A novel fusion-based approach for the classification of packets in wireless body area networks

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ABSTRACT

This abstract focuses on the significance of wireless body area networks (WBANs) as a cutting-edge and self-governing technology, which has garnered substantial attention from researchers. The central challenge faced by WBANs revolves around upholding quality of service (QoS) within rapidly evolving sectors like healthcare. The intricate task of managing diverse traffic types with limited resources further compounds this challenge. Particularly in medical WBANs, the prioritization of vital data is crucial to ensure prompt delivery of critical information. Given the stringent requirements of these systems, any data loss or delays are untenable, necessitating the implementation of intelligent algorithms. These algorithms play a pivotal role in expediting diagnosis and treatment processes during medical emergencies. This study introduces an innovative protocol termed collaborative binary Naive Bayes decision tree (CBNBDT) designed to enhance packet classification and transmission prioritization. Through the utilization of this protocol, incoming packets are categorized based on their respective classes, enabling subsequent prioritization. Thorough simulations have demonstrated the superior performance of the proposed CBNBDT protocol compared to baseline approaches.

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1. INTRODUCTION

Wireless body area network (WBAN) has a significant role to play in the healthcare system. It's a spin on a tried-and-true method for analyzing patient health data and making informed decisions promptly. Taking reliable action in the dynamic, uncertain context of healthcare WBAN is difficult because of the necessity for adaptability and the presence of hidden dangers [1], [2]. It becomes even more crucial that accurate categorization and prompt transmission of critical data are in place to ensure the patient's safety under these conditions [3]. However, there is a major problem with the classification of diverse data. In light of these restrictions, we set out to create a multiclass classifier that fuses collaborative binary Naive Bayes decision tree (CBNBDT) based techniques for more precise packet classification [4]. This fusion classifier is utilized by the centralized controller node to determine the appropriate priority for each incoming packet based on its class. We divide all incoming data into four distinct types: alert, real-time, on-demand, and normal. Classifying and sending heterogeneous packets in priority order helps boost efficiency in the highly dynamic healthcare WBAN [5]. To get good results, the suggested work integrates two classification methods based on machine learning. The simulation results show that the efficiency of the system is much improved by using the suggested fusion classifier approach. We provide a novel technique for prioritizing packet categorization as well as transmission based on CBNBDT. The remainder of the essay is structured as follows: section 2 contains a similar work, section 3 introduces the recommended method, the examination of the experiment's findings is in section 4, and section 5 contains the conclusion.

2. METHOD

This study examines a range of technical approaches and research articles authored by different writers. An analysis was conducted on well-known communication wave patterns in WBAN applications [6]. These patterns were classified into long and short ranges to ascertain the optimal conditions for each type. The study also compares advancements in long-range remote communication. The trend in global systems involving medical sensors highlights the significance of electronic circuit and convention advancements as well as their impact on public health, a concern that has persisted over time.

Research by Salih and Alsewari [7], the focus shifts to network performance and the attributes of sensor nodes. The study delves into the monitoring of patient systems using a central control unit (CCU) within the context of WBAN applications supported by long-range wireless networks. This setup enables the utilization of minute, enduring sensors that are essential for detecting various physiological signals like electrocardiogram (ECG), photoplethysmogram (PPG), electroencephalogram (EEG), and temperature variations. Beyaztas *et al.* [8] lay out energy-conserving solutions spanning the physical, media access control (MAC), and network layers. Additionally, potential research directions are outlined based on application requirements. Given the challenges tied to recharging or replacing nodes, energy consumption emerges as a pressing concern. Consequently, this concern gives rise to emergency frame retransmissions, ultimately diminishing node longevity and increasing energy demands. To address this, it is recommended to schedule node access based on their associated risks, thus mitigating collisions.

An evaluation of severe attacks on WBAN systems is conducted to comprehend their destructive mechanisms [9]. Simulation-based investigations utilizing Castalia and OMNET++ reveal the substantial impact of intrusion detection systems (IDS) in detecting network jamming. Existing approaches exhibit drawbacks such as excessive energy expenditure due to intricate calculations and false alarms stemming from inadequate parameters. Additionally, some IDS fail to recognize various forms of jamming. Yaseen *et al*. [10] presents an integrated security architecture that employs biometric and digital signature applications to fortify the network against intrusions and bolster its credibility and stability. Empirical results underline the efficacy of this strategy, with a focus on maintaining system security and stability. The strategy maintains optimal residual energy levels of 20 J, with a majority of nodes surviving over 2000 data transfer cycles. The design of the network must inherently account for security considerations. Nyangaresi *et al*. [11] proposes a classification methodology for sensor nodes, leveraging an adaptive neuro-fuzzy inference system (ANFIS) classifier to distinguish reliable from unreliable nodes, thereby enhancing WBAN network efficiency. This approach is enhanced by an improved genetic algorithm and judicious use of limited data buffers. Notably, this effort doesn't introduce additional complexities to the WBAN setup.

Lastly, Salih *et al*. [12] introduces a hybrid MAC strategy designed to optimize multi-class channel access within the WBAN. The strategy employs a multi-objective optimization framework to determine the optimal duration of the contention phase and the maximum count of biomedical devices capable of transmitting during the transmission phase. This optimization accounts for system-wide throughput, packet success-access ratio, and reservation ratio. The broader realm of WBAN technology and its applications in healthcare and beyond are explored in studies ranging from [13]–[23]. These works delve into not only medical applications but also hobbies, laboratory activities, and the measurement of non-health-related data facilitated by WBAN technology [24]–[28].

3. PROPOSED METHODOLOGY

A developing technology called WBANs makes it possible to monitor physiological data such as vital signs non-invasively. To provide reliable communication, it is necessary to create effective algorithms for categorizing packets owing to the constrained resources available in WBANs. In this article, we provide a brand-new fusion-based method for classifying packets in WBANs. The suggested method integrates various classifiers into a single system that can be used to precisely categorize packets according to their content. Using actual data from a WBAN system installed at a hospital, the suggested method is assessed. The findings demonstrate that the suggested method performs better than current ones in terms of accuracy and robustness. Furthermore, the suggested method can accurately categorize packets even when there is a lot of noise in the data. Because of this, it may be used in settings where noise levels can be high in the real world. Overall, the fusion-based technique for packet categorization in WBANs presented in this work may be utilized to increase communication accuracy and dependability. Multiclass classification design is more challenging than two-class design. Since there has been a lack of research into this area thus far, we attempt to design a multiclass packet classification system to address these issues. The three modules of the proposed WBAN system interact with one another and their ever-changing surroundings. In the proposed system architecture, the functioning is divided into distinct units for efficient management of data flow and decision-making.

The WBAN unit serves as the initial data aggregation point. Data obtained from diverse sensor nodes are consolidated in the pre-processing unit before being dispatched to the controller unit (CU). In the CU, decision-making authority is vested across various tiers, and these decisions are promptly communicated to the medical server unit (MSU). The aggregation unit within the CU compiles data collected from all sensors, while the CU packet handling unit, organized into five components, manages incoming data packets. Notably, the alerting unit triggers the alert index field in the packet header upon detecting unexpected values in the sensed data. Meanwhile, the packet classification unit arranges incoming data, according to priority, while the queuing unit temporarily stores classified packets until processing can occur. The scheduling unit then prioritizes these packets, ensuring timely transmission to the MSU. The prioritization unit plays a pivotal role, dynamically updating the significance of each sensor node based on pre-defined parameters such as critical signal range, tolerance threshold, time intervals, and on-demand requests. This dynamic prioritization is executed in close collaboration with healthcare providers, thereby facilitating swift and contextually informed adjustments.

At the core of the system is the MSU. This unit assumes responsibility for receiving data packets from the CU, channeling them to the packet monitoring unit for thorough analysis, and subsequently engaging the decision-making unit for informed determinations. In situations where an alarm packet is detected, the MSU promptly notifies the relevant healthcare professional, enabling timely and appropriate actions to be taken. To maintain accurate data processing and decision-making, the healthcare provider collaborates with the CU to ensure that the priorities and predefined parameters for all sensor nodes remain up to date, thereby safeguarding the efficacy and responsiveness of the overall system.

In critical situations where a patient's life is at risk, swift and precise medical intervention is imperative. The CU plays a pivotal role in this process by ascertaining the priority of each incoming data packet before forwarding it to the healthcare provider's server. The central objective of the proposed protocol is to devise an effective packet classification system utilizing a synergistic approach of CBNBDT techniques. This approach aims to accurately identify the class of each packet and assign an appropriate priority level within the dynamically evolving environment of a healthcare-centric WBAN.

The CBNBDT framework leverages the principles of Naive Bayes (NB), a straightforward probability-based classifier that determines class probabilities based on data point frequencies and permutations. Operating on the foundation of Bayes' theorem, the algorithm assumes the independence of all variables with respect to the class variable's value. Although this conditional independence assumption might not always hold true in real-world scenarios, the algorithm's quick learning capacity proves advantageous in controlled classification contexts. Named after the 18th-century British mathematician Thomas Bayes, Bayes' theorem stands as a formula to compute conditional probabilities, contributing to the foundation of probabilistic reasoning (1):

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \tag{1}$$

Where P (A|B) represents the likelihood of event A occurring given the presence of Event B; P(A) indicates the likelihood of event A happening independently, P(B|A) signifies the probability of event B taking place when event A has occurred, and P(B) denotes the probability of event B happening in general.

NB is used to analyzing the data, and from that comes the confusion matrix for the class gender, which can take on two values (the two probable genders). Compared to other classification strategies, the NB classifier offers superior and more precise results. It performs admirably on cross classifications, but testing takes longer as data is larger.

Each node in a CBNBDT, including the root node, carries an attribute for evaluating the governing principle. To create the hierarchical tree structure with left and right sub trees, a binary split occurs at every level of the tree except the leaf node. Attribute reduction occurs during iteration, leading to a state where all data are categorized similarly. This terminal node will be the leaf node that declares the class. Once the tree has been formed, classifying the test set in binary decision trees (BDT) is faster than alternative methods. It offers a low-cost, noise-resistant classification policy. In addition to its inability to correctly classify data and detect previously hidden data, BDT's mistake rate rises as complexity rises.

The approach of a CBNBDT based fusion classifier is adopted within the context of these limitations. This strategy involves the amalgamation of CBNBDT techniques in constructing a classifier. This fusion classifier technique is specifically designed to address the challenges associated with heterogeneous packet transmission in a WBAN, effectively resolving issues associated with BDT and NB. In this protocol, due consideration is given to the advantages offered by CBNBDT. While CBNBDT excels in terms of classification accuracy, BDT demonstrates swifter performance in classifying new instances. The operational dynamics of the proposed classifier unit are illustrated in Figure 1.

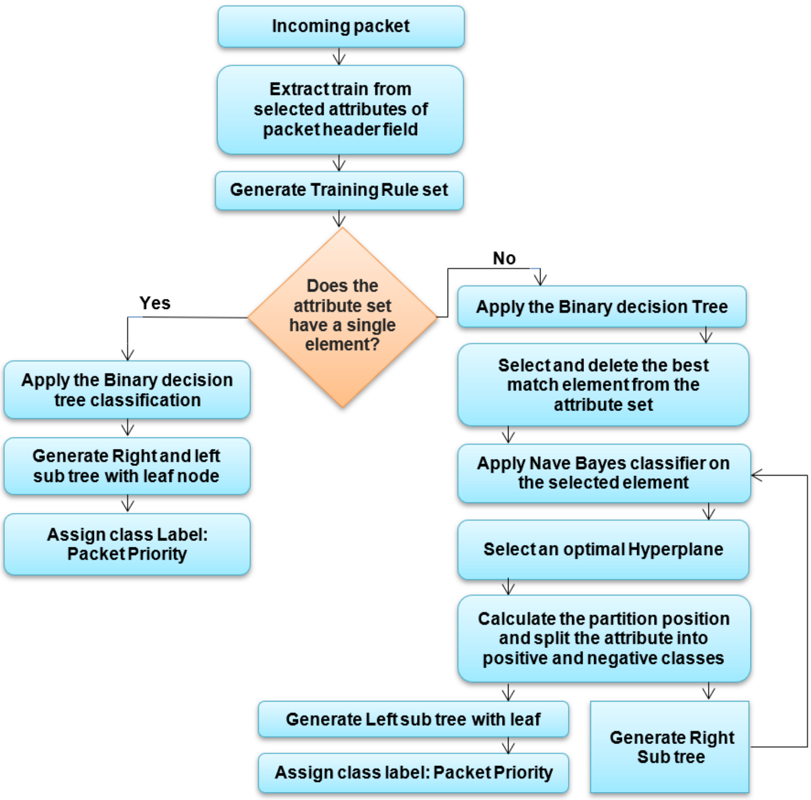

Figure 1. Activity of the proposed classifier unit

The following describes the functional principle underlying the suggested packet classification unit:

- When early as a packet is received, it is sent to the alerting unit following the data aggregation unit.
- By comparing the sensed value to the true vital range value, the alerting device may determine the critical state. An alert index field in the incoming packet is activated if an abnormality is identified.
- The arriving packet's header is inspected in the classification section. Strength and conditioning rule set as well as a character set are formed based on packet size, network throughput, packet flow style, alert index value, and on demand index value.
- The CBNBDT classifier receives the training set as well as the extracted attribute set. With the assistance of the NB classifier, it determines which attribute from the attribute set is the best match and then builds a tree using the nodes' relationships. Using rule sets, the NB classifier divides the qualities into positive and negative categories before producing the left and right sub-tree. In the left sub-tree, there is just one node, termed a leaf node, which has the priority label. The remaining characteristics are located in the right sub-tree. This process will continue until there are no more attributes to retrieve.
- Every BDT node in the network uses an NB classifier to determine the packet's priority based on predetermined criteria.
- During the aforementioned training step, we classify the extracted samples and build the classification tree. The CBNBDT classifier has been trained, and can now determine the true classification of an unlabeled test sample.

The algorithms deliver the most accurate classification as the strongest qualities are prioritized during the selection process. Figure 2 depicts the principle of the CBNBDT classifier. Before building the classification tree, the CBNBDT approach determines which attribute is the best candidate for the intermediate node. Where:

- R1: When (Flow_type = true status)
  Priority is set to Zero provided (Packet_size = Bandwidth Utilization)

- R2: When (Flow_type = true status)
  Set priority=2 when (Packet size = Bandwidth utilization).
- R3: When (Flow_type = non-true status)
  A priority of 1 is assigned if (Alert_Index = 1)
- R4: When (Flow_type = non-true status)
  Priority = 3 when (On_Demand Indices = 1)
- R5: When (Flow_type = non-true status)

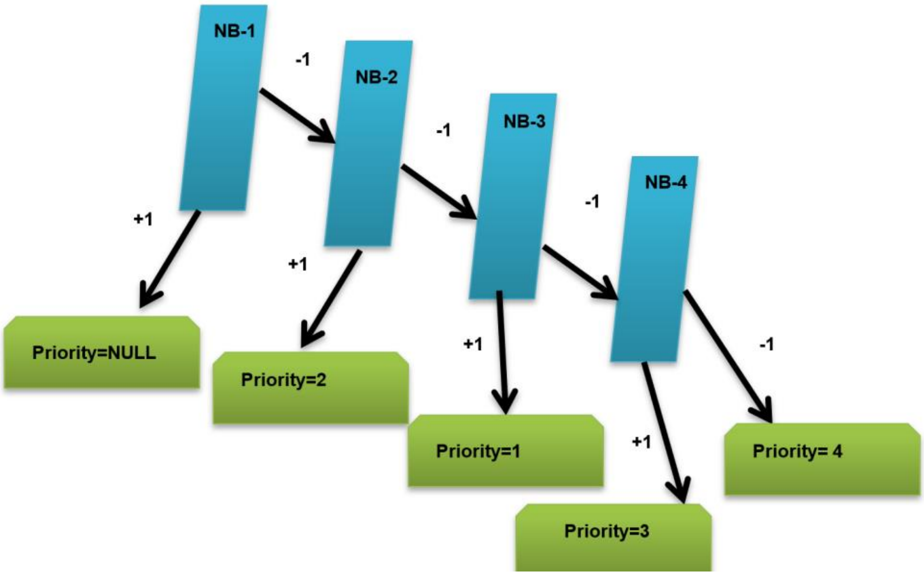

Figure 2. Principal of CBNBDT classifier

This rule states that if the alert index is equal to one, therefore A priority level 4 is assigned if the (On_Demand Index!) equals 1. Algorithm 1 depicts the fusion classification with CBNBDT. Algorithm 2 shows the NB split function.

Algorithm 1. Fusion classification with CBNBDT
Start
CBNBDT (Train-rule, features -set. Finest)
If output a single tree with R equal to "+" when all criteria are good.
Otherwise, if every instruction in the training is negative, output a single tree with a node labeled "-."
Otherwise, if there isn't a predicting property, output a single tree whose root node's label matches the Finest in Train-most particular rule closely.
Otherwise
Take the feature with the most value from a set of characteristics and replace it with A=Best-attribute.
 Alter Root = A
  For every conceivable value of a, A
   Call NB- Split (a)s
     Add a new subtree to the root
      Set A=a,
     If Train rules (a,) ==Empty, then
       Add a new sub-tree with leaf node and assign priority
      Otherwise
       Create new sub-tree
     Call CBNBDT (Train-rule, features -set. Finest-{A})
 Stop

Algorithm 2. CBNBDT-split function
CBNBDT _ Split (ai)

Select a hyperplane with the best separation principle.
Starting with ai with all possible samples
Find the partition position
Splits them into two class i.e.' +' or '
Generate two subtrees for node ai
To finish training all nodes, start repeating steps (1-3).
Add more branches to this tree and send them to the back
stop

4. EXPERIMENTAL RESULTS

The efficacy of the proposed protocol is assessed using the network simulator-2 (NS-2). A comparative analysis is performed between the suggested method and the existing protocol. Through simulation outcomes, the proposed approach's enhancement over the current state-of-the-art is evident across all pertinent metrics. Notably, the evaluation encompasses key indicators such as packet delivery rate (PDR), end-to-end (E2E) delay, and throughput, collectively gauging the system's overall efficiency.

Throughput is calculated as the ratio of accurately delivered data packets to the total number of nodes involved in the simulation. This metric offers insights into the packet rate or speed, indicating how many packets are received per second. The network's throughput is quantified using the provided as in (2), which takes into account these factors and provides a comprehensive perspective on the network's capacity to transmit data effectively.

$$Throughput = \frac{(\sum_{k=1}^{n} P_k^{\text{Success\_Delivered}})*(packet_{size})}{T_{simuiation}} \tag{2}$$

where the total simulation time ($T_{Simulation}$), packet size ($packet_{size}$), and packet delivery success rate ($P^{Success\text{-}Delivered}$) are all numbers.

The throughput comparison graphs depicted in Figure 3 highlight the favorable performance of the proposed protocol, surpassing that of the existing standard. This improvement can be attributed to the elevated PDR and reduced E2E delay. In particular, the PDR is computed by dividing the total count of packets transmitted from the source node by the total count of packets received at the central controller node. The calculation of PDR is facilitated through the utilization as in (3):

$$PDR = \frac{\sum_{j=1}^{n} P^{j}_{\text{Success\_Delivered}}}{\sum_{j=1}^{n} P^{j}_{\text{Send}}} * 100 \tag{3}$$

$P_{Success\text{-}Delivered}$ is the quantity of packets innovation and better at the sensor nodes, and P_{Send} is the amount transmitted from the origin sensor node.

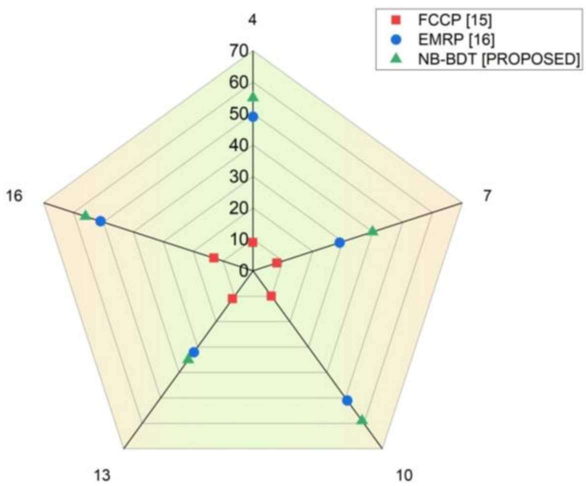

Figure 3. Comparison of throughput in proposed and existing protocols

Figure 4 provides a comparative analysis of the PDR between the suggested and existing protocols. A higher PDR value indicates the enhanced performance of the proposed protocol, reinforcing its efficacy. The E2E delay quantifies the time taken for a packet to traverse from its origin at the initial sensor node to its destination at the centralized processing facility. This measure encompasses factors such as propagation, processing, queuing, and transmission delay. Another perspective on E2E delay is the temporal gap between the moment of packet transmission and its eventual reception. The calculation of E2E delay is facilitated through the use as in (4), which comprehensively accounts for the various time components contributing to the overall delay.

$$\mathrm{E2}E_{Delay} = \frac{\sum_{j=1}^{n}\left(Received_j^{Time} - Send_j^{Time}\right)}{n} \quad (4)$$

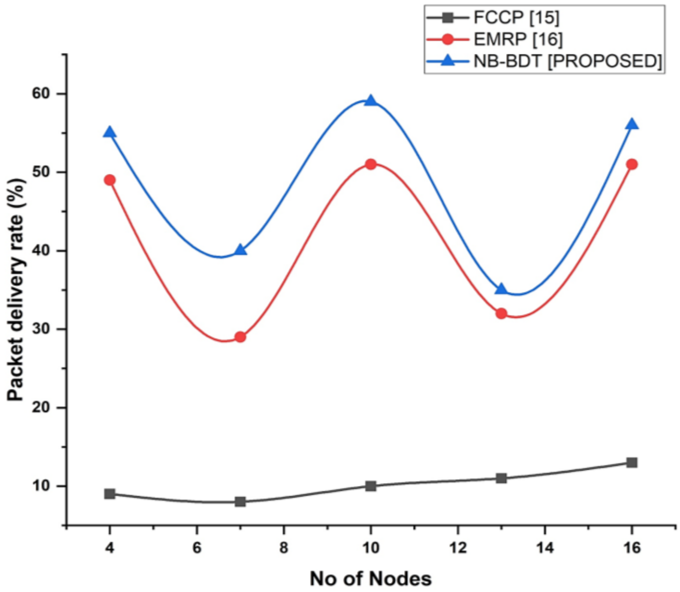

Figure 4. Comparison of PDR in proposed and existing protocols

After the investigation, we consider a scenario wherein individual packets undergo distinct time intervals for traversal between the source node and the sink node. Specifically, denoted as "ReceivedTime," this temporal parameter signifies the duration requisite for a packet to navigate from the source to the sink node. Additionally, an accompanying interval labeled as "SendTime" accounts for the time required for the packet's journey from the source node to the sink node. Notably, within this framework, "n" assumes representation as the total count of packets transmitted. Thus, in each instance of packet transmission, there is an interval of "SendTime" seconds allocated for its transmission from the source to the sink node, followed by an additional temporal span of "ReceivedTime" seconds to complete its return journey. It is essential to underscore that the magnitudes of "SendTime" and "ReceivedTime" are influenced by multifaceted factors including network conditions, transmission mediums, and processing latencies. The variable "n" embodies the aggregate quantity of packets subjected to transmission, reflecting the diverse scope of packet exchanges inherent to the underlying application or experimental setting.

Figure 5 shows approximated E2E delay for proposed and existing methods. The suggested protocol has less delay variation than the existing method. The suggested system runs more smoothly because of the dynamic priority-based scheduling strategies. WBAN has gained recognition for its advanced technology and autonomy, prompting many scientists to research it. A major challenge for WBAN is providing quality of service (QoS) in the fast-paced healthcare industry, as well as managing different types of traffic with limited resources. To ensure that vital data is delivered quickly, an intelligent algorithm must be used to prioritize it in medical WBANs. To this end, this study proposes a CBNBDT protocol for packet classification and transmission. Through simulations, the proposed approach was found to outperform the baseline.

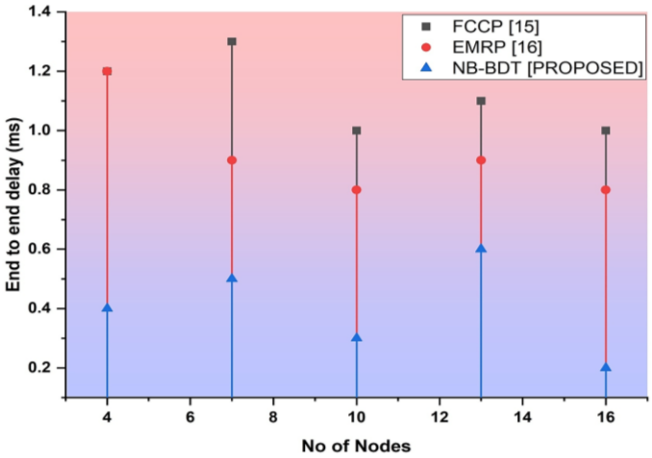

Figure 5. Comparison of E2E delay in proposed and existing protocols

5. CONCLUSION

Two approaches to classification based on machine learning were examined in this study (CBNBDT) are combined to create a heterogeneous packet classification system for dynamic prioritization. The combined advantages of CBNBDT (high classification accuracy) and BDT considerably improve the performance of the classification unit. Hence, BDT-structured CBNBDT algorithms tackle multiclass classification challenges efficiently and accurately. The validation uses NS-2.35. The simulation results show that the suggested classifier helps decrease E2E delay while simultaneously increasing PDR and throughput. CBNBDT-based packet classification saves time and space. The packet is utilized for constant as well as event-triggered health monitoring. Future research may involve designing protocols to decrease resource complexity and address malfunction as well as security problems.

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