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OPTIMAL SELECTION OF NETWORK IN HETEROGENEOUS ENVIRONMENT BASED ON FUZZY APPROACH

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Abstract: Since quality of service of the wireless network is changing over time, there is need of systematic and periodic analyzing of network traffic to get connected with the optimal network among the heterogeneous technologies. To cope with this scenario, this work has proposed a stream data mining based on ST-DR (Dynamic relaxation) fuzzy c means clustering to classify the network traffic effectively. Subsequently classified data would be sent to the web usage mining based on Probabilistic Latent Semantic Analyzer which analyzes the traffic information. Even though being classified and analyzed the network traffic information itself can't get connected to the optimal network due to its dynamic nature so to handle this situation this work has incorporated an ensemble machine learning algorithm applying sequential AdaBoost which predicts the quality of service of the each network during network traffic and enables the user to get connected with an optimal network which have superior Quality of Service (QoS).

Keywords: Stockwell transform (ST); dynamic relaxation (DR); fuzzy c means clustering (FCM); probabilistic latent semantic analyzer; sequential AdaBoost.

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1. INTRODUCTION

The utilization of internet in modern era is increasing by leaps and bounds. Due to this explosion, we have continuous new network generation such as 3G, 4G and 5G as well as development of new mobile devices equipped with multiple network interfaces such as blue-tooth, Wifi, 3G and others. These problems can be encountered by Heterogeneous Wireless Networks (HWNs).

The major advantage of these HWNs is lies on the complementary characteristics between different access networks. For that, the optimal network selection is required for providing continuous connectivity [1] even during the roaming from one network to other.

The optimal network selection problem is tedious and very challenging. Several mathematical algorithms using the utility theory, the cost function, fuzzy logic, game theory, combinatorial optimization, Markov chain etc. have been developed for proper selection of network [2],[3],[4],[5]

Since topologies of heterogeneous network can changes very frequently due to its dynamic nature, it is not easy to find the optimal network and get connected. Therefore, in order to select the best optimal network in heterogeneous networks, this work has focused on designing a superintend network traffic analyzer. We proposed a stream data mining based on ST-DR (Dynamic relaxation) fuzzy c means clustering to classify the network traffic effectively. Subsequently classified data would be sent to the web usage mining based on Probabilistic Latent Semantic Analyzer which analyzes the traffic information. Even though being classified and analyzed the network traffic information itself can't get connected to the optimal network due to its dynamic nature so to handle this situation this work has incorporated an machine learning algorithm based on sequential adaboost which predicts the quality of service of the each network during network traffic and enables the user to get connected with an optimal network.

The outline of the paper encompasses Section 2 with discussion of the related researches which coordinates with the field of research, Section 3 with brief description of the proposed methodology and the working characteristics of the superintend network traffic analyzer, Section 4 gives the results and discussion of our proposed method and Section 5 provides conclusion of this paper which is then followed by references.

2. LITERATURE SURVEY

Some of the recent researches related to our research are given below:

Santosh Kumar Das et.al [11],[13] proposed a Fuzzy based Intelligent Energy Efficient Routing protocol (FIE2R) for WANET. Mohamed Lahby et.al [12] proposed a new mechanism based on graph theory for the selection of the best path for network selection decision. Pengfei Ren et.al [14] studied a distributed machine learning problem by applying a distributed optimization algorithm over an undirected and connected communication network. Raman Kumar Goyal [15] proposed a novel fuzzy-Analytic Hierarchy Process (AHP) based network selection in heterogeneous wireless networks. Triangular fuzzy numbers are used to represent the elements in the comparison matrices for voice, video and best effort applications.

Consequently, the recent works discussed above vigorously epitomize the demand for designing a superintend network traffic analyzer to enhance quality of service (QoS) through properly analyzing the network traffic and connected with the optimal network along with the use of graphical representation. Thus, in this work it is focused to deliberately design a superintend network traffic analyzer which brings efficient results for the improvement of quality of service (QoS).

3. STURDY NETWORK TRAFFIC ANALYZER BASED ON FUZZY APPROACH

Wireless Sensor Networks (WSNs) are formed by hundreds or thousands of low cost and low energy sensor devices. To provide better QoS, it is necessary to analyze the traffic loads in each sensor networks and afford an optimal network for data transmission. To obtain optimal network, data mining is utilized for analyzing. Figure 1 depicts the general architecture of WSN.

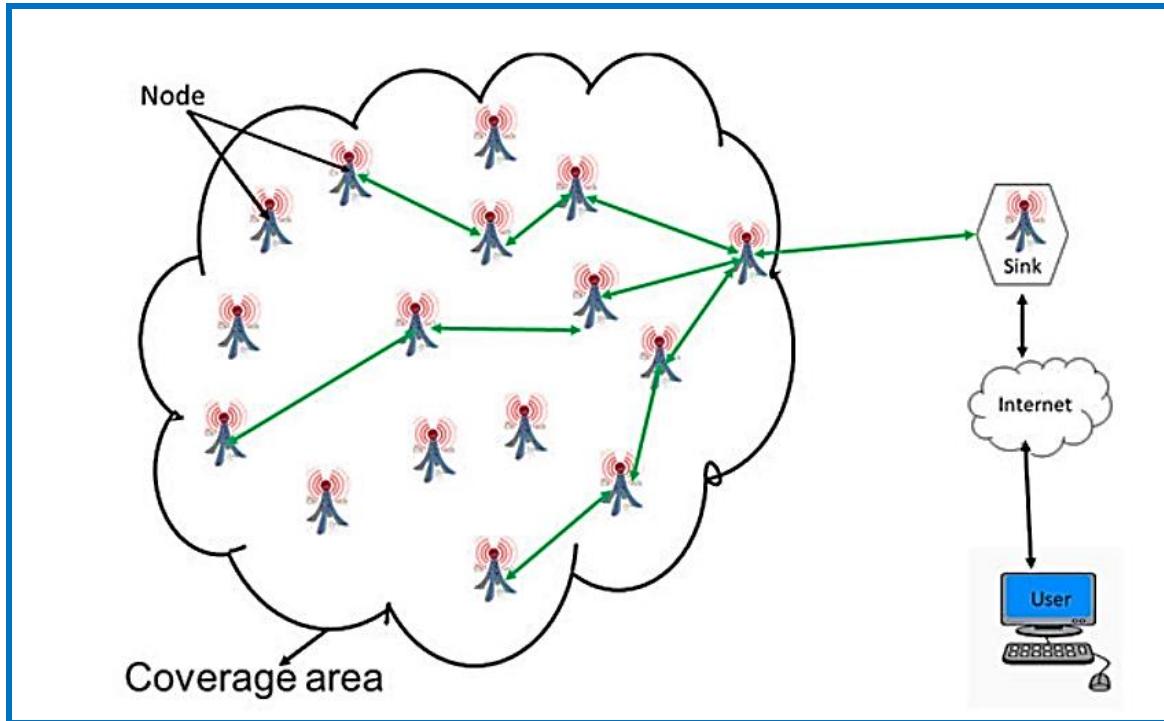


Figure 1: General Architecture of WSN.

Existing techniques based on statistical approaches have suffered in selecting best network due to lack of less amount of past information as well as lack of functioning in proactive manner. Therefore, in order to choose the best optimal network in heterogeneous networks based on quality of service, this work has focused on designing a superintend network traffic analyzer.

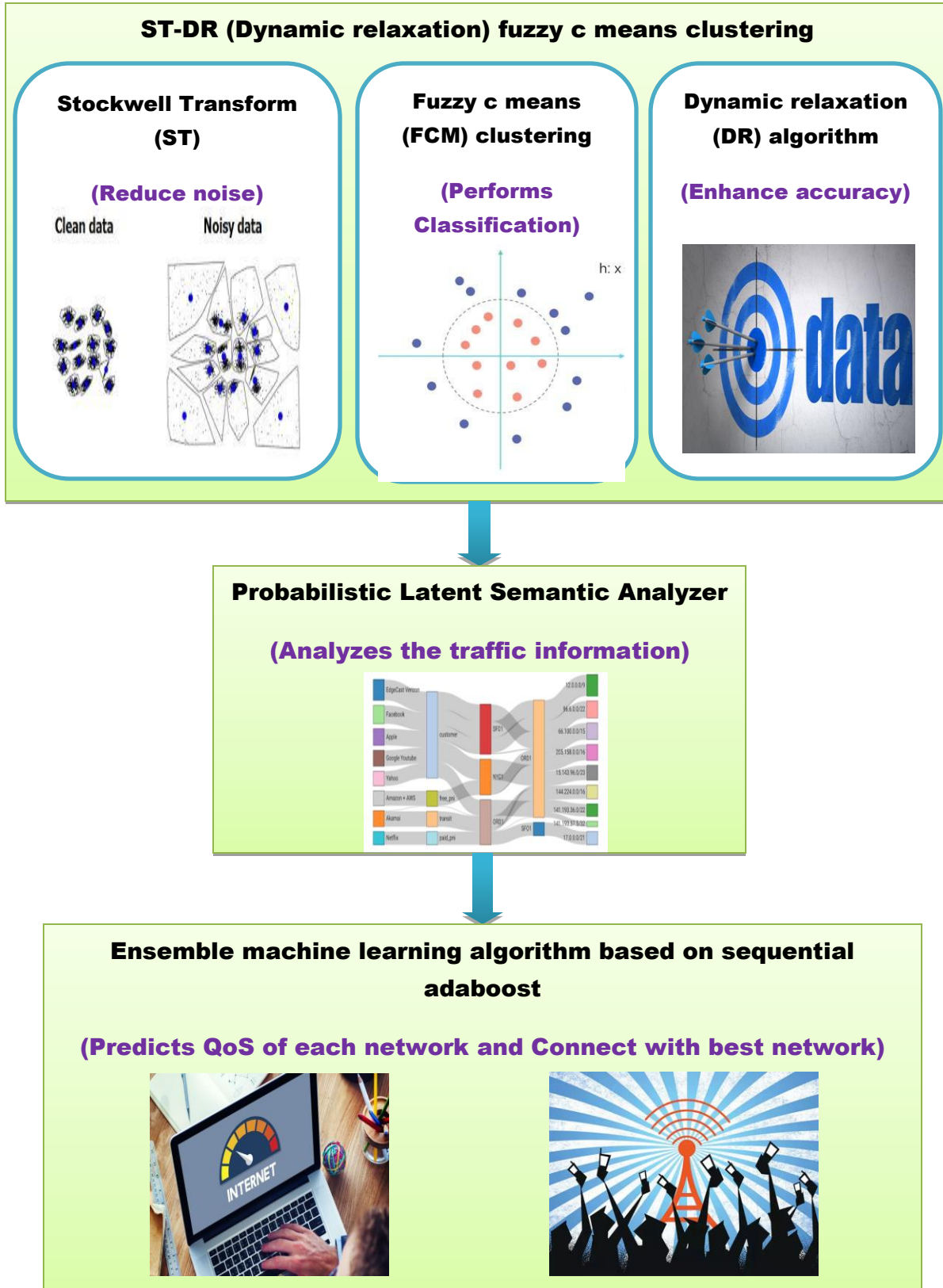


Figure 2: Overall representation of our proposed method.

Since quality of service of the wireless network is changing over time, there is need of systematic and periodic analyzing of network traffic to get connected with the optimal network among the heterogeneous technologies. To cope with this scenario, this work has proposed a stream data mining based on ST-DR (Dynamic relaxation) fuzzy c means clustering to classify the network traffic effectively. Subsequently classified data would be sent to the web usage mining based on Probabilistic Latent Semantic Analyzer which analyzes the traffic information. Even though being classified and analyzed the network traffic information itself can't get connected to the optimal network due to its dynamic nature so to handle this situation this work has incorporated an ensemble machine learning algorithm based on sequential adaboost which predicts the quality of service of the each network during network traffic and enables the user to get connected with an optimal network which holds high packet delivery ratio, less packet loss and high throughput. This entire proposed method is represented as a diagrammatic block diagram in figure 2.

3.1. ST-DR (Dynamic relaxation) fuzzy c means clustering

3.1.1. Stockwell Transform (ST)

The S-transform has been applied in order to reduce the size of the transmitted data without losing the significant features of the data.. The ST of a time series $u(T)$ is defined as [16] follows:

$$\begin{aligned} s(T, f) &= \int_{-\infty}^{\infty} u(t) \rho(T-t, f) e^{-2i\pi ft} dt \\ &= \int_{-\infty}^{\infty} u(t) \frac{1}{S.D(f)\sqrt{2\pi}} e^{\frac{-(T-t)^2}{2S.D(f)^2}} e^{-2i\pi ft} dt \end{aligned} \quad (1)$$

The standard deviation $S.D(f)$ of the opening o of the standardST in (1) is as follows:

$$S.D(f) = 1/|f| \quad (2)$$

For the modified Gaussian opening, we have chosen the standard deviation $S.D(f)$ to be

$$S.D(f) = l/(x + y/\sqrt{f}) \quad (3)$$

where x and y are positive constants, f = signal fundamental frequency, and $l = \sqrt{x^2 + y^2}$. In (1), the usually chosen opening o is the Gaussian one. Thus, the spread of the original Gaussian function is being varied with frequency to generate the new modified Gaussian opening as

$$o(T, f) = \frac{x + y\sqrt{|f|}}{l\sqrt{2\pi}} e^{-\frac{(x+y/\sqrt{|f|})^2 T^2}{2l^2}}, l > 0 \quad (4)$$

Thus, an alternative representation for the generalized ST with modified Gaussian opening is as follows:

$$s(T, f) = \int_{-\infty}^{\infty} U(A + f) e^{(-2\pi^2 A^2 L^2) / \left((x+y/\sqrt{|f|})^2 \right)} e^{2i\pi A t} dA \quad (5)$$

The discrete version of the ST of a signal is obtained as

$$s(n, b) = \sum_{a=0}^{B-1} U[a + b] e^{(-2\pi^2 a^2 L^2) / \left((x+y/\sqrt{|f|})^2 \right)} e^{i \frac{2\pi a n}{B}} \quad (6)$$

where $U[a + b]$ is obtained by shifting the discrete Fourier transform of $u(l)$ by b , $U[a]$ being given as

$$U[a] = \frac{1}{B} \sum_{l=0}^{B-1} u[l] e^{-k \frac{2\pi a k}{B}} \quad (7)$$

Further ST of signal $u(T)$ and noise $c(T)$ is as follows:

$$S(u(T) + c(T)) = S(u(T)) + S(c(T)) \quad (8)$$

In (8), it can be seen that the noise can be removed from the ST output by a simple thresholding technique.

3.1.2. Fuzzy C Means (FCM)

Fuzzy C Means (FCM) is a method of clustering which allows one piece of data to be in the right position to two or more clusters. Starting with an initial guess and by iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the correct place within a dataset. This iteration is based on minimizing an objective function that symbolizes the distance from any given data point to a

cluster center weighted by that data point's membership rank. The fuzzy c-means (FCM) algorithm [17] has numerous applications. It is based on the concept of fuzzy c-partition, introduced by Ruspini [18].

In fuzzy C-means clustering, we determine the cluster center H_m and the membership matrix V . It is based on the minimization of the following objective function:

$$N_a = \sum_{m=1}^B \sum_{n=1}^H v_{mn}^a \|u_a - h_b\|^2 \quad (9)$$

where a is the number of clusters, v_{mn} is the degree of membership of u_m in cluster n , u_m is the m_{th} of b -dimensional measured data, and h_n is the b -dimensional center of the cluster.

$$h_n = \frac{\sum_{m=1}^B v_{mn}^a \cdot u_m}{\sum_{m=1}^B v_{mn}^a} \quad (10)$$

$$v_{mn}^a = \sum_{l=1}^h \left[\frac{\|u_m - h_n\|}{\|u_m - h_l\|} \right]^{-\frac{2}{a-1}}$$

3.2. Probabilistic Latent Semantic Analyzer

The overall process of Web usage mining consists of three phrases: data preparation and transformation, pattern discovery, and pattern analysis. The discovered patterns may then be analyzed and interpreted for use in such applications as Web personalization [16].

One of the main advantages of PLSA model in Web usage mining is that it generates probabilities which quantify relationships between Web users and tasks, as well as Web pages and tasks. From these basic probabilities, using probabilistic inference, we can derive relationships among users, among pages, and between users and pages. Thus, this framework provides a flexible approach to model a variety of types of usage patterns.

The PLSA model generates probabilities $\wp(k_j)$, which measures the probability of a specified task is chosen; $\wp(e_p | k_j)$, the probability of observing a user session given a certain task; and $\wp(g_q | k_j)$, the probability of a page being visited given a certain task. Applying

Bayes' rule to these probabilities, we can generate the probability that a certain task is chosen given an observed user session:

$$\wp(k_j | e_p) = \frac{\wp(e_p | k_j) \wp(k_j)}{\sum_{w=1}^z \wp(e_p | k_w) \wp(k_w)} \quad (11)$$

and the probability that a certain task is chosen given an observed pageview:

$$\wp(k_j | g_q) = \frac{\wp(g_q | k_j) \wp(k_j)}{\sum_{w=1}^z \wp(g_q | k_w) \wp(k_w)} \quad (12)$$

Here, k_j refers the latent factor, e_p stands for user session and g_q represents pageview.

The PLSA analyzes the entire network information effectively. Though, it is impossible for the system to get connected with the optimal network. In order to obtain better connection with the optimal network, we have to predict the QoS of various network and find appropriate network that have high packet delivery ratio, less packet loss and high output

3.3. Ensemble machine learning algorithm based on sequential adaboost

In machine learning, ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone [20]. Boosting involves incrementally building an ensemble by training each new model . By far, the most common implementation of boosting is Adaboost. AdaBoost training process selects only those features known to improve the predictive power of the model [21].

3.3.1. Training phase

AdaBoost indicates a specified method of training a boosted classifier of the form

$$C_I(p) = \sum_{i=1}^I c_i(p) \quad (13)$$

where each c_i is a weak learner that takes an object p as input and returns a value indicating the class of the object. Each weak learner produces an output hypothesis, $h(p_m)$, for each sample in the training set. At each iteration I , a weak learner is chosen and directed a coefficient ε_i such that the sum training error M_i of the resulting i -stage boost classifier is minimized.

$$M_i = \sum_m M[C_{i-1}(p_m) + \varepsilon_i h(p_m)] \quad (14)$$

Here $C_{i-1}(p)$ is the boosted classifier that has been built up to the previous stage of training, $M(C)$ is some error function and $c_i(p) = \varepsilon_i h(p)$ is the weak learner that is being considered for addition to the final classifier.

3.3.2. Weighting

At every iterative process of the training process, a weight $\omega_{m,i}$ is assigned to each sample in the training set equal to the current error $M(C_{i-1}(p_m))$ on that sample. These weights can be used to inform the training of the weak learner, for instance, decision trees can be grown that favor splitting sets of samples with high weights.

3.3.3 Derivation

Suppose we have a data set $\{(p_1, q_1), \dots, (p_B, q_B)\}$ where each item p_m has an associated class $q_m \in \{-1, 1\}$, and a set of weak classifiers $\{S_1, \dots, S_\ell\}$ each of which outputs a classification $S_n(p_m) \in \{-1, 1\}$ for each item. After the $(a-1)$ -th iteration our boosted classifier is a linear combination of the weak classifiers of the form:

$$F_{(a-1)}(p_m) = \varepsilon_1 s_1(p_m) + \dots + \varepsilon_{a-1} s_{a-1}(p_m) \quad (15)$$

At the a -th iteration we desire to explore this to a better boosted classifier by adding different weak classifier s_a , with another weight ε_a

$$F_a(p_m) = F_{(a-1)}(p_m) + \varepsilon_a s_a(p_m) \quad (16)$$

So it remains to determine which weak classifier is the best choice for s_a , and what its weight ε_a should be. We define the total error M of F_a as the sum of its exponential loss on each data point, given as follows:

$$M = \sum_{m=1}^B e^{-q_m F_a(p_m)} \quad (17)$$

Letting $\omega_m^{(1)} = 1$ and $\omega_m^{(a)} = e^{-q_m F_a(p_m)}$ for $a > 1$, we have:

$$M = \sum_{m=1}^B \omega_m^{(a)} e^{-q_m \varepsilon_a s_a(p_m)} \quad (18)$$

$$\begin{aligned}
M &= \sum_{q_m = s_a(p_m)} \omega_m^{(a)} e^{-\varepsilon a} + \sum_{q_m \neq s_a(p_m)} \omega_m^{(a)} e^{-\varepsilon a} \\
&= \sum_{m=1}^B \omega_m^{(a)} e^{-\varepsilon a} + \sum_{q_m \neq s_a(p_m)} \omega_m^{(a)} (e^{\varepsilon a} - e^{-\varepsilon a})
\end{aligned} \tag{19}$$

Since the only part of the right-hand side of this equation that depends on S_a is $\sum_{q_m \neq s_a(p_m)} \omega_m^{(a)}$, we see that the M is the one that minimizes $\sum_{q_m \neq s_a(p_m)} \omega_m^{(a)}$, i.e. the weak classifier with the lowest weighted error (with weights $\omega_m^{(a)} = e^{-q_m s_{a-1}(p_m)}$).

To determine the cherished weight ε_a that optimizes M with the S_a that we just determined, we differentiate:

$$\frac{dM}{d\varepsilon_a} = \frac{d\left(\sum_{q_m = s_a(p_m)} \omega_m^{(a)} e^{-\varepsilon a} + \sum_{q_m \neq s_a(p_m)} \omega_m^{(a)} e^{\varepsilon a}\right)}{d\varepsilon_a} \tag{20}$$

putting this to zero, we have:

$$\varepsilon_a = \frac{1}{2} \ln \left(\frac{\sum_{q_m = s_a(p_m)} \omega_m^{(a)}}{\sum_{q_m \neq s_a(p_m)} \omega_m^{(a)}} \right) \tag{21}$$

We calculate the weighted error rate of the weak classifier to be $E_a = \sum_{q_m \neq s_a(p_m)} \omega_m^{(a)} / \sum_{m=1}^B \omega_m^{(a)}$, so it follows that:

$$\varepsilon_a = \frac{1}{2} \ln \left(\frac{1 - E_a}{E_a} \right) \tag{22}$$

which is the negative logit function multiplied by 0.5.

Thus we have derived the AdaBoost algorithm: At each iteration, choose the classifier S_a , which minimizes the total weighted error $\sum_{q_m \neq s_a(p_m)} \omega_m^{(a)}$, use this to calculate the error

rate $E_a = \sum_{q_m \neq s_a(p_m)} \omega_m^{(a)} / \sum_{m=1}^B \omega_m^{(a)}$, use this to calculate the weight

$\varepsilon_a = \frac{1}{2} \ln \left(\frac{1 - E_a}{E_a} \right)$, and finally use this to improve the boosted classifier $F_{(a-1)}$ to

$F_a = F_{(a-1)} + \varepsilon_a s_a$. Thus, adaboost classifier predicts the network that has better QoS and allows the user to connect with that ideal network.

As a consequence, our proposed method effectively analyzes and classifies the optimal network for effective data transmission with superior Quality of Service (QoS). Initially the network information is preprocessed and the noise is eradicated by Stockwell Transform (ST). Then it is send to fuzzy c means (FCM) clustering for classifying the network information. However, the FCM clustering attains 80% accuracy only. Therefore, Dynamic Relaxation (DR) algorithm is utilized to obtain maximum accuracy. Afterwards the network information is analyzed through Probabilistic Latent Semantic Analyzer for getting the genuine information about network traffic in each sensor node. Thus, the method classifies and analyzes the network information automatically though it doesn't able to connect with the best network because of its dynamic nature. Hence, we utilize an ensemble machine learning algorithm based on sequential adaboost that forecast the network information even during the network traffic and empowers the user to connect with the best network which has better QoS. The overall architecture of this system efficiently performs the classifying and analyzing task and helps the user to attain better network for communication.

4. RESULT & DISCUSSION

This section provides the entire results obtained from our proposed method which was explained in detail in the above section 3. We initially perform the stockwell transform for eradicating the noise in the network information. Then fuzzy c means clustering technique is applied in the noise removed data in order to classify the network information. However, 80% of accuracy is obtained in the fcm method; hence to achieve more accuracy we utilize dynamic relaxation method. Thus, the classification is accomplice in the ST-DR fuzzy c means clustering section. Moreover, to analyze the network traffic in each node, we utilize Probabilistic Latent Semantic Analyzer. Thus, the network traffic classification and analyzing is accomplished.

Though the aim of our method is to forecast the network traffic of each sensing node and empowers the user to connect with the best optimum network. Hence to accomplish this process, this method uses ensemble machine learning algorithm based on sequential adaboost, which diagnose the QoS of each network and predicts the optimal network to connect. Consequently, our proposed method attain all the above goals efficiently which is executed using graph theory and also in graphs are presented in this section.

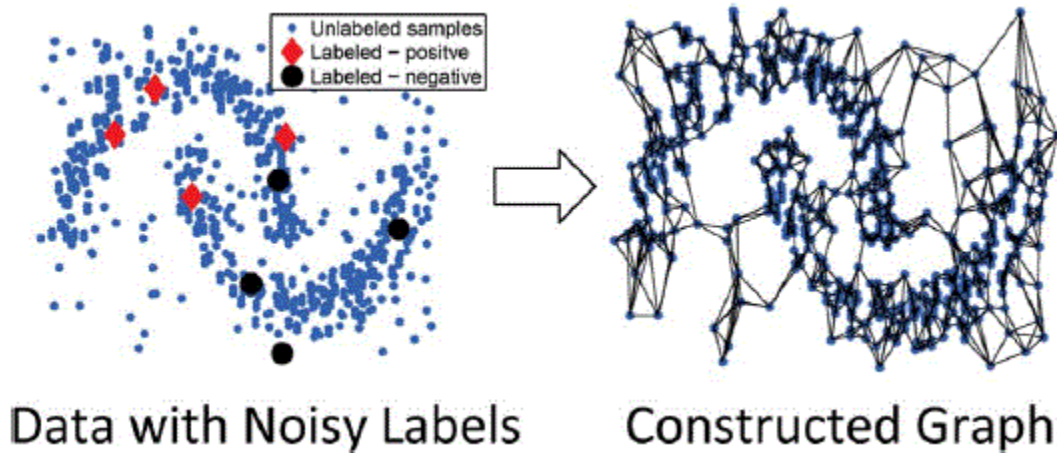


Figure 3: Stockwell transform (ST)

In the above figure 3, ST analyzes the noisy network information from the safe data and eradicating the noise from the entire information in order to obtain noiseless network information.

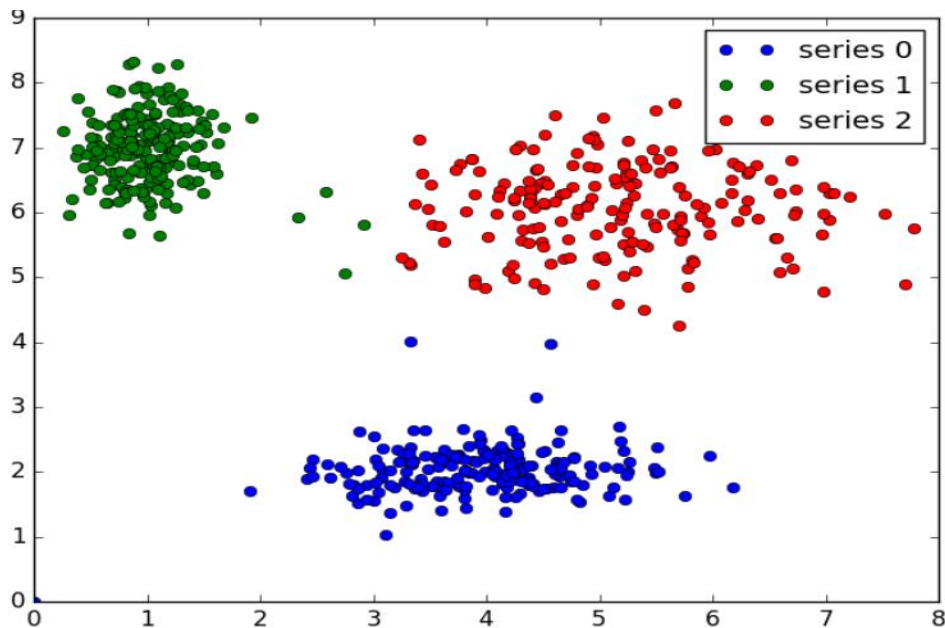


Figure 4: Fuzzy C Means (FCM) clustering

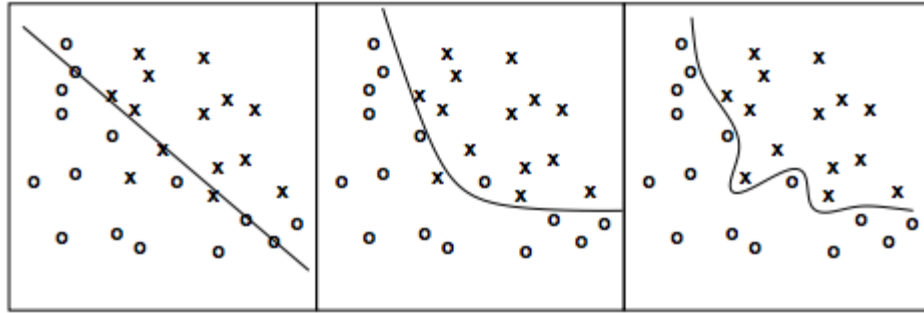


Figure 5: Dynamic relaxation (DR) method

Fuzzy C Means (FCM) clustering performs the classification process so as to know the network which performs well. The classification is done based on the network traffic of each sensor node. Figure 4 displays the classification process accomplished by FCM clustering.

Figure 5 presents the classified network information with better accuracy. This maximum accuracy is obtained using dynamic relaxation method which enhances the classification accuracy of fuzzy c means clustering technique.

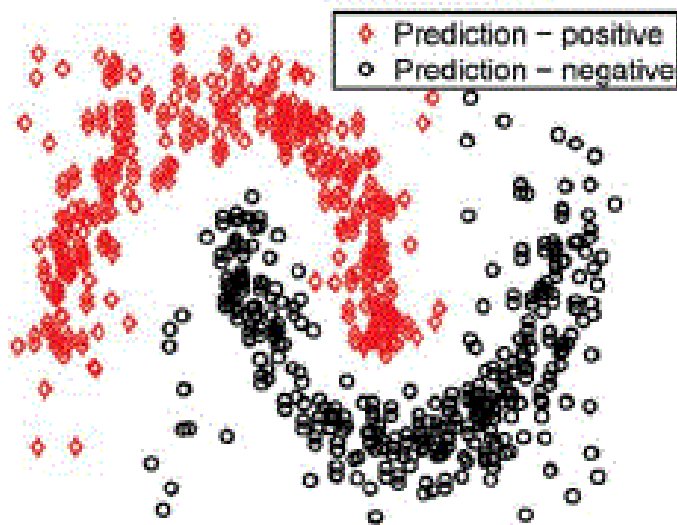


Figure 6: Probabilistic Latent Semantic Analyzer

Figure 6 illustrates the analyzed network information using Probabilistic Latent Semantic Analyzer. Using this we can analyze the network traffic each sensor node.

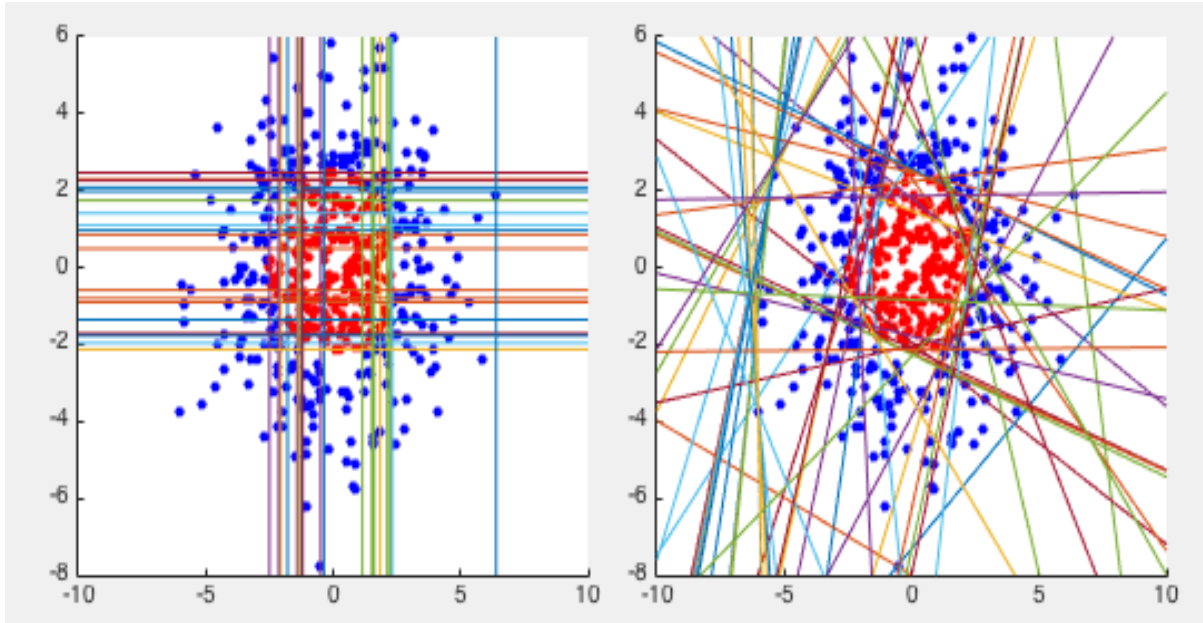


Figure 7: Sequential adaboost method

Figure 7 shows the output obtained from ensemble machine learning algorithm based on sequential adaboost method that predicts the QoS of each network and helps the user to connect with ideal network.

A. Packet Delivery Ratio

The calculation of Packet Delivery Ratio (PDR) is based on the received and generated packets as recorded in the trace file. In general, PDR is defined as the ratio between the received packets by the destination and the generated packets by the source.

$$Packet\ delivery = \frac{total\ number\ of\ packets\ received}{total\ number\ of\ packets\ sent} \times 100 \quad (29)$$

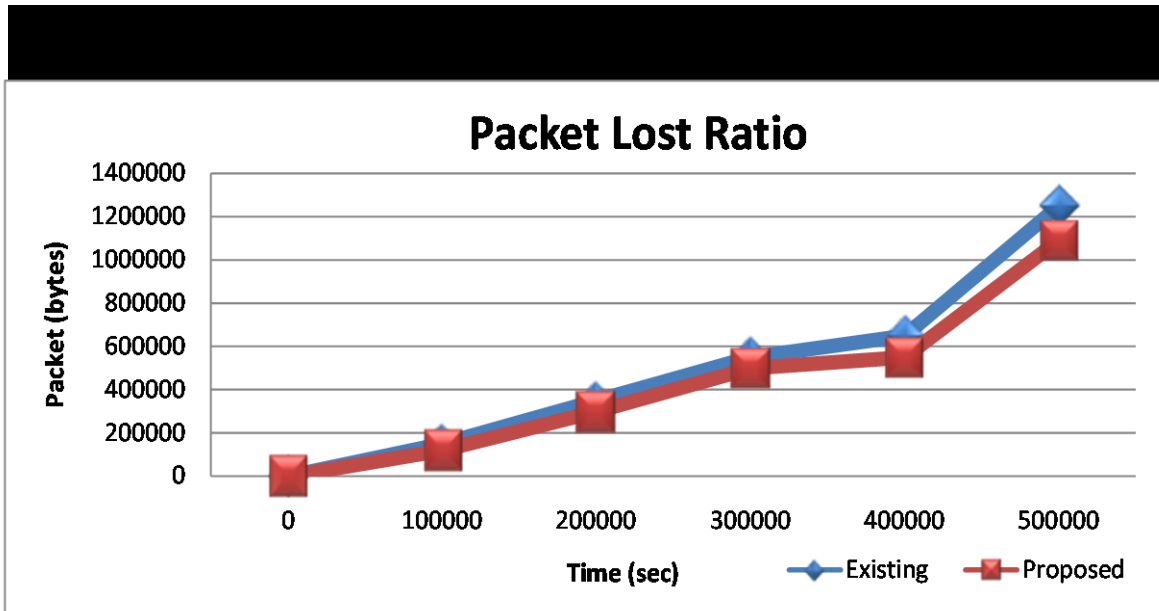


Figure 8: Packet Delivery Ratio (PDR)

The figure 8 shows the packet delivery ratio of proposed scheme and existing scheme. Compare to existing scheme the proposed scheme gives 98% of the packet delivery ratio.

B. Packet Loss Ratio

Packet loss happens when one or more packets of transmitting over a communication channel do not reach the destination. Packet loss is measured in terms of percentage of packets loss with respect to the packets sent.

$$Packet\ loss = \frac{Total\ number\ of\ packets\ sent - Total\ number\ of\ packets\ recieved}{Total\ number\ of\ packets\ sent} \times 100 \quad (30)$$

Figure 9: Packet Loss Ratio (PLR)

The figure 9 shows the packet lost ratio of proposed scheme and existing scheme. Compare to existing scheme the proposed scheme reduces 40% of the packet lost ratio.

4. CONCLUSION

In this paper, we designed a superintend network traffic analyzer for classifying and analyzing the optimal network effectively for enabling the user to get connected with the optimal network

so as to attain maximum Quality of Service (QoS). Since QoS of wireless sensor network fluctuates often, we design a stream data mining based on ST-DR (Dynamic relaxation) fuzzy c means clustering for classifying the network traffic effectually and for analyzing, web usage mining based on Probabilistic Latent Semantic Analyzer was utilized in our proposed method. Ultimately, to predict the QoS of each and every network during network traffic, an ensemble machine learning algorithm based on sequential adaboost is utilized and enables the user to connect with the ideal network that has maximum QoS. The proposed system accomplished the entire projected performance with greater accuracy.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

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