A novel Optimization Model for Efficient Packet Classification in WBAN

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Abstract

With self-automaton and used of advanced technology, Wireless Body Area Network (WBAN) has attracted significant interest. So many researchers are exploring this field. The most rigorous issue in WBAN is to sustain its Quality of Service (QoS) under the dynamic changing environment such as healthcare. Another important issue is to manage heterogeneous traffic within this kind of resource-constrained network. In the healthcare WBAN, some sensed data are considered as more important than others due to their critical nature. Such important data need to be delivered within a précised time bound. Delivery of data with loss and delay may not be tolerated in these systems; hence the use of an intelligent algorithm needs to be addressed to deals with these kinds of systems. By doing so, this system can get practically implemented into medical emergency situations for timely diagnose and treatment procedure. In this paper, a novel fusion based multi-class classification protocol is proposed for classification and transmission packets according to defined priority. In this protocol two unique machine learning classification policies i.e. Support Vector Machine and Binary Decision Tree classifiers are fused to obtain a better search performance and high classification accuracy in heterogeneous WBAN. This classification technique is responsible for detecting the class of each incoming packet and assigning them a priority. The simulation results show that the proposed protocol outperforms under extensive conditions.

Keywords: Wireless Body Area Network, Packet classification, Machine Learning, Fusion, Support Vector Machine, Binary Decision Tree

1. Introduction

Healthcare system is a critical application of WBAN. It is an adaptation of the decision support system commonly used to analyze patient health-related data to help healthcare providers to take correct and in time decisions more easily. Accurate decision making within a frequent change environment of healthcare WBAN is a challenging task, due to versatile nature, and suspicious health conditions. In these circumstances, correct classification and fast transmission of urgent data are much more essential for the safety of the patient. But the classification of heterogeneous data is a serious issue. These limitations motivate us to design a Support Vector Machine (SVM) and Binary Decision Tree (BDT) based fusion based multiclass classifier for accurate packet classification. This fusion classifier is used to identify the class of incoming packet at central controller node and assign them a priority accordingly. Each incoming packet is categorized into the following four classes, i.e. Alert packets, Real-time packets, On_Demand packets and Normal packets. Classification and transmission of heterogeneous packets with priority order can improve the productivity of frequently varying healthcare WBAN. So in the proposed work, two machine learning based (*i.e.*, SVM and BDT) classification techniques are fused to generate very good results. The simulation shows that the proposed fusion classifier method improves the performance of the system greatly.

The rest of the paper is structured as follows. Section 2 gives the brief idea about related work. Section 3 describes the proposed work. Section 4 illustrates the experimental results. Section 5 provides the conclusion part.

2. Related Work

This section discusses the existing healthcare system along with various classification policies.

Authors in [6] designed an optimized healthcare system with fair scheduling policy. It assigns dynamic weights to each child node, which further decides the amount of resource assignment to each node. It provides fair bandwidth utilization process in a better way and achieves better performances. Here a single queue was divided into multiple numbers of virtual queues to store the different priority based traffic. It utilizes buffer by assigning free or available space of one's virtual queue to other. This helps in reducing the loss rates, congestion, and enhance throughput. However, it does not properly deal with a dynamic and heterogeneous traffic in an emergency situation.

An Adaptive Binary Cuttings (ABC) algorithm in designed in [11]. It facilitates the decision tree to adapt geometric distribution of the filters. It constructs the decision by using stronger and more straightforward criteria. It also provides an efficient node encoding scheme, to enables a smaller, shorter, and well-balanced decision tree. The ABC algorithm outperforms the other decision tree-based algorithms but unable to handle the multiclass problems.

Authors proposed an optimized hybrid artificial intelligence model to integrate a fast messy genetic algorithm (fmGA) with a support vector machine (SVM) in [12]. Here the SVM mainly provides learning while the fmGA optimizes SVM parameters. It achieves early and better prediction accuracy compared to other baseline models (*i.e.*, CART, CHAID, QUEST, and C5.0), but takes more computation time.

In [13] developers maximize the efficiency of the classifier by applying one-versus-all multi-class support vector machine (OVA-SVM) policy. Here the prediction of class was made by using probability scores from all classifiers. It helps in improving the predictive accuracy of classification for unbalanced samples, but the probability based decision does not give true and fair classification.

3. Proposed Work

The design of multiclass classification is relatively difficult as compared to two-class problems. Till now limited research work has been done in this aspect, so we try to implement a multiclass packet classification method to overcome above problems.

3.1. Proposed System

The proposed WBAN system is consists of three units that work in a dynamic environment.

3.1.1. WBAN Unit: Information sensed from different sensors nodes in *Data Sensing unit* and processed into a packet in the *Pre-processing unit*. Packets are transferred to the central Controller Unit (CU) with the help of *Packet Dispatching unit*.

3.1.2. Controller Unit: The CU has the capability to make the decision at different levels and sent the data to the Medical Server Unit (MSU) in time. The *Aggregation unit* of CU is responsible for collection and aggregation data from various sensors. The main task of *Packet handling unit* of CU is to manage incoming packets and is consists of five sub-units. i) *Alerting unit*: It activates the Alert index field in packet header upon detection of an abnormal value in sensed data. ii) *Packet Classification unit*: It classifies the incoming

packets and assigns them priorities. iii) *Queuing unit*: It keeps the classified packets until resources are available. iv) *Scheduling unit*: It schedules the packets according to their priority and transmits them towards MSU. V) *Prioritization unit*: It timely updates the priority of each sensor node and other pre-defined parameters like the range of vital signals, threshold value, time interval, On_Demand request etc. with the permission of healthcare person.

3.1.3. Medical Server Unit: After reception of packets at the MSU, it monitors the packet in *Packet monitoring unit* and takes the decision with the help of *Decision making unit*. If it receives alert packets, then it informs immediately to the healthcare person so that he should take proper decision. The healthcare person is responsible for the updating of each sensor node's priority and the pre-defined parameters values with the help of CU.

3.2. Proposed Classifier

Critical and emergency condition needs urgent responses by healthcare person to take correct action and cure the patient. It is the responsibility of the CU to classify the incoming packet according to their urgency and transmit it to the medical server accordingly. So the main objective of the proposed protocol is to design a packet classifier with the fusion of SVM and BDT methods, to identify the actual class of the packet and assign it a precise priority in dynamic healthcare WBAN environment.

3.2.1. Support Vector Machine Classifier: The main motive of SVM machine learning based classifier is to select the correct position of decision boundaries so that it can produce the optimum split-up of classes. It was basically designed for binary classification or two-class problems, but the demand in practical applications expands the SVM classification to multiclass classification problems. In multiclass classification problems, the multiclass problems are divided into different two-class problems. It selects a margin between the two classes, where the margin is defined as the sum of the distances to the hyperplane from the closest points of the two classes. The SVM finds a new hyperplane that maximizes the margin and minimizes the number of misclassification errors, while the two classes are not linearly separable. Here the data points termed as "support vector". The Support vectors those are closest to the hyperplane are used to measure the margin. The gap between margin and misclassification error is controlled by a constant.

SVM classifier provides enhanced and better classification accuracy in comparison to other classification methods. It works well for multiple parameter classifications, but the testing time increases with the increase in the size of data.

3.2.2. Binary Decision Tree Classifier: In Binary Decision Tree classification technique, each intermediate node along with root node contains a specific attribute for the inspection of the rule. All the nodes except leaf node follow a binary split to generate hierarchical tree structure with left and right subtrees. With the iterations, the number of attributes will get reduced and finally reaches a point where all the data belong to the same group. The end node becomes the leaf node which states the class.

The advantage of BDT is that it takes less time for the classification of the test set, once the tree was constructed. It provides an inexpensive classification policy which is robust to noise. One major drawback of BDT is that the error rate increases with increase in complexity and it is unable to detect earlier hidden data and fails to provide correct classification.

3.2.3. SVM-BDT based Fusion Classifier: The above limitations inspire us to design a classifier by considering both SVM and BDT approaches. This fusion classifier policy will overcome the issues related to both BDT and SVM and handle heterogeneous packet

transmission problem in WBAN effectively. In this protocol, we are considering the plus points of both BDT and SVM. The BDT is considerably faster than SVM in classifying new examples while SVM performs better than BDT in terms of classification accuracy. The workflow diagram of proposed classification unit is given in figure 1.

The functional principle of the proposed packet classification unit is described as below.

- Initially after the data Aggregation unit, the incoming packet is fed into Alerting unit.

- The Alerting unit identifies the critical state by monitoring the sensed value against the actual vital range value. If an abnormal situation detected, then it activates the alert index field of the incoming packet.

- In the Classification unit, it checks the header field of the incoming packet. It extracts some attributes such as packet size, available bandwidth, packet flow type, Alert index value, On_Demand index value etc. and generates the training rule set and attribute set from these attributes.

- This training set along with extracted attribute set is fed into the BDT classifier. It selects the best match attribute from the attribute set and creates a tree with the help of SVM classifier. The SVM classifier classifies the attributes into positive and negative groups with the help of rule sets and generates a left subtree and a right subtree. The left subtree has only one node called a leaf node and was assigned with a label called priority. The right subtree contains rest of attributes. This procedure will be repeated until the attribute set become empty.

- Each intermediate node of the BDT is following an SVM classifier, which follows the defined rules and assigns the priority accordingly (i.e. 1 for Alert, 2 for Real-time, 3 for On_Demand, and 4 for Normal packets).

- In the above training phase, extracted samples are categorized and create the classification tree accordingly. After being trained, now the SVM-BDT classifier is ready to predict the actual class for the fresh test sample.

- As here the strongest attributes are selected, the prediction error rate of our algorithms is extremely low, and it provides the best and accurate classification.
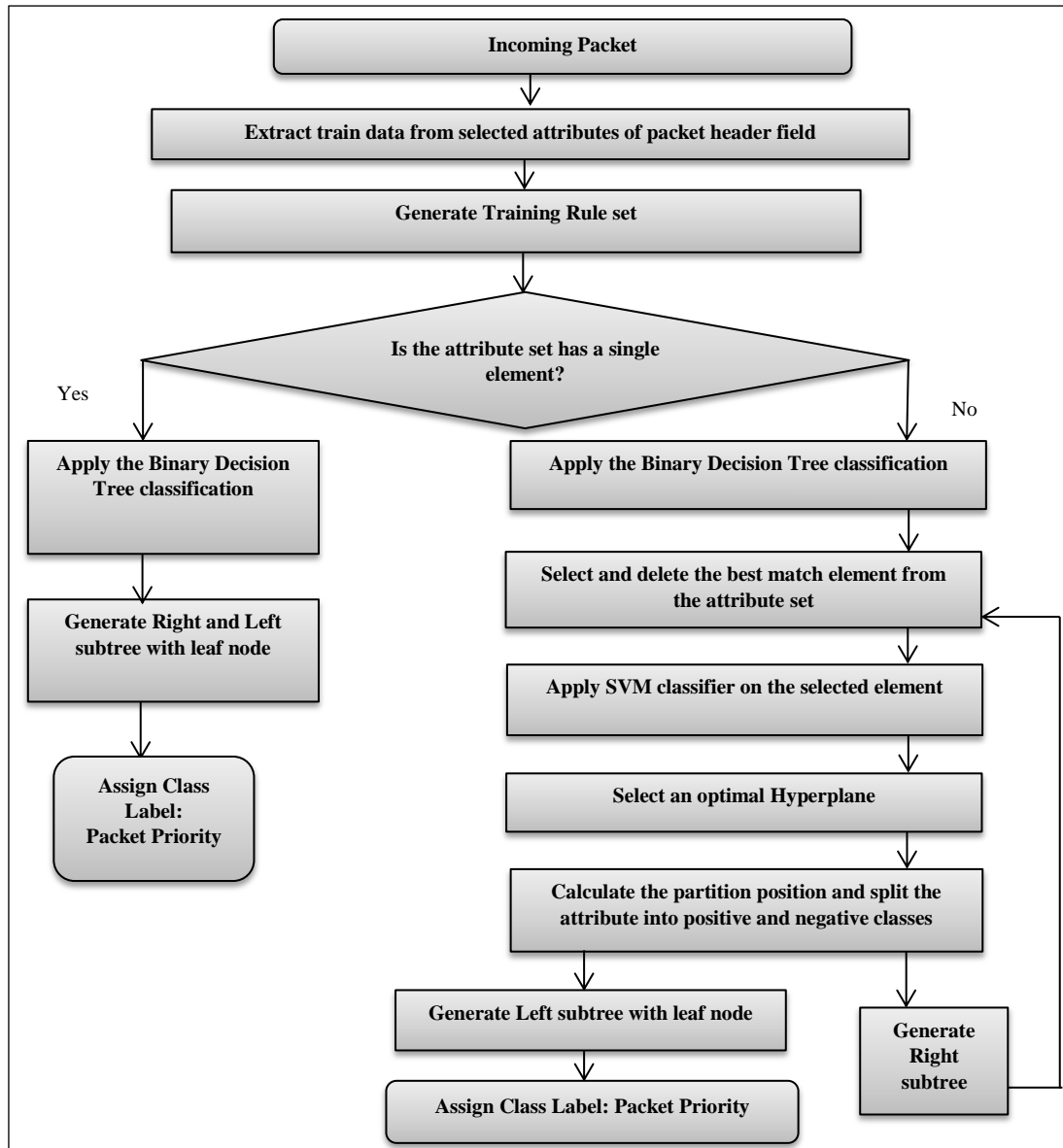
Figure 1. Workflow Diagram of Proposed Classification Unit

SVM-BDT classifier method first selects the best match attribute as an intermediate node for the classification tree.

- R_1: If (Flow type = Real-time), then

    If (Packet size <= Available bandwidth), then assign priority= NULL.

- R_2: If (Flow type = Real-time), then

    If (Packet size <= Available bandwidth), then assign priority= 2.

- R_3: If (Flow type = Non-Real-time), then

    If (Alert Index = 1), then assign priority= 1.

- R_4: If (Flow type = Non-Real-time), then

    If (On_Demand Index =1), then assign priority= 3.

- R_5: If (Flow type = Non-Real-time), then

    If (Alert Index! = 1), then

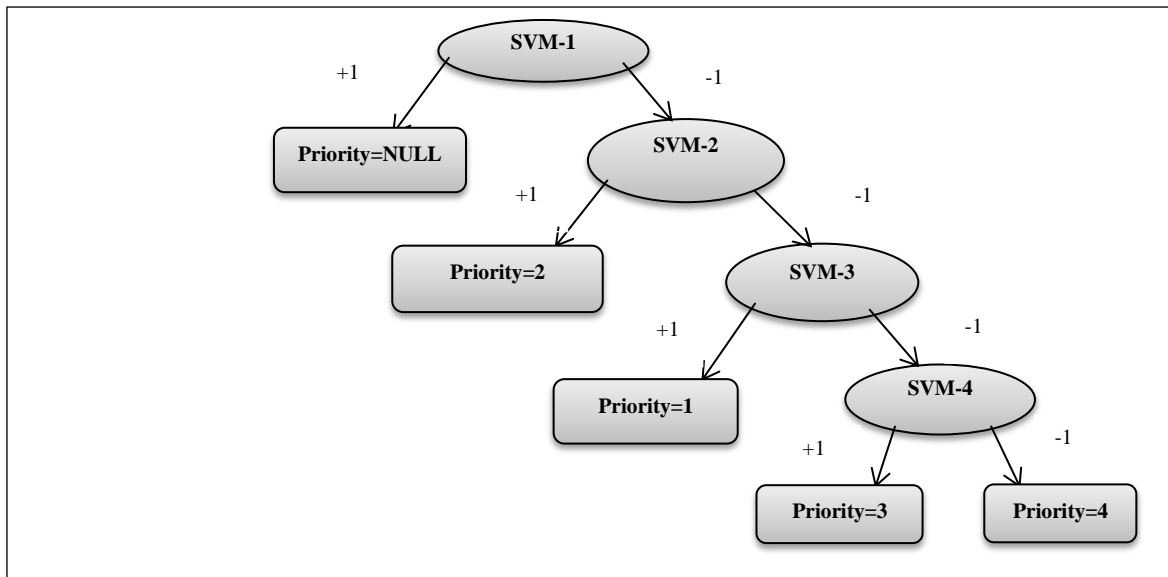   If (On_Demand Index! =1), then assign priority= 4.

Figure 2. Classification Principle of SVMBDTF Classifier

Algorithm: SVM-BDT based Fusion Classifier

SVM-BDT (Train_rule, Attribute_set, Best_attribute)

1. If all train rules are positive, then return a single tree having Root node with a label '+'.
2. Else if all train rules are negative, then return a single tree having Root node with a label '-'.
3. Else if no predicting attribute is present, then return the single tree having Root node with the label is the most matched value of the Best_attribute in Train_rule.
4. Else
   4.1 Select the Best_attribute from the Attribute_set and Set A= Best_attribute
   4.2 Set Root=A
   4.3 For each possible value $a_i \in A$
       4.3.1 Call SVM_Split (a_i)
       4.3.2 Add new subtree to the root
       4.3.3 Set A= a_i
       4.3.4 If Train_rules (a_i) ==Empty, then
           4.3.4.1 Add new subtree with leaf node and assign priority
       4.3.5 Else
           4.3.5.1 Create new subtree
           4.3.5.2 Call SVM-BDT (Train_rules, Target_attribute, Attribute_set-{A})
5.   Exit

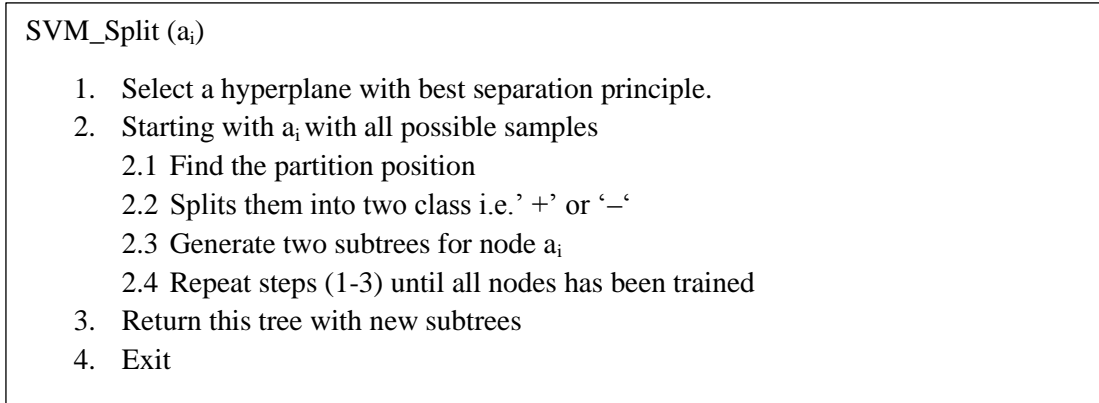**Figure 3. Algorithm for SVM-BDT based Fusion Classifier**

SVM_Split (a$_i$)

1. Select a hyperplane with best separation principle.
2. Starting with a$_i$ with all possible samples
   2.1 Find the partition position
   2.2 Splits them into two class i.e.' +' or '−'
   2.3 Generate two subtrees for node a$_i$
   2.4 Repeat steps (1-3) until all nodes has been trained
3. Return this tree with new subtrees
4. Exit

Figure 4. Algorithm for SVM_Split Function

3.3. Mathematical Model of Proposed Classifier

The main task of proposed classifier is to construct such a classification tree which can separate multiple classes accurately with minimum time.

Let five samples are extracted from the packet header field of the incoming packet *i.e.*, Packet size, Availability of allocating bandwidth, Packet flow types (real-time or non-real-time), Alert index, and On_Demand index fields and generate the attribute set. The training set having l number of samples and can be represented as:

$$\{a_i | o_i\}_{i=1}^l \tag{1}$$

where the input vector $a_i \in A^l$ provides the value of attribute i in the header field of the packet, $o_i \in \{NULL, 1, 2, 3, and\ 4\}$, is the classification outcomes *i.e.*, the priority of packets.

In the first phase, the BDT classifier selects the best match attribute as the separating node (*i.e.*, root or intermediate node). This node is fed into the SVM classifier to recursively partition of the space such that the samples with same labels are grouped together.

Let the attribute at the intermediate node is represented by a_i. Then partition the attribute into two groups (i.e. Left and Right subtrees) by using SVM classifier.

where
$$a_i(Left - subtree) = \{(a_i, o_i) | If\ Rule_i\ satisfied\} \tag{2}$$

$$a_i(Right - subtree) = \left\{A^l - \{a_i\}\right\} \tag{3}$$
Repeat this step until A^l set becomes empty.

The hyperplane of a multiclass SVM is model as:

$$f(a_i) = Weight_{P,N} * \varphi(a_i) + Bias_{P,N} \tag{4}$$

where $Weight_{P,N}$ is the weight vector and the $Bias_{P,N}$ is the optimal bias which is selected randomly, *P, N* means positive and negative partitions of internal node which are separated by a hyperplane, and φ defined the nonlinear mapping function applied to input vectors and expressed as given in equation (5).

$$\varphi(v) = \begin{cases} (A^{RT} | Flow\ type = Real - Time) \\ (A^{NRT} | Flow\ type = Non - Real - Time) \end{cases} \tag{5}$$

where

$$A^{RT} = \begin{cases} (Priority = NULL|Packet\_size \leq Bandwidth_{Available}) \\ (Priority = 2| \ otherwise) \end{cases} \tag{6}$$

$$A^{NRT} = \{P^{Alert_{Index}}|P^{On\_Demand_{Index}}\} \tag{7}$$

$$A^{Alert_{Index}} = \begin{cases} (Priority = 1|Alert_{Index} = 1) \\ (Priority = 4| \ otherwise) \end{cases} \tag{8}$$

$$A^{On\_Demand} = \begin{cases} (Priority = 3| \ On\_Demand_{Index} = 1) \\ (Priority = 4| \ otherwise) \end{cases} \tag{9}$$

The accurate optimization is done by minimizing the weight $Weight_{P,N}$ which results in maximized distance between the closest point of the hyperplane and the hyperplane itself. The new optimal equation with penalty becomes:

$$min(\varphi(a_i)) = \frac{1}{2} * \|Weight_{P,N}\|^2 + C * \sum_{i=1}^{l} err_i \tag{10}$$

Subject to

$$o(Weight_{P,N} * \varphi(a_i) + Bias_{P,N}) \geq 1 - err_i \tag{11}$$

where C is the constant used for regularization, and err$_i$ is the normalized variation or error with err$_i$ >=0, and i=1.........l.

By applying dual lagrangian multipliers, the above equation becomes:

$$max \ L_i(a) = \sum_{i=1}^{l} m_i - \frac{1}{2}\sum_{i,j=1}^{l} m_i m_j o_i o_j \left(\varphi(a_i).\varphi(a_j)\right)$$

$$= \sum_{i=1}^{l} m_i - \frac{1}{2}\sum_{i,j=1}^{l} m_i m_j o_i o_j K\left((a_i),(a_j)\right) \tag{12}$$

Subject to

$$\sum_{i=1}^{l} m_i o_i = 0 \tag{13}$$

where $K(a_i, a_j)$ is the kernel function, which is the substitute of the inner dot product $[\varphi(a_i). \ \varphi(a_j)], m_i$ and m_j are the lagrangian multipliers and value of m_i lies between $C \geq m_i \geq 0$.

On solving the above equation, the final classification equation can be expressed as given below:

$$L_{err} = \begin{cases} 0, & if \ |o_i - f(a_i)| \leq err \\ |o_i - f(a_i) - err|, & if \ |o_i - f(a_i)| > err \end{cases} \tag{14}$$

where err is the maximum allowed error.

The accuracy of classification depends on the magnitude of the parameter C and err.

4. Experimental Result

The performance of proposed protocol is evaluated through network simulator NS-2.35. The proposed protocol is compared with the existing OCMP protocol [6]. The experimental results obtained from the simulation shows that the performance of the proposed protocol is better than the existing ones in all aspects. The system performance is evaluated from Packet Delivery Rate (PDR), Delay and Throughput with respect to the number of nodes.

4.1. Packet Delivery Rate (PDR)

The Packet Delivery Rate is defined as the ratio of the total number of packets delivered successfully to the central controller node with respect to the total number of packets directs from the source node. The PDR can be calculated from Equation (15).

$$PDR = \frac{\sum_{j=1}^{n} P_j^{Success\_Delivered}}{\sum_{j=1}^{n} P_j^{Send}} * 100 \tag{15}$$

where $P^{Success\_Delivered}$ denotes the total number of packets received successfully at the sink node and P^{Send} denotes the number of packets transmitted from the source sensor node.

In Figure 4, the comparison graph of PDR for both proposed and existing protocol is given. The greater value of PDR indicates better performance in the proposed protocol.
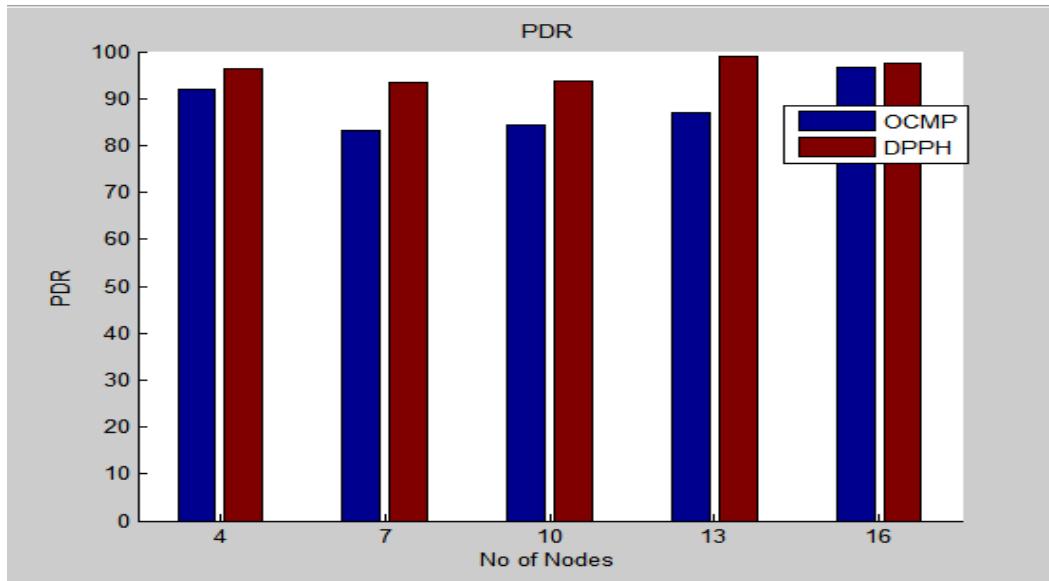

Figure 4. Packet Delivery Rate in Proposed and Existing Protocols

It shows that the rate of successful reception of packets is more in proposed protocol than the existing protocol because of fusion based packet classification mechanism, which enhances the PDR by sending a large amount of more useful packets within the significant time bound and minimizing packet loss rate.

4.2. End-to-End Delay

The end-to-end delay is defined as the total time required for reaching a packet from the source sensor node to the central controller node. It also includes propagation, processing, queuing and transmission delay. The end-to-end delay is also defined as the difference between packet receiving time and the packet sending time. The end–to-end delay is calculated using equation (16).

$$E2E_{Delay} = \frac{\sum_{j=1}^{n}(Received_j^{Time} - Send_j^{Time})}{n} * 100 \tag{16}$$

Where $Received^{Time}$ denotes the time in which the packet arrives at the sink node, $Send^{Time}$ denotes the time when a packet is sent from the source node, and n denotes the total number of packets transmits.

The simulation results for the end-to-end delay for proposed and the existing protocol is given in Figure 5. It shows that the variation in end-to-end delay in proposed protocol is less as compared to existing one. The dynamic prioritization based scheduling policies reduce delay in the proposed system.
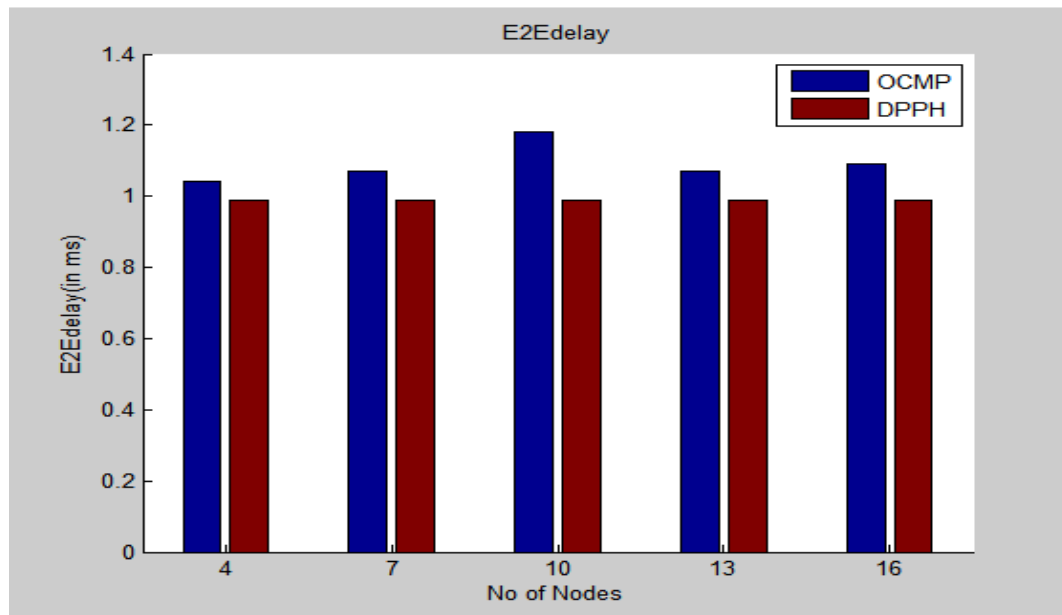
Figure 5. End-to-End Delay in Proposed and Existing Protocols

4.3. Throughput

It defines the ratio of the total amount data successfully delivered to the controller node within the simulation time. It also provides the knowledge of packet rate or speed of the received packet in bits per seconds *i.e.*, packets per second. The throughput of the network is calculated from the formula given in (17).

$$Throughput = \frac{(\sum_{k=1}^{n} P_k^{Success\_Delivered}) * (Packet_{Size})}{T_{Simulation}} \tag{17}$$

where $P^{Success\_Delivered}$ denotes the number of packets received at the sink node, $Packet_{Size}$ denotes the size of a packet, $T_{Simulation}$ denotes the total simulation time period.

The comparison graphs for throughput given in Figure 6. The proposed protocol has good and better throughput than the existing one. The increase in packet delivery rate and the decrease in delay are the main factors for the improvement in throughput.
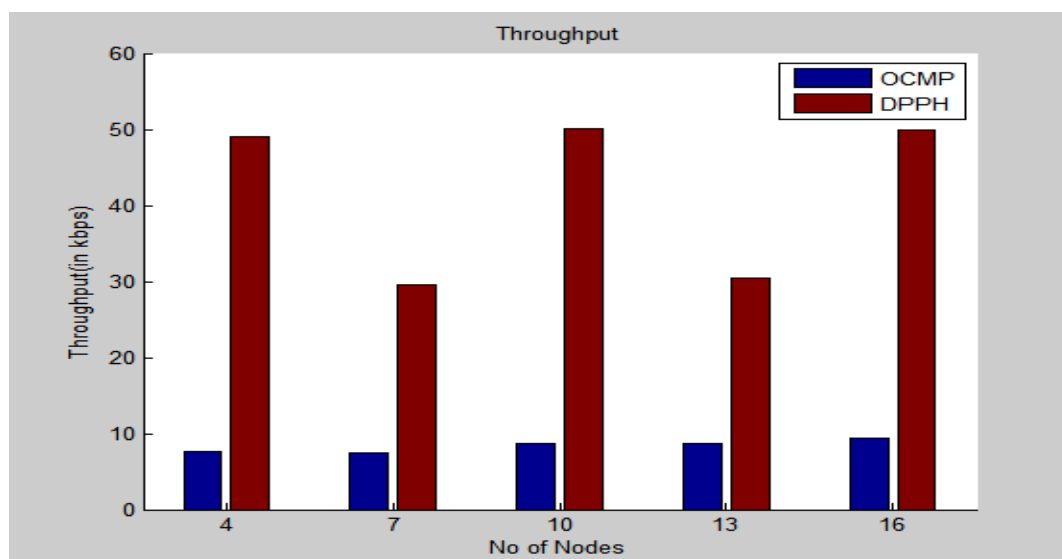

Figure 6. Throughput in Proposed and Existing Protocols

The above graphs indicate that the overall performance of the system is improved due to the proposed SVM-BDT based packet classification unit.

5. Conclusion

In this paper, heterogeneous packet classification for dynamic prioritization is designed with the fusion of two machine learning based classification techniques (*i.e.*, SVM and BDT). It enhances the performance of classification unit greatly from the combined benefits of both SVM (*i.e.*, high classification accuracy) and BDT (*i.e.*, efficient computation time). Here the SVM classifiers arranged in a BDT structure for solving accurate multiclass classification problems with minimum searching time. The validation is done through the ns-2.35 network simulator. The simulation result shows that the proposed classifier is efficient enough to reduce the end-to-end delay, and improve the packet delivery rate as well as throughput of the healthcare WBAN system.

References

[1] K. Suriyakrishnaan, and D. Sridharan, "Critical Data Delivery Using TOPSIS in Wireless Body Area Networks", vol. 7, **(2016)**, pp. 622-629.

[2] G. N. Bradai et al.,"QoS architecture over WBANs for remote vital signs monitoring applications", 12th Annual IEEE Consumer Communications and Networking Conference, **(2015)**, pp. 1-6.

[3] M. Kathuria, and S. Gambhir, "Quality of service provisioning transport layer protocol for WBAN system", International Conference on Optimization, Reliability and Information Technology (IEEE Xplore), **(2014)**, pp. 222-228.

[4] Long Hu, Yin Zhang, Dakui Feng, M.M. Hassan, A. Alelaiwi, and Atif Alamri, "Design of QoS-Aware Multi-Level MAC-Layer for Wireless Body Area Network", Journal of Medical Systems (ACM), vol. 39, no. 12, **(2015)**, pp. 1-11.

[5] M. Kathuria, and S. Gambhir, "Layer wise Issues of Wireless Body Area Network: A Review", International conference on Reliability, Infocom Technologies and Optimization (ICRITO), **(2013)**, pp. 330-336.

[6] A. A. Rezaee, M. H. Yaghmaee, and A. M. Rahmani, "Optimized Congestion Management Protocol for Healthcare Wireless Sensor Networks", Wireless Personal Communications (Springer), vol. 75, no. 1, **(2013)**, pp. 11-34.

[7] S. Misra, V. Tiwari, and M. S. Obaidat, "LACAS: Learning Automata-Based Congestion Avoidance Scheme for Healthcare Wireless Sensor Networks", IEEE Journal on Selected Areas in Communications, vol. 27, no.4, **(2009)**, pp. 466-479.

[8] S. Gambhir, V. Tickoo, and M. Kathuria, "Priority based congestion control in WBAN", Eighth International conference on contemporary computing (SCOPUS, DBLP, IEEE Xplore), **(2015)**, pp. 428-433.

[9] Xu Wu, "A Lightweight Trust-based Access Control Model in Cloud-Assisted Wireless Body Area Networks, International Journal of Security and Its Applications", vol.8, no.5, **(2014)**, pp.131-138.

[10] D. E. Taylor, and J. S. Turner, "ClassBench: a packet classification benchmark", IEEE/ACM Transactions on Networking, vol. 15, no. 3, **(2007)**, pp. 499-511.

[11] Haoyu Song, and J. S. Turner, "ABC: adaptive binary cuttings for multidimensional packet classification", IEEE/ACM Transactions on Networking (TON) Journal, vol. 21, no. 1, **(2013)**, pp. 98-109.

[12] Jui-Sheng Chou, Min-Yuan Cheng, and Yu-Wei Wu, "Optimizing parameters of support vector machine using fast messy genetic algorithm for dispute classification", Journal Expert Systems with Applications: An International Journal of ACM, vol. 41, no. 8, **(2014)**, pp. 3955-3964.

[13] Asish Anand, and Ponnuthurai N. Suganthan, "Multiclass cancer classification by support vector machines with class-wise optimized genes and probability estimates", Journal of Theoretical Biology, vol. 259, no. 3, **(2009)**, pp. 533-540.

[14] F. Huang, and Y. Lu-Ming, "Research on classification of hyper spectral remote sensing imagery based on BDT-SMO and combined features", Journal of Multimedia, vol. 9, no. 3, **(2014)**, pp. 456-462.

[15] N. Xue, "Comparison of multi-class support vector machines", Computer Engineering and Design, vol. 32, no. 5, **(2011)**, pp. 1792-1795.

[16] Q. Ai, Y. Qin, and J. Zhao, "An improved directed acyclic graphs support vector machine", Computer Engineering and Science, vol. 33, no. 10, **(2011)**, pp. 145-148.

[17] G. Feng, "Parameter optimizing for Support Vector Machines classification", Computer Engineering and Applications, vol. 47, no. 3, **(2011)**, pp. 123-124.

[18] C. C. Chung, and C. J. Lin, "LIBSVM: A library for support vector machine", ACM Transactions on Intelligent System and Technology, vol. 2, **(2011)**, pp.1-27.

[19] M. Kathuria, and S. Gambhir, "Leveraging machine learning for optimize predictive classification and scheduling E-Health traffic", International Conference on Recent Advances and Innovations in Engineering (IEEE Xplore), (**2014**), pp. 1-7.

[20] K. K. Reddy, and V. Reddy, "A Survey on Issues of Decision Tree and Non-Decision Tree Algorithms", International Journal of Artificial Intelligence and Applications for Smart Devices (SERSC), vol. no. 1, (**2016**), pp. 9-32.

[21] M. Kathuria, and S. Gambhir, "Genetic Binary Decision Tree based Packet Handling schema for WBAN system", Recent Advances in Engineering and Computational Sciences (IEEE Xplore), (**2014**), pp. 1-6.

[22] G. Madzarov, D. Gjorgjevikj, and I. Chorbev, "A Multi-class SVM Classifier Utilizing Binary Decision Tree", Informatics, vol. 33, (**2009**), pp.233-241.

[23] Hyesook Lim, Nara Lee, Geumdan Jin, Jungwon Lee, Youngju Choi, and Chanhoon Yim, "Boundary cutting for packet classification", Journal IEEE/ACM Transactions on Networking (TON), vol. 22, no. 2, (**2014**), pp. 443-456.

[24] M. Kathuria, and S. Gambhir, "Comparison Analysis of proposed DPPH protocol for Wireless Body Area Network", International Journal of Computer Applications (IJCA), vol. 144, (**2016**), pp. 36-41.

[25] Jinhong Guo, Zhi Chen, Yong-Ling Ban, and Yuejun Kang, "Precise Enumeration of Circulating Tumor Cells Using Support Vector Machine Algorithm on a Microfluidic Sensor, IEEE Transactions on Emerging Topics in Computing, 2013, pp. 1-8.

[26] Husheng Guo, and Wenjian Wang, "An active learning-based SVM multi-class classification model", Journal of Pattern Recognition", (**2015**), vol. 48, no. 5.

[27] M. Kathuria, and S. Gambhir, "Reliable delay sensitive loss recovery protocol for critical health data transmission system", International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (IEEE Xplore), (**2015**), pp. 333-339.

[28] J. Wang, Z. Zhang, Y. Zheng, L. Zuo and J. Kim, "A MultiTiers Service Architecture based Diabetes Monitoring for Elderly Care in Hospital, International Journal of Multimedia and Ubiquitous Engineering, vol. 8, no. 3, (**2013**), pp. 387-398.

[29] S. Gambhir, and M. Kathuria, "DWBAN: Dynamic Priority based WBAN Architecture for Healthcare System", 3rd International Conference on Computing for Sustainable Global Development, (**2016**), pp. 6133-6139.

[30] M. Kathuria, and S. Gambhir, "Security and Privacy Assault of Wireless Body Area Network System", International conference on Reliability, Infocom Technologies and Optimization, (**2013**), pp. 223-229.