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Iot Enabled Dichotomous Regressive Ranking Decision Forest Node Classification For Efficient Data Transmission In Wireless Sensor Networks

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Abstract

An Internet of Things (IoT) permits several sensors that are connected to the Internet. The sensor nodes are a significant component of Wireless Sensor Networks assisted IoT networks to perform data acquisition for long-term monitoring. In this case, energy-efficiency is the most significant factor for long-term data acquisition to enhance the network lifetime. Therefore, developing a robust and energy-aware routing technique is a difficult task to expand the network lifetime. A novel IoT enabled Dichotomous Regressive Ranking Decision Forest Node Classification (IoT-DRRDFNC) technique is introduced for efficient data transmission in WSN. The IoT-DRRDFNC technique includes three processes namely data collection, classification, and data transmission. Initially, IoT devices are used for patient data collection at different locations. After that, sensor nodes are classified into two classes such as high-performance sensor nodes and less-performance sensor nodes by using the Dichotomous Regressive Ranking Decision Forest node Classifier. The sensor node has higher residual energy and minimum bandwidth consumption is classified as higher performance. In the IoT-DRRDFNC technique, a Dichotomous Regression tree is taken as a weak learner to classify the sensor nodes. Then the weak learner results are combined to make strong classification results by applying the ranking preferential voting scheme. After the classification, the only higher performance sensor node is taken for performing data transmission. Every sensor node selects the neighbouring sensor node with higher signal strength for minimizing the delay and packet loss rate during the data transmission in WSN. Experimental evaluation is carried out on factors such as energy consumption, packet delivery ratio, packet loss rate, and delay concerning several patient data packets and sensor nodes.

Keywords: Wireless Sensor Networks, Internet of Things, Dichotomous Regressive Ranking Decision Forest node Classifier, Ranking preferential voting scheme, signal strength

1.INTRODUCTION

Wireless sensor network (WSN) is integrated with the internet of things (IoT) for providing sufficient solutions for data handling and information access, in a ubiquitous manner. The WSN based IoT appliances generally suffer from end-to-end delay, packet loss during data communication. To solve these issues, a well-defined routing method is required to develop the network performance and also enhance the Quality of Service.

A Priority-based Energy-Efficient Routing Protocol (PEERP) was introduced in [1] for efficient data communication using IoT. The designed method enhances the network lifetime to guarantee the delivery ratio and reliability. However, the end-to-end delay was not minimized.

An Application-Centric Information-Aware Routing (ACIAR) method was introduced in [2] using iterative decision process and weighted neighbouring node selection for route path identification and information management to enhance seamless communication. However, it failed to consider the different parameters' bandwidth and signal strength to further improve the delivery and minimize the delay.

Various energy-efficient techniques were developed in [3] for green IoT-based wireless systems. However, the designed technique failed to utilize different enabling technologies and emerging techniques consisting of energy-harvesting and machine learning-based mechanisms.

An energy-efficient routing protocol was designed in [4] to improve the performance and increase QoS and transmit the data from the source to the destination via an optimal path. The designed protocol increases the packet delivery ratio and network lifetime but failed to apply for delay-constrained applications. A novel compressive sensing routing method was introduced in [5] to decrease energy utilization and extend the network lifetime. However, the designed routing method was not efficient to enhance data transmission. Energy Harvesting Wireless Sensor Network (EH-WSNs) method was developed in [6] for data communication. However, the performance of the data drop rate was not minimized.

A novel middleware architecture was designed in [7] for appropriate and simple integration of WSNs and IoT. The designed architecture provides better scalability and service maintenance but the energy-aware architecture design was not performed.

A Reliable Data Dissemination using Harris Hawks Optimization for Internet of Things was developed in [8] based on Harris Hawks Optimization. The designed scheme increases reliability, delay, and energy consumption. However, the performance of data loss was not minimized. A data transmission model was introduced in [9] to choose the next forwarding node for data transmission. The model increases network stability and reduces the number of data packet lost packets in the data transmission.

An efficient environment-aware fusion-based reliable routing algorithm was designed in [10]. The designed routing algorithm minimizes the delay but the higher delivery ratio was not achieved. Forwarding Zone (FZ) enabled Multi-objective PSO was developed in [11] to minimize packet loss and delay. However, the signal strength and bandwidth were not considered to further minimize the delay of data transmission.

A new energy-efficient method was developed in [12] based on fuzzy logic and reinforcement learning to increase the network lifetime. However, the performance of the packet delivery ratio was not improved. Reinforcement Learning-based Routing schemes were developed in [13] merged with Multi-optimality routing conditions. Though the designed scheme minimizes the delay, the loss rate was not minimized.

Energy-efficient and reliable routing algorithms were designed in [14] to minimize the packet loss rate and improve the data delivery between the nodes. The method reduces the end-to-end delay, but the major routing parameter such as bandwidth was not considered. The power line connection method was introduced in [15] to fully balance the energy with the best hop counts. The method only considers the energy parameter and it failed to consider the bandwidth, signal strength.

An energy-efficient routing protocol based on reinforcement learning (EER-RL) was developed in [16]. The model increases the network lifetime, but it failed to handle the other routing factors to improve the data transmission. Cooperative multipath routing protocols were developed in [17] based on path bridging for inter-path data transmission. But the lesser packet loss rate was not achieved.

A novel guaranteed network lifetime method was developed in [18] for energy-constrained IoT-based WSNs. Though the method increases the packet delivery ratio and reduces energy consumption, the delay of data transmission was not minimized.

A dynamic routing algorithm was designed in [19] based on the energy-efficient relay selection to solve the energy-efficient routing problem. However, the complexity of the routing algorithm was increased while the impact of the large network size. An energy-efficient region source routing protocol was designed in [20] to select the nodes with high residual energy for efficient data transmission. But the performance of packet loss rate was not performed.

To solve the existing issues, a novel IoT-DRRDFNC technique is introduced. The proposed IoT-DRRDFNC technique highlights thefollowing major contributions.

- To improve reliable data transmission, the IoT-DRRDFNC technique is developed based on energy and bandwidth, and signal strength estimation. This contribution is achieved based on Dichotomous Regressive Ranking Decision Forest node Classifier.
- The IoT devices are used in sensor nodes to collect patient data. Then the Dichotomous Regressive Ranking Decision Forest technique is applied to classify the sensor nodes based on residual energy and bandwidth consumption. The node with higher residual energy and minimum bandwidth consumption is selected using a ranking preferential voting scheme as high performance for efficient data transmission. This helps to improve the delivery ratio and reduces energy consumption.
- To minimize the delay as well as packet loss, the IoT-DRRDFNC technique selects the neighboring node with higher signal strength for efficient data transmission between sensor nodes and the sink node.
- Finally, the simulation is carried out to compare the performance of the proposed IoT-DRRDFNC techniquewith that of existing techniques based on different metrics.

The remaining sections of the paper are organized into different sections: Here, section
2 provides a brief description of the proposed IoT-DRRDFNC technology. In Section 3,

simulations are performed with the medical dataset. In Section 4, the performance evaluation of the proposed IoT-DRRDFNC and existing methods are discussed with different performance metrics. Finally, Section 5 provides the conclusion of the paper.

2. METHODOLOGY

WSN-assisted IoT in a wireless network has the significant advantages of low cost, suitable deployment, and good scalability. The data transmission in the IoT network architecture is reliable to provide effective and efficient communication among the devices for the precise implementation of IoT systems. The major drawback is limited energy resources. In general, energy consumption plays a vital design issue in WSN since the nodes are powered by batteries. Therefore, enhancing the life span of WSNs is very important. A novel IoT-DRRDFNC technique is introduced to perform energy and bandwidth-aware data transmission for enhancing the network lifetime. An IoT-DRRDFNC technology is applied to a healthcare application for improving the quality of life.

Figure 1 illustrates an architecture diagram of the proposed IoT-DRRDFNC technique to perform patient data transmission in WSN. Figure 1 depicts the typical structure of a health data transmission using the IoT-DRRDFNC technique. The sensors are positioned on the patient body to monitor various vital signs and the collected health information is then sent to the sink for further processing. These gathered and stored medical data are accessible at anytime and anywhere. During the data transmission, the higher performance sensor nodes are determined by applying the dichotomous regressive ranking decision forest node classifier based on the energy and bandwidth. Followed by, the higher performance sensor nodes are used for data transmission. After that, the higher performance sensor node finds the neighboring sensor node which has higher signal strength to minimize the delay and packet loss. Finally, the data transmission is carried out to improve the data delivery.

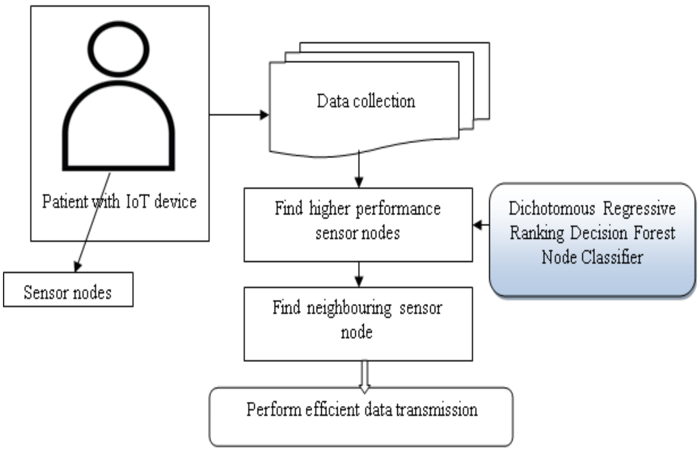

Figure 1 Architecture diagram of the proposed IoT-DRRDFNC technique

2.1 NETWORK MODEL

The network model of the proposed IoT-DRRDFNC technique is designed in this section. The number of sensor nodes $S_i \in Sn_1, Sn_2, Sn_3 \dots Sn_n$are deployed in a squared area 'n*n' within the transmission range'T_R'. Each device in the network collects the patient information. Then the source node (SN) routes the collected patient information or data packets '$dp_i = dp_1, dp_2, \ldots, dp_n$ to the sink node 'S' via the high performance neighbouring nodes'$NN_i = NN_1, NN_2, \ldots, NN_n$ to extend the network lifetime.

2.2 DICHOTOMOUS REGRESSIVE RANKING DECISION FOREST NODE CLASSIFIER

A Dichotomous regressive ranking decision forest node classifier is an ensemble learning technique to classify the given input by constructing several decision trees as a weak learner at the training period. The weak learner is a base classifier to categorize the input into different classes based on residual energy and bandwidth consumption. Then the weak learner results are summed to make a strong one for obtaining accurate classification results.

Figure 2 illustrates the Dichotomous Regressive Ranking Decision Forest Node Classifier. The technique considers the training sets $\{x_i, y_i\}$ where x_i denotes an input sample (i.e. number of sensor nodes) and $y_i$symbolizes an ensemble classification results. The random forest classifier initially constructs a 'k' number of weak learners$\{Q_1, Q_2, Q_3, \ldots . Q_k\}$. The Dichotomous regression tree is used as a weak learner to classify the sensor nodes as high performance or low performance based on residual energy and bandwidth consumption. The regression tree is used to analyze the bandwidth and energy consumption of each sensor node. The regression tree comprises a root node, branch node, and leaf nodes. In the tree, the root node analyzes the energy and bandwidth with the threshold level. The branch node refers to the outcome of the test. Finally, the leaf node represents a class label.

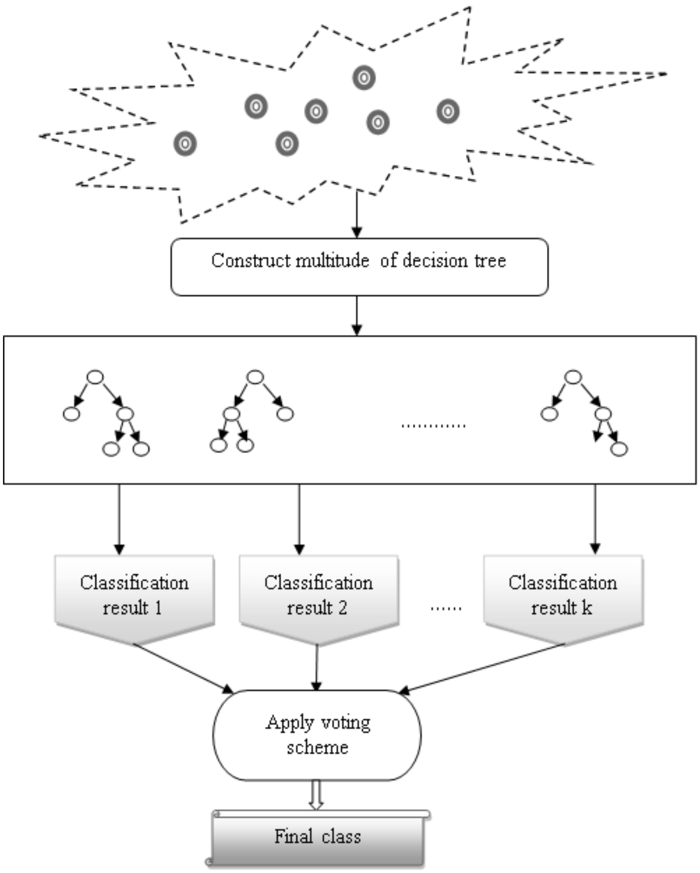

Figure 2 Structure of the Dichotomous Regressive Ranking Decision Forest Node Classifier

For each node in the network, the energy of the sensor node is expressed as given below,

$$e = p * t \qquad (1)$$

From (1), 'e' indicates the energy of the sensor nodes, 'p' specifies a power measured in terms of watts, and t stand for the time measured in seconds (Sec). The energy of each sensor node is measured in joule (J). The initial energy level of the node gets degraded during the sensing and monitoring process in WSN. Therefore, the remaining or residual energy of the sensor node is expressed as given below,

$$e_R = T_e - T_c \qquad (2)$$

From (2), 'e_R' symbolizes the residual energy of the node, T_e be the total energy (i.e. initial energy) of the nodes,$T_c$indicates the consumed energy of the node. The bandwidth consumption of the node is measured as follows,

$$Bw_{con} = Bw_t - Bw_a \quad (3)$$

From (3), Bw_{con} denotes bandwidth consumption, Bw_t specifies a total bandwidth, Bw_a indicates an available bandwidth.

The root node decides to classify the sensor nodes as follows,

$$R = \begin{cases} \text{if}[\ (e_R > e_t) \text{ and } \arg\min(Bw_{con})] & ;\ \text{high performance sensor nodes} \\ \text{Otherwise} & ; \text{Low performance sensor nodes} \end{cases} \qquad (4)$$

Where, R denotes a regression tree output, e_R denotes residual energy, e_t denotes a threshold residual energy, Bw_{con} denotes a bandwidth consumption, $\arg\min$ denotes an argument of the minimum function.

Figure 3 illustrates the Dichotomous regression tree that classifies the sensor nodes into high or low performance. Similarly, all the weak learners display the results. The weak classifier has some training error in the classification results. In order to obtain the strong classification results, the weal learner results are combined.

$$y_i = \sum_{i=1}^{k} Q_i\ (Sn_n) \qquad (5)$$

From (5), y_i indicates the output of strong learner, Q_i (Sn_n) denotes an output of the weak learners. For each weak learner, the training error is estimated to find the accurate classification results. The error rate is measured as the squared difference between the actual classification results and observed classification results.

$$E = (Q_A - Q_o)^2 \qquad (6)$$

From (6),E represents the training error, Q_A symbolizes the actual output of the weak learner,Q_o represents the observed results of the weak learner.

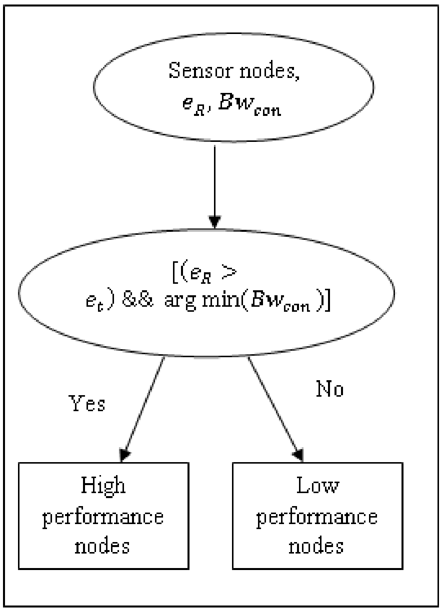

Figure 3 Dichotomous regression tree-based node classification

After calculating the error rate, the ranked preferentialvoting scheme is applied to rank the weak learner based on the error rate. The weak learner results having the minimum error are ranked first then the other results.

Weak learners	Ranks
Q_1 (Sn_n)	1
Q_3 (Sn_n)	2
Q_4 (Sn_n)	3
Q_2 (Sn_n)	4

After the ranking process, the votes are applied to higher-ranked results, and other results having higher errors are removed. The higher-ranked classification results are counted and identify the majority to be elected.

$$y_i = \arg\max_{b} \beta\,(Sn_i) \qquad (7)$$

Where $y_i$represents the strong classification results, arg max denotes an argument of the maximum function to discover the majority vote (β) of the samples (i.e. sensor nodes) whose decision is known to the b^{th}classifier. Finally, the ensemble classifier provides the majority of the samples as strong classification results. In this way, high and low-performance sensor nodes are identified for further processing.

After the classification, the only higher performance sensor node is taken for performing data transmission. Every sensor node finds the neighbouring sensor node with the higher signal strength to improve the data delivery and minimize the delay as well as packet loss during the data transmission in WSN. The received signal strength of the node is calculated as given below,

$$R_{sp} = T_{sp} * \frac{G_t * G_r * v_t^2 * v_r^2}{d^4} \qquad (8)$$

From (8), R_{sp} symbolizes a received signal strength, S_t indicates a transmitted signal power of the node, G_t, G_r are a transmitter and receiver antenna gain, v_t^2 denotes a transmitter antenna height, v_r^2 indicates a receiver antenna height, d indicates a distance between transmitter and receiver node. Therefore, the node having high signal strength is chosen for efficient data transmission with lesser delay. The algorithmic process of the IoT enabled Dichotomous Regressive Ranking Decision Forest Node Classification (IoT-DRRDFNC) technique is described as given below,

Algorithm 1: IoT enabled Dichotomous Regressive Ranking Decision Forest Node Classification

Input: Sensor nodes $\mathrm{S_i} = \mathrm{Sn_1}, \mathrm{Sn_2}, \mathrm{Sn_3} \dots \mathrm{Sn_n}$, Patient data $\mathrm{dp_i} = \mathrm{dp_1}, \mathrm{dp_2}, \dots, \mathrm{dp_n}$

Output: Increase data delivery and minimize delay

1. Construct ‘k’ number of weak learners
2. **foreach** sensor node $\mathrm{S_i}$
3. **Measure** residual energy ‘$\mathrm{e_R}$’, bandwidth consumption ‘$\mathrm{Bw_{con}}$’
4. **If [**$(\mathrm{e_R} > \mathrm{e_t})$ and $\arg\min(\mathrm{Bw_{con}})$**]then**
5. Sensor nodes are classified as high performance
6. **else**
7. Sensor nodes are classified as low performance
8. **end if**
9. Obtain weak learner results ‘ $\mathrm{Q_i(Sn_n)}$ ’
10. **end for**
11. Combine all weak learners $\mathrm{y_i} = \sum_{\mathrm{i=1}}^{\mathrm{k}} \mathrm{Q_i}\,(\mathrm{Sn_n})$
12. **For** each $\mathrm{Q_i(Sn_n)}$
13. Calculate error ‘E’
14. Rank the weak learners in ascending order
15. Select the weak learners with minimum error
16. Find the majority votes of the input$\arg\max_{\mathrm{b}}\ \beta\,(\mathrm{Sn_i})$
17. Obtain strong classification results
18. **end for**
19. **For** each high-performance node ‘$\mathrm{Sn_i}$’
20. Measure signal strength ‘$\mathrm{R_{sp}}$’
21. **If (** $\mathrm{argmaxR_{sp}}$) **then**
22. Selected as a neighbouring node
23. **else**
24. Find another neighbouring node
25. **End if**

26. Send data packets $dp_i = dp_1, dp_2, \ldots, dp_n$ via neighbouring node's

End

Algorithm 1 explains the step-by-step process of ensemble classification to improve the data delivery and minimize the error rate. Initially, the ensemble classifier constructs 'k' number of weak learners for categorizing the sensor nodes. For each sensor node, the residual energy and bandwidth consumption are measured. If the residual energy of the sensor node is greater than the threshold and minimum bandwidth consumption is classified as high-performance sensor nodes. Otherwise, the nodes are classified as low-performance sensor nodes. Then the weak learner results are combined and calculate the training error. Followed by, the ranked preferential voting scheme is applied to rank the weak learners based on error rate. After that, the majority votes of the samples are taken as final classification results. In this way, high and low-performance sensor nodes are identified. Then the high-performance nodes are used for data transmission. Finally, the node with maximum signal strength is chosen for delay-aware data transmission in WSN.

3.SIMULATION SETTINGS

The simulation of the proposed IoT-DRRDFNC technique and existing methods namely PEERP [1] and ACIAR [2] are implemented using the NS2.34 simulator. 500 sensor nodes are deployed over the squared area of A^2 (1100 m * 1100 m) with the node's speed of 0-20m/s. The Random Waypoint is used as a node mobility model for conducting the simulation. The DSR protocol is employed to conduct efficient patient data transmission from source and destination.

Table1 Simulation Parameters

Simulation parameter	Value
Simulator	NS2 .34
Network area	1100m * 1100m
Number of mobile nodes	50,100,150,200,250,300,350,400,450,500
Data packets	100,200,300,400,500,600,700,800,900,1000
Protocol	DSR
Simulation time	300sec
Mobility model	Random Way Point model
Nodes speed	0-20m/s
Number of runs	10

The IoT devices are fit into the patient and the data is collected from the dataset Disease Outbreaks in Nigeria Datasets in India [https://www.kaggle.com/eiodelami/disease-outbreaks-in-nigeria-datasets]. The dataset consists of patient information such as ID, name, gender, and patient health information, and so on. This information is collected and sent from source to sink node. The simulation time is set as 300 sec. The simulation parameters are listed in table 1.

4.PERFORMANCE EVALUATION

The simulation performance of the proposed IoT-DRRDFNC technique and two other existing methods namely PEERP [1] and ACIAR [2] are discussed with four performance measurements such as energy consumption, packet delivery ratio, packet loss rate, and an end-to-end delay. The simulation results of different parameters are discussed in the table and graphical results.

4.1 IMPACT OF ENERGY CONSUMPTION

The energy consumption is measured as the amount of energy consumed by the sensor nodes to distribute the patient healthcare data (i.e. data packets) from the source to the sink node.The overall energy consumption of the node is assured as given below,

$$\mathrm{Con_E} = \mathrm{n} * \mathrm{Con_E}\ (\text{single sensor node}) \qquad (9)$$

From (9),$\mathrm{Con_E}$ represents the energy consumption, ‘n’ indicates the number of sensor nodes. The overall energy consumption is measured in terms of joule (J).

Table 2 Comparison of energy consumption

Number of sensor nodes	Energy consumption (Joule)		
	PEERP	ACIAR	IoT-DRRDFNC
50	15	17	11
100	18	20	16
150	23	24	20
200	26	28	23
250	28	30	25
300	30	33	27
350	32	35	30
400	34	37	32
450	36	40	34
500	40	42	37

Table 2 describes the performance analysis of energy consumption against a number of sensor nodes. Energy consumption is evaluated based on the amount of energy utilized by sensor nodes to transmit data packets. The number of sensor nodes is taken in the ranges from 50,100, 150...500. Among three methods, the proposed IoT-DRRDFNC technique achieves lesser energy consumption than the existing methods. This is proved through the statistical evaluation. Let us consider 50 sensor nodes to conduct the experiment. The energy consumption of the sensor nodes using the IoT-DRRDFNC technique is 11 joule. The energy consumption of the sensor nodes using PEERP [1] and ACIAR [2] techniques are 15 joule and 17 joule respectively. Likewise, various energy consumptions of sensor nodes are observed for each method. The obtained performance results of the proposed IoT-DRRDFNC technique are compared to the existing methods. The comparison of the ten results indicates that the overall energy consumption using the proposed IoT-DRRDFNC technique is considerably reduced by 11% when compared to [1] and 18% when compared to [2].

Figure 4 illustrates the performance results of energy consumption versus a number of sensor nodes. The sensor nodes are taken as input to calculate the energy consumption.As shown in figure 4, the energy consumption using the IoT-DRRDFNC technique, and two existing methods PEERP [1]and ACIAR [2] are represented by green, violet, and orange colour columns respectively. From the graphical results, the energy consumption is minimized using the IoT-DRRDFNC technique when compared to the other two techniques. The reason for this improvement using IoT-DRRDFNC is to find the higher performance sensor nodes through the dichotomous regressive ranking decision forest node classification technique. The high-performance sensor nodes utilizing lesser energy resulting in enhanced network lifetime.

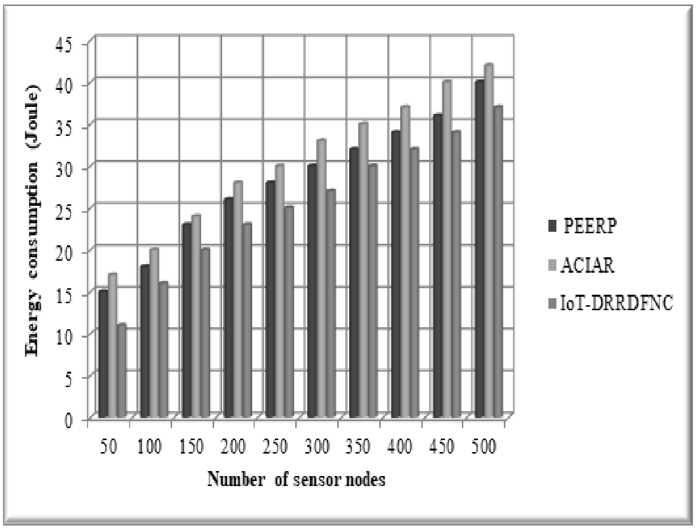

Figure 4 Performance results of energy consumption

4.2 IMPACT OF PACKET DELIVERY RATIO

Packet delivery ratio is measured as the ratio of the number of patient data (i.e. data packets) are received to the total number of data packets being transmitted from the source node. The packet delivery ratio is formulated as given below,

$$R_{PD} = \left[\frac{NPR}{NPS}\right] * 100 \qquad (10)$$

From (10), R_{PD} signifies a packet delivery ratio, NPR indicates the number of packets received, NPS represents the number of packets sent. The overall delivery ratio is measured in percentage (%).

Table 3 Comparison of Packet delivery ratio

Number of patient data	Packet delivery ratio (%)		
	PEERP	ACIAR	IoT-DRRDFNC
100	88	86	92
200	87	85	93
300	86	84	92
400	88	86	93
500	89	85	92
600	87	83	91
700	88	86	92
800	87	84	94
900	89	86	93
1000	88	85	92

Table 3 reports the simulation results of packet delivery versus a number of patient data i.e. data packets in the ranges from 100,200,300 ...1000. The tabulated results indicate that the IoT-DRRDFNC technique provides superior performance than the two techniques. Let us consider the 100-patient data being sent from the source node. By applying the IoT-DRRDFNC technique, 92 data packets are successfully received at the destination and the delivery ratio is 92%. Whereas, the delivery ratio of two existing methods PEERP [1] and ACIAR[2] are 88% and 86%. Similarly, nine remaining runs are carried out to estimate the performance of the IoT-DRRDFNC technique and the existing methods. The average is taken for ten results and the results confirm that the IoT-DRRDFNC technique increases the packet delivery ratio by 5% and 9% when compared to conventional methods.

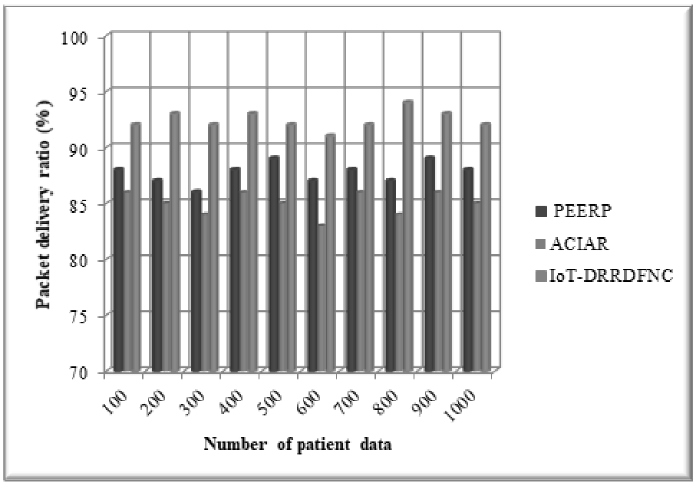

Figure 5 Performance results of packet delivery ratio

Figure 5 shows the simulation performance results of packet delivery ratio versus a number of patient data. The number of data is taken in the horizontal axis and the results of packet delivery ratio are observed in the vertical axis. The graphical chart shows that the packet delivery ratio of the IoT-DRRDFNC technique is higher than the other two existing methods. This improvement of the proposed IoT-DRRDFNC technique is to select the high performance and maximum signal strength of sensor nodes. Then the data transmission is performed through the selected high-performance sensor nodes. As a result, the patient data are successfully received at the destination increasing the data delivery rate.

4.3 IMPACT OF PACKET LOSS RATE

The packet loss rate is defined as the ratio of the number of patient data (i.e. data packets) lost to the total number of data packets sent from the source node. The loss rate of different methods is estimated as given below,

$$R_{PD} = \left[\frac{NPL}{NPS}\right] * 100 \qquad (11)$$

Where, R_{PD} symbolizes the packet loss rate, NPL denotes the number of packets lost, NPS represents the number of packets sent. The packet loss rate is measured in percentage (%).

Table 4 Comparison of packet loss rate

Number of patient data	Packet loss rate (%)		
	PEERP	ACIAR	IoT-DRRDFNC
100	12	14	8
200	13	15	7
300	14	16	8
400	12	14	7
500	11	15	8
600	13	17	9
700	12	14	8
800	13	16	6
900	11	14	7
1000	12	15	8

Table 4 reports the simulation results of packet loss rate for varying numbers of patient data in the range of 100 to 1000. The tabulated result confirms that the packet loss rate of the proposed IoT-DRRDFNC technique is considerably decreased when compared to the existing methods. Let us consider the 100 patient data being sent from the source node. The loss rate of the IoT-DRRDFNC technique is 8% and the loss rate of existing PEERP [1] and ACIAR [2] are 12% and 14%. The above results indicate that the packet loss rate of the IoT-DRRDFNC technique is found to be minimized than the other two methods. The average of ten results indicates that the packet loss rate of the IoT-DRRDFNC technique is comparatively minimized by 38% and 49% when compared to existing PEERP [1] and ACIAR [2].

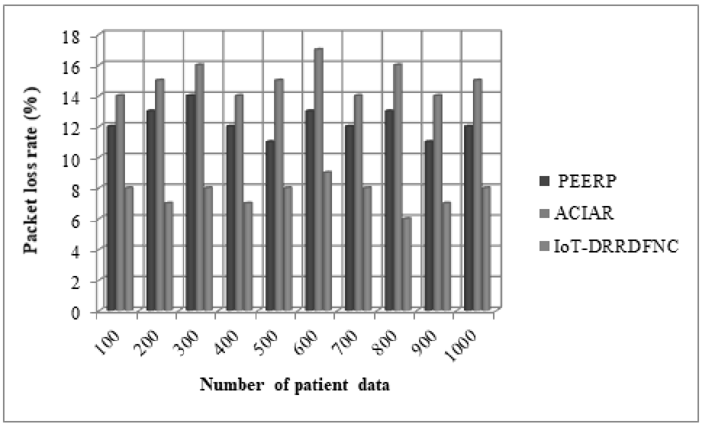

Figure 6 Performance results of packet loss rate

Performance results of packet loss rate versus a number of patient data transmissions are shown in figure 6 using three different methods namely the proposed IoT-DRRDFNC technique compared with existing PEERP [1] and ACIAR [2]. The above figure demonstrates that the packet loss rate of the proposed IoT-DRRDFNC technique outperforms well in terms of minimizing a packet loss rate during the patient data transmission. The reason is to identify the higher energy and better signal strength of the node. The higher signal strength and maximum bandwidth availability of the sensor node deliver the number of packets to the destination. This in turn decreases the packet loss rate.

4.4 IMPACT OF END-TO-END DELAY

End-to-end delay is defined as the expected arrival time of the patient data and the actual arrival time of the data packets at the destination end. The overall delay is measured as follows,

$$\mathrm{Delay_{EE}} = [\mathrm{t_{act}}] - [\mathrm{t_{ex}}] \qquad (12)$$

Where, '$\mathrm{Delay_{EE}}$' symbolizes the end to end delay, $\mathrm{t_{act}}$ indicates an actual arrival time, $\mathrm{t_{ex}}$ indicates an expected arrival time. The delay is calculated in terms of milliseconds (ms).

Table 5 Comparison ofend-to-end delay

Number of patient data	End-to-end delay (ms)		
	PEERP	ACIAR	IoT-DRRDFNC
100	16	19	13
200	17	21	15
300	20	23	17
400	22	25	20
500	25	27	22

600	27	30	24
700	31	33	28
800	33	35	30
900	37	39	35
1000	40	42	38

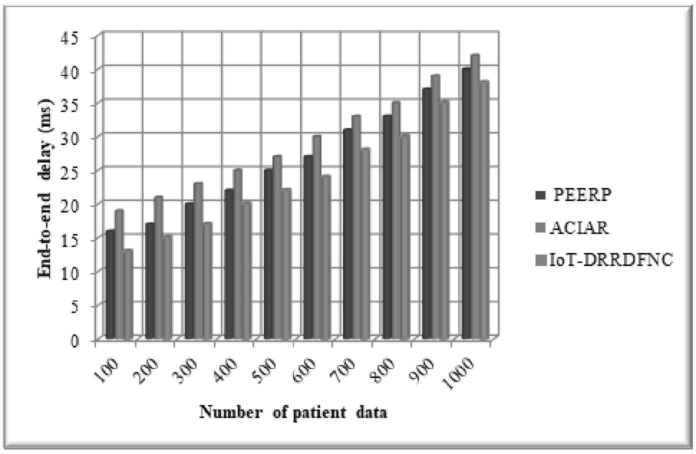

Figure 7 Performance results of end-to-end delay

Table 5 and figure 7 depict the simulation results of end-to-end delay of data transmission in WSN. As shown in the table and graph, the delays of all the methods are showed in the increasing trend while varying the number of patient data. But comparatively, the end-to-end delay of the IoT-DRRDFNC technique is found to be minimal than the other two existing methods. Let us take the number of patient data is 100 being sent from the source node. By applying a proposed IoT-DRRDFNC technique, the delay of data transmission is 13ms whereas the end-to-end delay of data transmission of the other two existing methods PEERP [1] and ACIAR[2] are 16ms and 19ms respectively. Therefore, the overall end-to-end delay is minimized by 11 % and 10% when compared to existing methods. The most important reason for this improvement is to find the neighbouring node with higher signal strength instead of using entire nodes. The higher signal strength node delivers the packet continuously and minimizes the delay of data arrival.

5.CONCLUSION

The rapid development and large-scale operation of the IoT-based WSN have caused dispersing a huge amount of energy. This directs to a major need to save the energy of the battery-operated devices and expand their life span. In this paper, a novel IoT-DRRDFNC technique is employed in the IoT-based heterogeneous WSNs. Initially, the patient data are recorded by IoT devices and sent to the hospital server (i.e. sink). Then the high-performance sensor nodes are selected based on higher residual energy and lesser bandwidth consumption using Dichotomous Regressive Ranking Decision Forest node Classifier. In addition, the neighboring nodes are identified with the higher signal strength to transmit the number of packets with minimal packet lost and delay. The simulation is conducted to evaluate the efficiency of our IoT-DRRDFNC technique with different performance metrics. The discussed results have revealed that the IoT-DRRDFNC technique has significantly enhanced the lifetime of the networks and also improves the delivery ratio and minimizes the delay as well as packet loss rate.

REFERENCES

[1] Ben othman soufienea, Abdullah Ali Bahatta, Abdelbasset Trad, Habib Youssef, “PEERP: An Priority-Based Energy-Efficient Routing Protocol for Reliable Data Transmission in Healthcare using the IoT”, Procedia Computer Science, Volume 175, 2020, Pages 373-378

[2] Kavita Jaiswal and Veena Anand, “EOMR: An Energy-Efficient Optimal Multi-path Routing Protocol to Improve QoS in Wireless Sensor Network for IoT Applications”, Wireless Personal Communications, Springer, Volume 111, 2020, Pages 2493–2515

[3] Antar Shaddad H.Abdul-Qawy, Nasr Musaed S. Almurisi, and Srinivasulu Tadisetty, “Classification of Energy Saving Techniques for IoT-based Heterogeneous Wireless Nodes”, Procedia Computer Science, Elsevier, Volume 171, 2020, Pages 2590-2599

[4] K. Sakthidasan Sankaran, N. Vasudevan, Ashok Verghese, “ACIAR: application-centric information-aware routing technique for IOT platform assisted by wireless sensor networks”, Journal of Ambient Intelligence and Humanized Computing, 2020, Pages 1-11

[5] Ahmed Aziz1, Karan Singh, Walid Osamy, Ahmed M. Khedr, “An Efficient Compressive Sensing Routing Scheme for Internet of Things Based Wireless Sensor Networks”, Wireless Personal Communications, Springer, Volume 114, 2020, Pages 1905–1925

[6] Pradip Kumar Sharma, Young-Sik Jeong, Jong Hyuk Park, “EH-HL: Effective Communication Model by Integrated EH-WSN and Hybrid LiFi/WiFi for IoT”, IEEE Internet of Things Journal, Volume 5, Issue 3, 2018, Pages 1719 – 1726

[7] Ayoub Benayache, Azeddine Bilami, Sami Barkat, Pascal Lorenz, Hafnaoui Taleb, “MsM: A microservice middleware for smart WSN-based IoT application”, Journal of Network and Computer Applications, Elsevier, Volume 144, 2019, Pages 138–154

[8] Ali Seyfollahi & Ali Ghaffari, “Reliable data dissemination for the Internet of Things using Harris hawks optimization”, Peer-to-Peer Networking and Applications, Springer, Volume 13, 2020, Pages 1886-1902

[9] Alireza Izaddoost, Matthew Siewierski, “Energy Efficient Data Transmission in IoT Platforms”, Procedia Computer Science, Elsevier, Volume 175, 2020, Pages 387–394

[10] Fatma H. El-Fouly, Rabie A. Ramadan, “E3AF: Energy Efficient Environment-Aware Fusion Based Reliable Routing in Wireless Sensor Networks”, IEEE Access, Volume 8, 2020, Pages 112145 – 112159

[11] Rashmi Chaudhrya, Shashikala Tapaswi, Neetesh Kumar, “FZ enabled Multi-objective PSO for multicasting in IoT based Wireless Sensor Networks”, Information Sciences, Elsevier, Volume 498, 2019, Pages 1-20

[12] Yalda Akbari & Shayesteh Tabatabaei, “A New Method to Find a High Reliable Route in IoT by Using Reinforcement Learning and Fuzzy Logic”, Wireless Personal Communications, 2020, Pages 1-17

[13] Peizhuang Cong, Yuchao Zhang, Zheli Liu, Thar Baker, Hissam Tawfik, Wendong Wang, Ke Xu, Ruidong Li, Fuliang Li, “A deep reinforcement learning-based multi-optimality routing scheme for dynamic IoT networks”, Computer Networks, Elsevier, Volume 192, 2021, Pages 1-11

[14] Liangrui Tang, Zhilin Lu and Bing Fan, “Energy Efficient and Reliable Routing Algorithm for Wireless Sensors Networks”, Applied Science, Elsevier, Volume 10, 2020, Pages 1-16

[15] Xuesong Liu and Jie Wu, “A Method for Energy Balance and Data Transmission Optimal Routing in Wireless Sensor Networks”, Sensors, Volume 19, 2019, Pages 1-14

[16] Vially Kazadi Mutombo, Seungyeon Lee, Jusuk Lee, and Jiman Hong, “EER-RL: Energy-Efficient Routing Based on Reinforcement Learning”, Mobile Information Systems, Hindawi Volume 2021, July 2019, Pages 1-12

[17] Sangdae Kim, Cheonyong Kim, Kwansoo Jung, “Cooperative multipath routing with path bridging in wireless sensor network toward IoTs service”, Ad Hoc Networks, Elsevier, Volume 106, 2020, Pages 1-9

[18] Babar Shah, Ali Abbas, Gohar Ali, Farkhund Iqbal, Asad Masood Khattak, Omar Alfandi, Ki-Il Kim, “Guaranteed lifetime protocol for IoT based wireless sensor networks with multiple constraints”, Ad Hoc Networks, Elsevier, Volume 104, 2020, Pages 1-10

[19] Zhaoming Ding, Lianfeng Shen, Hongyang Chen, Feng Yan, Nirwan Ansari, “Energy-Efficient Relay-Selection-Based Dynamic Routing Algorithm for IoT-Oriented Software-Defined WSNs”, IEEE Internet of Things Journal, Volume 7, Issue 9, 2020, Pages 9050 – 9065

[20] Chuan Xu, Zhengying Xiong, Guofeng Zhao, Shui Yu, “An Energy-Efficient Region Source Routing Protocol for Lifetime Maximization in WSN”, IEEE Access, Volume 7, 2019, Pages 135277 - 135289