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Cellular network bandwidth improvement using subscribers' classification and Wi-Fi offloading

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ABSTRACT

Cellular networks are highly prone to congestion especially at peak traffic periods. This is compounded by the fact that the blocking probability increases. In this study, a machine learning based subscriber classification along with an adaptive Wi-Fi offloading scheme is proposed to improve the throughput and lower the blocking probability of the network. The proposed subscriber classification was implemented using a back propagation based artificial neural network. The result of the subscriber classification was used to develop an adaptive Wi-Fi offloading algorithm based on bandwidth utilization and system throughput. The developed neural network models are shown to be effective, with 94.6% in one experiment, in classifying a user into user classes or levels based on previous data usage. The levenberg–marquardt (LM) algorithm gave the highest accuracy in categorizing the four classes. A relatively large sample size was used for the neural network training cycle and the resulting neural network was then made to use many neurons in its hidden layer. The implementation of the proposed subscriber classification and adaptive Wi-Fi offloading scheme led to a 20% drop in blocking probability and a 50.53% increase in the system throughput.

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1. INTRODUCTION

The volume of mobile traffic has greatly increased due to the proliferation of "data-hungry" devices. Every successive year since the early 2000s has been witnessing a mammoth growth in the volume of traffic that existing network infrastructure are struggling to manage. Cellular network operators keep up with mobile traffic demand using a lot of options but the effect of many intervention programmes has not clearly alleviated the problem of mobile traffic congestion especially in crowded places and areas with intermittent spike in traffic demands [1]. Expenditure on cellular network upgrades is prohibitive and many mobile network operators are looking at innovative ways to increase revenue, lower operating and capital expenditure without compromising quality of service (QoS) requirements. This has been a really challenging problem for mobile operators as implemented solutions have not produced satisfactory results especially in areas with large mobile data traffic. But a new paradigm that is emerging for the handling of mobile traffic is subscriber classification [2]. The network traffic generated by mobile devices have varying characteristics that can be explored for their classification.

In recent times, it has been discovered that a great percentage of cellular network traffic emanates from indoor environments [1] because traffic congestions are usually experienced most of the time within indoor environments. Thus, serious consideration is being given to the possibility of offloading mobile data traffic through alternative means that are inherently suited for the indoor environment. Subscriber classification is the process of categorizing cellular network traffic automatically [3] which enables tailoring of various policies to the peculiarities of the classes of subscribers identified [4]. The subscribers may be classified based on the volume of traffic generated, the protocol it uses, port numbers, deep packet inspection through signature analysis, pay-load sensitivity and other important metrics are used by mobile network operators to classify subscribers to ensure each class get the QoS outlined in the service-level agreements.

Cellular network subscriber classification has been used in fraud detection, cybersecurity and various degrees of measurement applications. Due to the problem of mobile traffic congestion and the attendant degradation in QoS, lots of mobile network operators are seriously considering the option of Wi-Fi offloading [5]. Wi-Fi offloading as known in the mobile network operators' parlance, is the automatic switching from cellular network to Wi-Fi without any perceptible interference to the connectivity of the subscriber [6]. The Wi-Fi network is either leased or maintained by the mobile network operator. The Wi-Fi network is able to automatically register mobile devices due to special features present in the mobile devices and the Wi-Fi access point [7]. Wi-Fi offloading is particularly attractive to mobile network operators because of its cheapness, reliability and efficiency. Wi-Fi offloading, when done automatically has a very potent capability to improve cellular network data availability.

A scalable solution for identifying influential subscribers from a telecommunication network's bank of subscribers was proposed by [8] and importance of classifying subscribers was mentioned in [9] using fuzzy-clustering algorithm. Research by Magnusson *et al*. [8] machine learning was utilized for subscriber classification using weighted social network analysis (SNA) metrics. The technique made it possible to aggregate several metrics and classify millions of subscribers. The result showed that the proposed solution was scalable and accurate. A group of researchers in [10] also classified network subscribers using social network analysis. The subscribers were classified using the complex relationships between all the subscribers in the network. Machine learning tools were also applied. The amount of energy produced by telecommunication equipment operators being consumed by subscribers formed the basics of their classification in [11].

Traffic classification was noted by the authors in [12] as the science of subscriber service differentiation that helps with network design. The authors submitted that traffic/subscriber classification problems keep evolving due to the prolific and varied ways subscribers use the available spectrum. The classification of access network types was proposed by [13] to enable the setup of networks with improved protocol and application performance. The intrinsic characteristic of the network, entropy of packet pair inter-arrival times and median were used to classify various networks used by subscribers. Ethernet, wireless local area network and low-bandwidth connections were the classes or categories of network created by the study. Attributes, rather than their addresses and locations was suggested by researchers in [14] as a means of classifying subscribers.

Data as assets was recognised by [15] as a viable means of increasing the return on revenue for connection service providers. A category engine that could generate a category vector for all users was proposed as the means of classifying subscribers based on internet preferences. The goal of the classifier was to track the subscribers to enable the design of personalized policies tailored to each class of subscribers. The use of load balancing, queuing theory, flow size statistics and a threshold policy for smart offloading of data was suggested by [16]. The smart mobile data offloading system assigns user traffic to either the Wi-Fi or cellular network based on the data rate supported by each mode of traffic offloading. Macro base stations can handle large data traffic through offloading at hours of peak traffic. Traffic offloaded to wireless access points [17], [18]. A virtual congestion-optimal Wi-Fi offloading based sub-gradient algorithm was used to optimally set the offloading ratio needed in a Cellular-Wi-Fi network to ensure maximum throughput [19].

Traffic offloading from vehicle peers in a vehicle-to-vehicle (V2V) network to Wi-Fi-by-the road was considered by [20]. Software defined radio was employed by [21] to help with the decision to either route network traffic through installed Wi-Fi access points or Wi-Fi based D2D links. Wi-Fi offloading was assisted using cache in [22] which lowers waiting time during offloading. Wi-Fi offloading through licensed assisted LTE access which implements connection admission control was used by [23] to minimize issues with bandwidth availability and QoS. Multi-rate and single-rate Apps for Wi-Fi offloading are options that are considered cellular traffic needs to be decongested [24]. Delayed packet offloading via Wi-Fi was studied by [25]. The delayed offloading model was subjected to different performance gauging metrics to determine how effectively it helped with network traffic decongestion and optimal network offloading options.

2. RESEARCH METHOD

2.1. Subscriber classification

The classification enables the switching mechanism to categorize the four usage classes (very high, high, medium and low) defined for users thereby classifying a user at every instant of the day based on previous characteristics of its data usage. Using the MATLAB neural network tool, a neural network was created by defining the network type, the input data, the desired output, the training function, the number of hidden layers, the number of neurons in each hidden layer and the neuron transfer function. The network type used was the feed-forward backpropagation. The inputs here are in a matrix of 8760 columns and with 437 rows which correspond to user events as in Figure 1 and Figure 2 showing the neural network training tool during and after training, validation and testing.

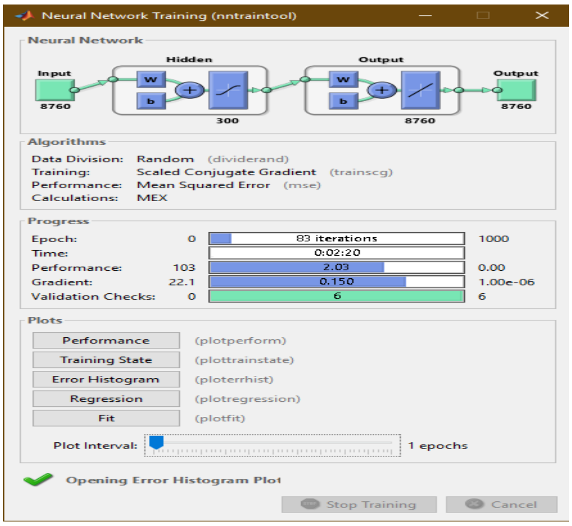

Figure 1. Neural network training

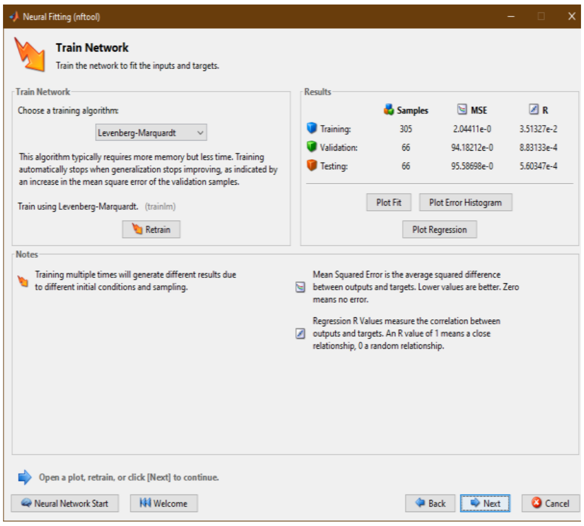

Figure 2. MATLAB neural fitting training network

Values in the columns are determined by the bandwidth and mean of all the current connections at that point in time. In the target matrix, the values are gotten by the already set calculation parameters that classify each user by given levels and assign the switching based on the system architecture design. The training functions typically used are gradient descent (traingd**)**, scaled gradient descent (trainsgd**)**, and Levenberg-Marquardt (trainlm**)**, depending on the experiments. With the volume of data that was to be analysed, the “trainlm” function was used and hidden neurons were adjusted until a satisfactory value was achieved. A small segment of the data captured from the remote database Firefox and translated to MATLAB data array is shown in [5] which serves as the input data for the ANN training model. Each column represents a unique user, each row represents a time interval and each cell represents the internet traffic data consumed within the time interval and classification of users based on their consumption weight. The data captured from the cloud database is queried to be the ANN model data input and target which were divided randomly into the training set, the validation set, and the test set. The training set is a 70% partition of the entire data set, and the other two sets are 15% partitions of the entire data set. The performance was measured using the Mean Square Error (MSE) for the validation set. The MSE was calculated using (1). The neural network regression for each segment of the data and error histogram are shown in Figure 3 and Figure 4 respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(n_i - d_i)^2 \qquad (1)$$

Where N is the size of the data set. Once the best–performing network was found, that is having the lowest MSE for the validation set, the training phase is completed. The purpose for the validation sets used during training of the network is to adjust its weights and biases of the ANN model while the test sets used is to measure the network performance. Each experiment is a neural network model run with a different combination of number of hidden neurons and learning algorithm. The search is for a neural network that gives a low MSE for the validation set using a low number of epochs. The basic parameters provided to create a neural network are the maximum number of epochs (1000), time (infinite), and minimum gradient value (10–7). The sigmoid function is the chosen transfer function, as it is commonly used in pattern classification with the backpropagation method. Five experiments were run using nntool, with the number of hidden neurons ranging from 32 to 300. The levenberg–marquardt algorithm was used as the learning rule which gave higher accuracy than other algorithms like scaled gradient descent. Table 1 shows the summary of the experiments and the best accuracy was 94.18%.

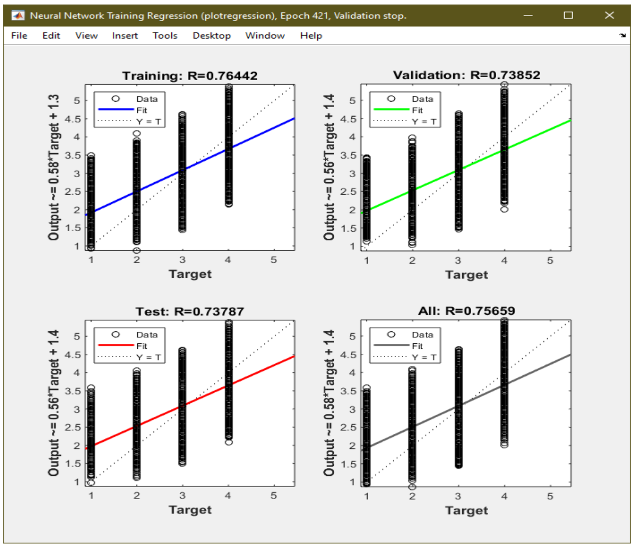

Figure 3. Neural network regression

Table 1. Classification accuracy against number of hidden neurons

No. of hidden neurons	No. of epochs	Percentage correct classification
32	12	12.3
64	40	22.10
128	233	40.86
256	32	83.10
300	83	94.18

2.2. Bandwidth computation

The bandwidth utilized is a summation of the uplink and downlink which is buffered for each user session and it makes it possible to get the total amount of traffic data passing through a network device at a given time. A user i connected to the internet on a cellular network would have made a download of d_i and upload of u_i in a time interval t_i. If the user logs on x_i sessions in a day then total bandwidth b_i bits used in a day and the throughput in bits per seconds (bps) are given respectively in (2) and (3).

$$b_i = \sum_{i=1}^{x_i}(d_i + u_i) \tag{2}$$

$$\beta_i = \frac{b_i}{t_i} = \frac{d_i+u_i}{t_i} \tag{3}$$

The bandwidth consumed by jth user who logs on for session x_i is b_{ij} and where x represents his different logon sessions. If there exists n users on the network, then, daily data consumption on the network by all users is B_j and the corresponding network throughput is β_j as given in (4) and (5) respectively. If y represents the number of days in a month and for kth day in a month, implies that bandwidth consumed by a user for days: y_1, y_2 y_3,……, y_k per month is B_k, so, bandwidth consumption on a monthly basis can be expressed generally as in (6) which is a three-dimensional matrix recursively computed and corresponding network throughput is as given in (7) while B_j and b_{ij} are 2-dimensional arrays. These are network performance evaluation parameters that can be logged for each month of the year and used for various statistical analysis of the network.

$$B_j = \sum_{j=1}^{n}\sum_{i=1}^{x} b_{ij} \tag{4}$$

$$\beta_j = \sum_{j=1}^{n}\sum_{i=1}^{x} \frac{b_{ij}}{t_{ij}} \tag{5}$$

$$B_k = \sum_{k=1}^{y}\sum_{j=1}^{n}\sum_{i=1}^{x} b_{ijk} \tag{6}$$

$$\beta_k = \sum_{k=1}^{y} \sum_{j=1}^{n} \sum_{i=1}^{x} \frac{b_{ijk}}{t_{ijk}} \quad (7)$$

2.3. Quality of service defined criteria

Bandwidth utilization (*U*) is the amount of bandwidth B_c used by consumers in relation to the total bandwidth B_s available from network service provider and 75% has been considered good in this research. QoS delivery is a function of the bandwidth utilization factor given in (8) while bandwidth supplied from provider is as represented in (9) where B_m, B_w, and B_s are respectively bandwidth of the cellular network, bandwidth of wifi network and total bandwidth from the service providers. The users' quality of experience (QoE) is defined as in (10) where R_d is the throughput experienced by the user while R_s is the system throughput. The Throughput demanded by user is the average amount of data the user regularly consumes at the specific time of the day or over the month.

$$\mathrm{U} = \frac{B_c}{B_s} * 100 \text{ , where } B_c < B_s \text{ always} \quad (8)$$

$$\mathrm{B_s} = \begin{cases} B_m + B_w, & if\ wifi\ is\ present \\ B_m, & if\ wifi\ is\ not\ present \end{cases} \quad (9)$$

$$QoE = \frac{R_d}{R_s} * 100 \quad (10)$$

2.4. Wi-Fi offloading algorithm

The process involves analysis of every users traffic database to obtain their bandwidth consumption, bandwidth utilization and throughput as part of the switching process which requires users' bandwidth consumption at every point in time. Also, MATLAB artificial neural network was used to predict the consumption level of the user and determine congestion status of the cellular network. If the average QoS of users is very low, the system recognizes the need to decongest the cellular network hence Wi-Fi Offload should be performed. The algorithm of the process is presented below. This shows the processes of switching between cellular and Wi-Fi networks based on the parameters explained above. Much of the switching is automated and this is due to the learning algorithm, that determines switchable behaviour, based on pattern that are unique to certain times and locations.

Start:
Step 1: get total bandwidth $\mathrm{B_t}$ supplied by network, available Wifi bandwidth $\mathrm{B_w}$ and throughput supplied β_s;
Step 2: Compute bandwidth and throughput demanded respectively:
$\mathrm{B_d} = \sum_{k=1}^{n} \sum_{j=1}^{y} \sum_{i=1}^{a} \mathrm{b_{ij}k}$, $\beta_d = \sum_{k=1}^{n} \sum_{j=1}^{y} \sum_{i=1}^{x} \frac{\mathrm{b_{ij}k}}{\mathrm{t_{ij}k}}$
Step 3: Do while; number of active users $\mathrm{N} > 0$
Step 4: Compute bandwidth consumed $\mathrm{B_c} = \mathrm{B_d} + \mathrm{B_w}$
Step 5: Compute Utilization: $\mathrm{U} = \frac{\mathrm{B_c}}{\mathrm{B_t}} \times 100$, $\mathrm{B_c} < \mathrm{B_s}$ always
Step 6: QoS and QoE evaluation criteria:
Default cellular utilization: 0.75:
If $\mathrm{U} > 0.75$; switch to WiFi
If $\mathrm{U} < 0.75$; remain active on cellular network
$\mathrm{QoE} = \frac{\mathrm{R_d}}{\mathrm{R_s}} * 100$
Step 7: Go to Step 2
Stop

In addition, bandwidth of the available cellular network and Wi-Fi network is determined and aggregated by the available service providers. It determines the number of active users in current session, there must be active users else the program shuts down. Hence, it loops through the number of active users for further analysis. Analyse the bandwidth utilization of the user in the given day of the month and month of the year. QoS is determined, buffered and users to be offloaded to Wi-Fi network (switch) or remain in cellular network are also determined.

3. RESULTS AND DISCUSSION

Over a hundred-hour period, the peak number of users for the cellular network only configuration was seventy-six (76) is shown in Figure 4. The lowest number of users recorded was sixty-three (63) and the average number of cellular network users was seventy (70). The total number of hundred users was observed over the hundred-hour period. The reason for the less than maximum number of users in the network at any given time was due to irregularity in connections and also the fact that some users may not be constantly connected. The high blocking probability resulting from congestion and anti-congestion algorithms designed to ensure that users are prevented from connecting to the cellular network once it gets congested can also be responsible.

This argument is buttressed by the bandwidth utilization plot in Figure 5. The average bandwidth utilization without any form of offloading is 95% and reaches 100% at several points in a hundred-hour period. This shows that the bandwidth utilization is at a critical point and could lead to a lot of call drops and a higher blocking probability for the users of the cellular network. The utilization plot also shows the need to implement some form of palliative or relief for the congested and fully utilized cellular network.

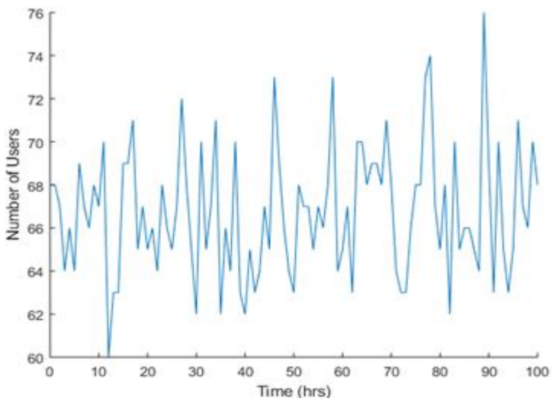

Figure 4. Hundred-hour period average usage

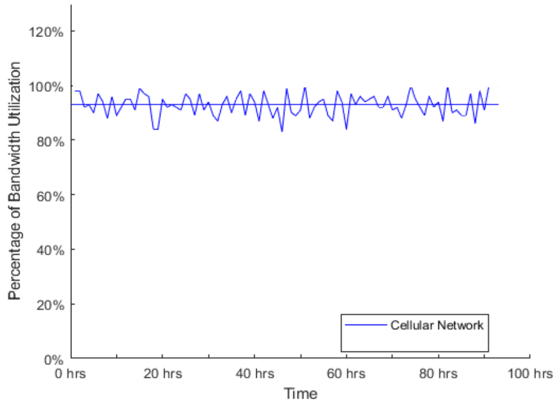

Figure 5. Congested cellular network before offloading

With the implementation of an offloading technique, in this case Wi-Fi, the bandwidth utilization drops to between 74% and 76% even at peak traffic periods. In Figure 6, the total bandwidth utilization for the cellular network and inclusive of the traffic handled by the adaptive Wi-Fi connection falls to about 85% even at the peak network traffic period. The adaptive Wi-Fi offloading scheme implemented on the network is capable of decongesting the network and admitting all users that wish to connect to the network. The adaptive Wi-Fi offloading scheme takes some of the burden of traffic handling from the cellular network and ensures that the network does not get congested (that is does not reach 100% bandwidth utilization). As seen from Figure 7, the blocking probability has dropped drastically as all hundred (100) users are admitted into the network due to the decongestion work of the proposed adaptive Wi-Fi offloading scheme implemented on the network. Thus, at periods of peak traffic, all users that wish to connect to the network are admitted without any form of blocking or dropping.

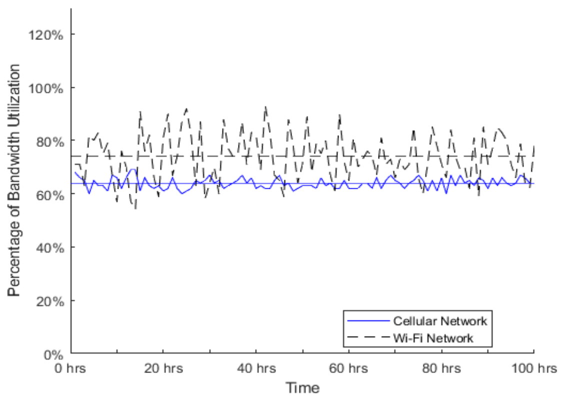

Figure 6. Mean bandwidth utilization after decongestion

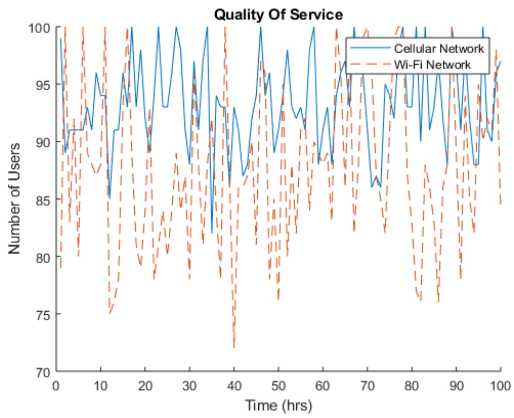

Figure 7. Mobile network with wi-fi-offloading

The maximum achievable throughput for the cellular network without any adaptive Wi-Fi offload is shown by Figure 8 to be about 4.6 Mbps at peak traffic. The cellular network has a limit in terms of the throughput especially at peak traffic periods. This is true, even when users wish to send and receive more information per second, the congested cellular network still places an upper bound on the peak amount of data that can be transmitted by all users in the network. Thus, the performance of the network without any form of Wi-Fi offloading is less than satisfactory considering the fact that at peak traffic period, about 20% of users are not admitted into the network. But with the implementation of the proposed adaptive Wi-Fi offloading scheme that is based on subscriber classification, all users are not only admitted at peak traffic periods, but the throughput reaches as high as 7 Mbps at peak traffic periods. This is evidence enough to show the massive gain, 50.53% of implementing the proposed adaptive Wi-Fi offloading scheme on the congestion prone network.

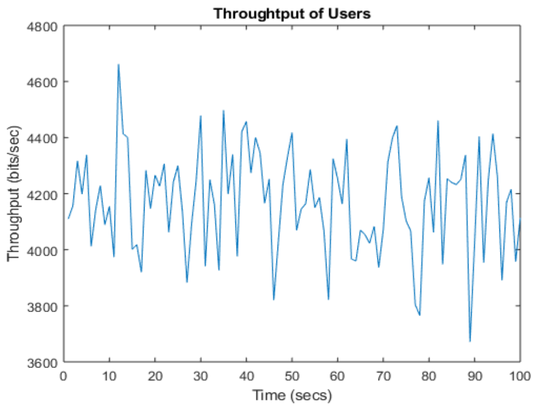

Figure 8. Congested mobile network without wifi-offload

4. CONCLUSION

This study has used the neural network approach to aid automatic switching mechanisms for mobile network users in a Wi-Fi offloading technology using bandwidth, QoS and mean available bandwidth of the current mobile network and the alternative Wi-Fi network. Adaptive Wi-Fi offload has proved to be a very effective means of decongesting cellular network. The experiments showed that bandwidth utilization, QoS and throughput are adequately optimized. To further improve the percentage accuracy, a larger data set should be considered. Different attributes characterizing different types of devices, locations could be used as additional features for the neural network. All the experiments of this work use the same partitioning. The experiments with the re–initialization of the weights and biases also use the same partitioning. Thus, it may be worthwhile to rerun all experiments with different partitions of the given data. The supervised learning method of feed–forward backpropagation has been used here. Experiments can be done using other learning methods such as clustering and self–organizing. In addition, the support vector machine can be used instead of the neural network.

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