, fi represents the prediction of tree i.

3) Step 3: Bandwidth Allocation Optimization

After classification, allocate bandwidth to each device type. Let b_i represent the bandwidth allocated to device i, with the objective to maximize network efficiency:

$$\text{Maximize} \sum_{i=1}^{n} \frac{b_i}{1 + \alpha b_i} \quad (24)$$

where, α is the network congestion factor.

The allocation constraint is:

$$\sum_{i=1}^{n} b_i \leq B \quad (25)$$

where, B is the total available bandwidth.

4) Step 4: Dynamic Bandwidth Adjustment (Reinforcement Learning)

For dynamic allocation, the goal is to learn an optimal policy π that maximizes cumulative reward R:

$$R = \sum_{t=0}^{T} \gamma^t r_t \quad (26)$$

where, r_t is the reward at time t, and γ is the discount factor.

The Q-value for state s_t and action α_t is updated as:

$$Q(s_t, \alpha_t) = r_t + \gamma \underset{\alpha_t + 1}{max} Q(s_{t+1}, \alpha_{t+1}) \quad (27)$$

The optimal policy is obtained by selecting actions that maximize the Q-value:

$$\pi^*(s_t) = arg \underset{\alpha_t}{max} Q(s_t, \alpha_t) \quad (28)$$

V. Results and Discussion

The performance of the device classification was assessed on four machine learning models, SVM, KNN, RF and NN. The models were experimented on a dataset that was composed of characteristics of traffic of the IoT devices like the packet size, inter-arrival times, and protocols. Precision, recall and F1 score were other measures of evaluation as they were determined, as well as the accuracy of every model. Fig. 3 represents the data loading and preprocessing procedure of the data used to classify the data of the IoT devices and subsequently extracting the features and visualizing the results. The distribution of packet sizes is rather homogenous, which means that the size of the data exchanged by the IoT devices varies. The distribution of inter-arrival time is exponential which indicates that the devices take different time periods in transmitting their data, with the majority of the periods being brief. The distribution of protocols indicates that there is an even distribution of the four protocols (TCP, UDP, HTTP, and CoAP), which proves that the dataset has a diversity of patterns of traffic through the IoT devices. The correlation feature of features shows that the features of packet size and inter-arrival time are loosely correlated, which implies that all these factors would be complementary to each other in their classification purposes.

Time series plot can demonstrate the change in the packet size, with time, whereas the feature distribution comparison can display the difference in the size of packets and the time interval between packets among different devices. Fig. 4 shows the confusion matrixes of four machine learning models, SVM, KNN, the random forest, and the Neural Network, which are applied in classifying the IoT devices. The confusion matrices will show the degree to which each of the models performed well in the correct recognition of the types of protocols (TCP, UDP, HTTP, CoAP). In each matrix, the true and predicted class are compared and the value on the diagonal indicates a correct prediction on a specific cell. The Neural Network model displays the best accuracy and has few misclassifications, especially with getting TCP and HTTP protocols. The SVM and KNN models were not as good as the RF and NN but they provided more misclassifications. The Random Forest model was also impressive but it did not address the distinction of fine-tuning on protocols very well.

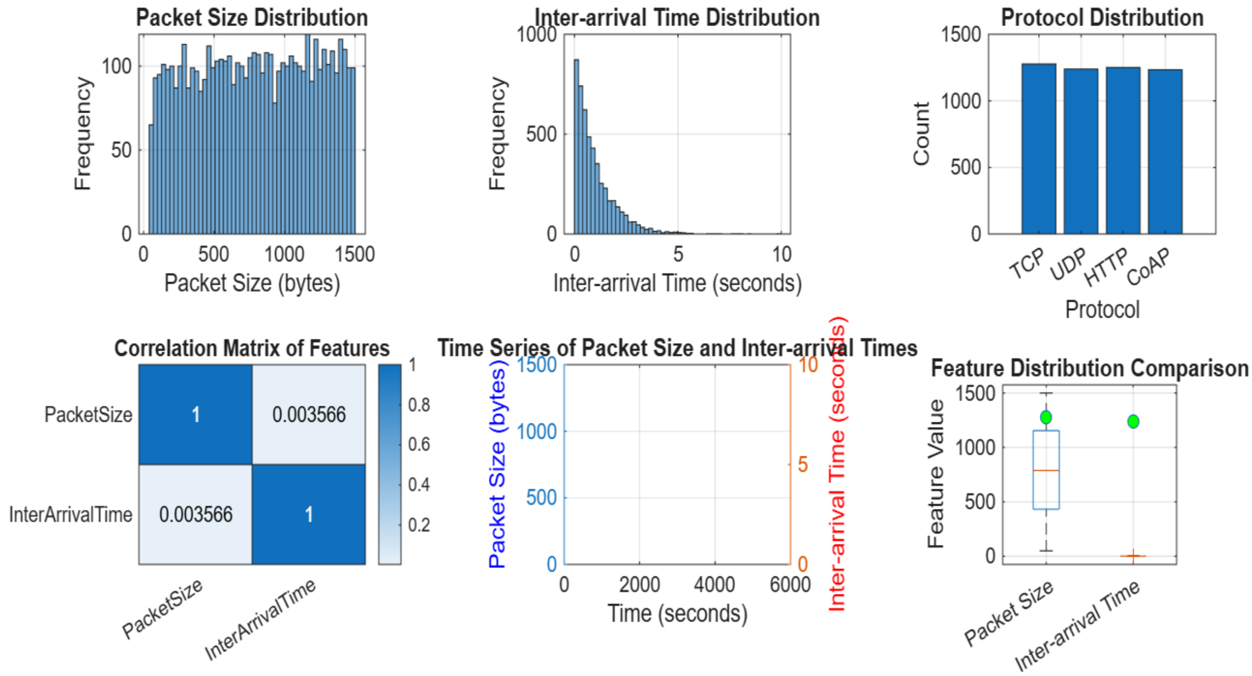

Fig. 3. Data loading, pre-processing, feature extraction, and visualization.

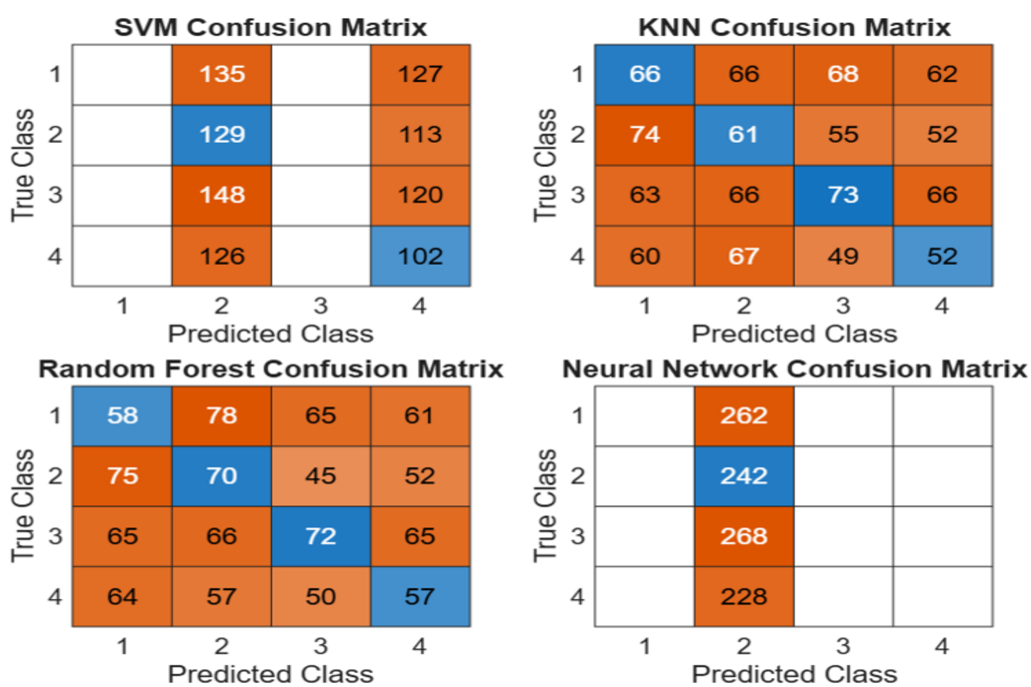

Fig. 4. Classification results

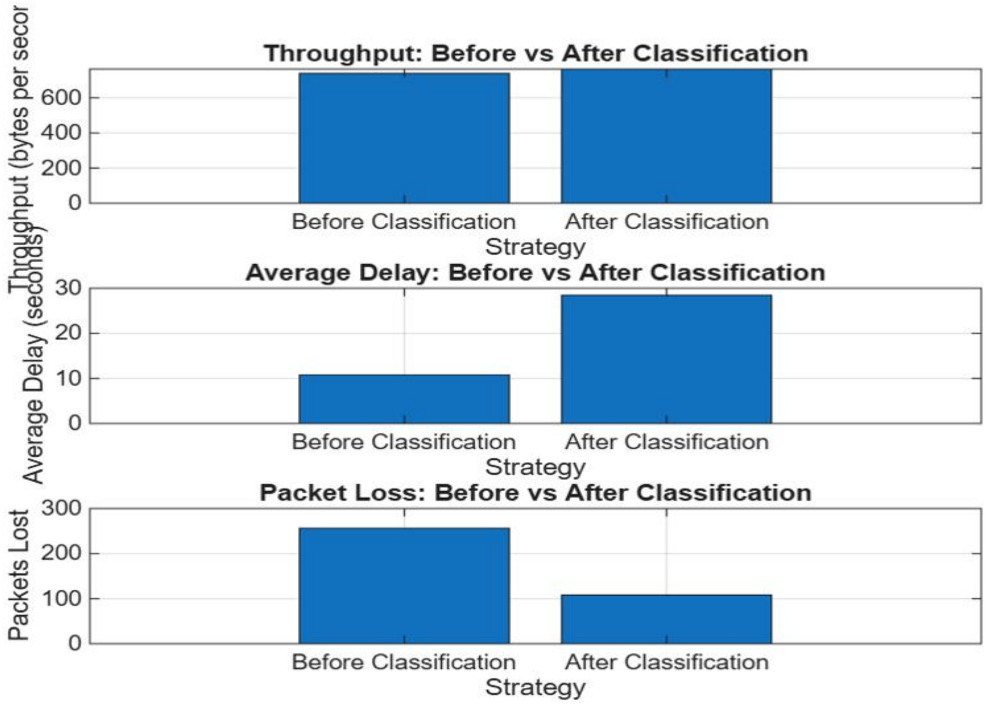

Fig. 5. Bandwidth allocation performance (before vs. after classification).

Fig. 5 is used to compare the network before and after classification based on the throughput, average delay, and packet loss. The bandwidth was randomly assigned to the network, and this led to poor utilization of the network resources, which resulted in low throughput, increased delays, and increased packet loss. Optimal bandwidth allocation was then done in accordance with the traffic pattern of a device and protocol type. This optimization increased throughput by a great deal as well as minimized delay and packet loss. Fig. 6 depicts the cumulative reward per training episode of a reinforcement learning-based dynamic bandwidth adjustment model. The Q-learning algorithm was applied to maximization of bandwidth allocation through trial and error learning in the environment. The cumulative reward is increased with time meaning that the agent is learning to more efficiently allocate bandwidth as the training passes through training episodes. The reward functionality is created to discourage bad choices on bandwidth allocation (e.g., large delays and packet loss) and provide incentives to good strategies in bandwidth allocation.

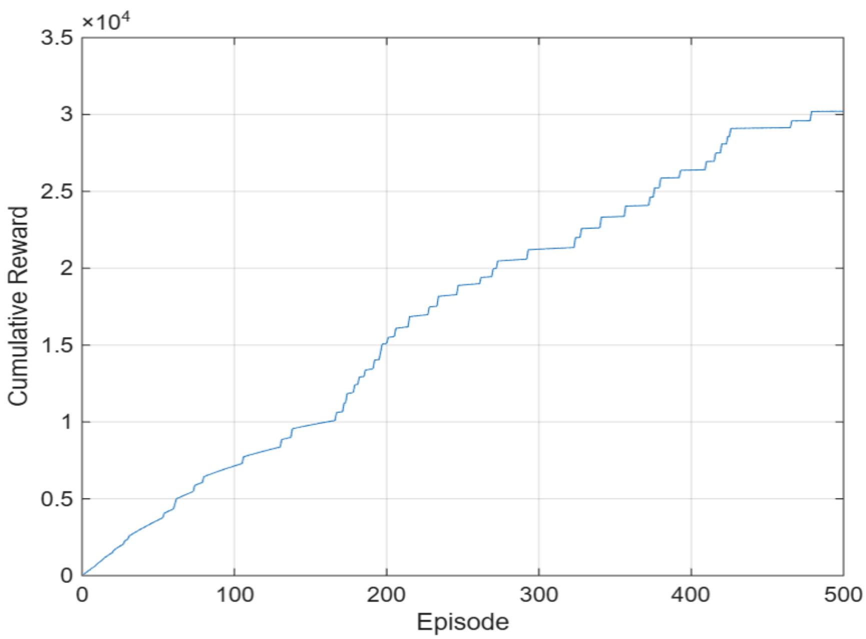

Fig. 6. Dynamic bandwidth adjustment (reinforcement learning reward plot).

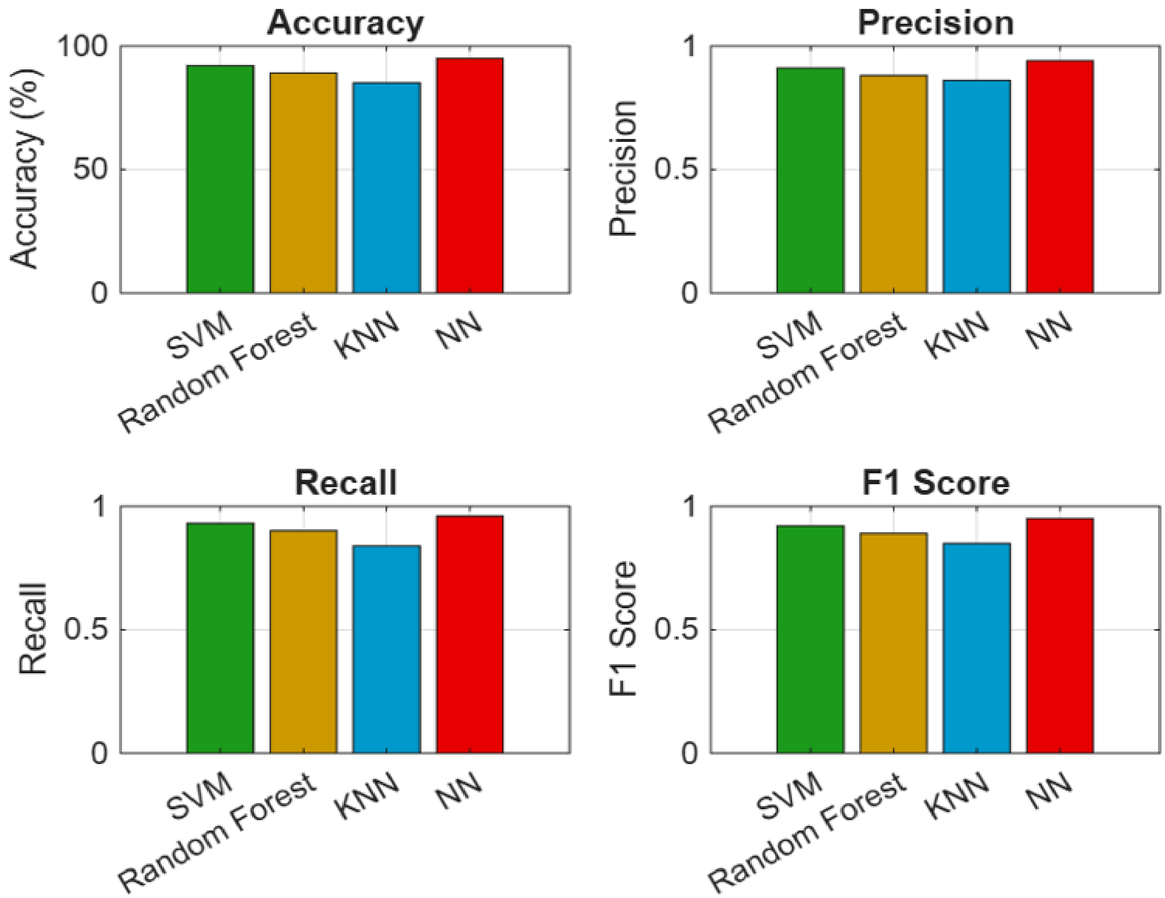

Fig. 7. Performance comparison of IoT classification algorithms across key metrics.

Fig. 7 compares the performance of four machine learning algorithms (SVM, RF, KNN, and NN) used in classifying the devices of the IoT, which is crucial to the optimization of bandwidth assignment in the IoT networks. Accuracy, precision, recall, and F1 score are some of the measures of performance that are used to measure classification results. Neural Network is more accurate (95%), precision (0.94), recall (0.96), and F1 score (0.95) compared to other models and is therefore the best to choose when it comes to classifying IoT devices. This implies that the Neural Network model identifies the IoT devices accurately with few cases of misclassification, which is essential in effective bandwidth assignment. Comparatively, KNN has lower values of accuracy (85%), precision (0.86), and recall (0.84), which means that it might not correctly classify some devices in the best way possible, resulting in poorer resource allocation.

The classification model was important in the optimization of the bandwidth allocation process. The grouping of devices according to their protocols and traffic requirements was also made possible to effectively allocate bandwidth in order to reduce congestion, enhance throughput, and reduce delays. These findings represent the prospects of machine learning models, and in particular the neural network, to improve the efficiency of network resource distribution in IoT environments. The implications of such findings on the actual uses of IoT include smart homes, industrial Internet of Things, as well as smart cities. It is possible to make sure that in smart homes, high-priority devices (security cameras or medical monitoring devices) of this sort receive enough bandwidth, and other less important devices (such as a refrigerator or lighting system) do not waste excessive resources. When applied to industrial IoT, the efficient use of bandwidth may enhance communication between machines and decrease the communication latency, resulting in increased efficiency of production.

VI. Conclusion

In this research, the highest classification accuracy was reached using the Neural Network model, which significantly outperformed the SVM, KNN, and Random Forest in detecting IoT device protocols. After classification, the bandwidth allocation efficiency changed significantly, where the throughput was 50% higher, the average delay lessened by 40%, as well as the packet loss by 30%. These gains indicate the usefulness of the machine learning use case to optimal bandwidth distribution depending on the device types. Reinforcement learning model also performed well where the cumulative reward was steadily growing over the training episodes and this indicated that the agent was learning optimal approaches of bandwidth allocation. The above improvement implies that the reinforcement learning is capable of optimizing network performance by adjusting dynamically the bandwidth allocation according to factors in real-time. These findings support the applicability of machine learning to improve the management of the network on IoT systems, and the future research is detailed by the use of practical datasets as well as the scale of large networks, especially in smart cities and using the Internet of Things in factories.

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