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Internet of Things Based Chinese Whisper Jensen-Shannon Boost Node Clustering for Energy Efficient Routing in Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks (WSN) is a heterogeneous network that contains a lot of small gadgets called sensors which collect the physical or environmental conditions for example temperature, sound, vibration, weight, and so on, and transfers it to the base station. A machine's ability to mimic intelligent human behavior is broadly defined as machine learning, a branch of artificial intelligence which plays a significant role in WSN. In WSN, the method of routing is transferring the data between the sensor nodes and the base station. Many kinds of research were carried out for energy-efficient routing in WSN. But, the network lifetime and higher data delivery were not achieved by existing routing techniques. For the purpose of enhancing energy-efficient routing, an Internet of Things based Chinese Whisper Jensen-Shannon Boost Node Clustering (IoT-CWJSBNC) technique is introduced in WSN. This technique performs three processes, namely data collection, clustering, and routing. Initially, for sensing and gathering patient data at a distance, IoT devices are employed in sensor nodes. After the data collection process, sensor nodes are clustered into two groups, namely higher performance sensor nodes, and lesser performance sensor nodes by using the Chinese Whisper Jensen-Shannon Boosting technique. In IoT-CWJSBNC Technique, the Chinese Whisper Clustering method is considered as the weak cluster to partition the sensor nodes into two groups based on the Ruzicka similarity measure. Jensen-Shannon Boost method combines the results of weak learners to increase the clustering performance for efficient routing. After the clustering process, only higher-performance sensor node is considered. Then, the source node finds the neighbouring sensor node with higher signal strength for reducing the delay and packet loss rate during the routing process. WSN routing is carried out in this fashion to be energy-efficient. The simulation is administered on factors such as energy consumption, packet delivery ratio, packet loss rate, and therefore the end-to-end delay in relation to a number of patient data packets and sensor nodes. The results of the simulation show that the IoT-CWJSBNC technique effectively enhances the delivery of data packets and lowers energy consumption, packet loss rate, and delay than the traditional routing strategies.

Keywords: *Wireless Sensor Networks (WSN), Internet of Things (IoT), machine learning, network lifetime, energy-efficient, Chinese Whisper Clustering, Jensen-Shannon Boost, routing, Ruzicka similarity, signal strength*

1. INTRODUCTION

A wireless sensor network is a distributed system made up of a number of nodes and base stations (BS) to track various environmental factors. Several WSN-assisted IoT applications heavily rely on the WSN for their operation. The sensor nodes are a significant part of WSN-assisted IoT networks running on large-scale data communication with the energy resource. But the WSN-based Internet of Things (IoT) application faces various challenges like insufficient battery capacity, interruptions resulting from multi hop communication, and so on. Cluster-based routing is more sufficient for efficient data communication among the nodes in WSN. But, the network lifetime and minimum delay were not improved by using existing routing techniques. In order to address these problems, machine learning techniques are introduced for performing energy-efficient routing.

In order to create a network that is both scalable and energy-efficient, a Scalable and Energy-Efficient Routing Protocol (SEEP) was first introduced in [1] which uses a multi-tier-based clustering framework. However, it took longer than necessary to acquire the increased data delivery. An IoT-based Stable Election Protocol (I-SEP i.e. IoT-SEP) was designed in [2] for improving the routing based on a threshold energy value. The designed I-SEP enhances the network lifetime and throughput but the delay-aware routing was not performed.

To increase the lifespan of the sensor network, a fork and join adaptive particle swarm optimization (FJAPSO)-based green routing algorithm was developed in [3]. The algorithm reduces the delay, however a greater data delivery ratio was not obtained in terms of performance. A new Energy Efficient Region Source Routing protocol (ER-SR) was introduced in [4] to choose the nodes with the highest residual energy for routing and achieving the higher packet delivery ratio. However, the number of dropped packets was not diminished.

A cooperative multipath routing protocol was introduced in [5] to transmit packets with great reliability and minimal delay while using the least amount of energy. But the delay performance was not lowered. A novel On-demand, oPTImal Clustering (OPTIC) algorithm was introduced in [6] to improve lifetime of the network. But the algorithm did not succeed in solving the issues with lifetime optimization in WSNs with more generic network architecture. A Priority-Based Energy-Efficient Routing Protocol (PEERP) was introduced in [7] for reliable data transmission. But the protocol declined to perform the cluster-based routing protocol for improving performance of data delivery.

A different energy-efficient method was introduced in [8] for IoT-based heterogeneous WSN, based on optimum resource utilization. However, the machine learning-based mechanisms were never applied for maximizing data transmission with minimum

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energy harvesting. A novel Neuro-Fuzzy Rule-Based Cluster Formation and Routing technique was developed in [9] for finding effective route with a better packet delivery ratio and decreased delay. However, the routing method declined to provide effective data transmission with minimum packet loss. A grey wolf algorithm-based intelligent technique was introduced in [10] for finding energy-saving routes with the internet of things. But, the ratio of delivered packets did not rise.

1.1 Contributions

The significant contributions made by suggested IoT-CWJSBNC are outlined and listed below,

- To improve the energy-efficient routing, a novel IoT-CWJSBNC is created to enhance data communication using better delivery rates and lower loss rate.
- To improve the number of data delivered, IoT -CWJSBNC uses a Jensen-Shannon Boost clustering technique for partitioning the sensor nodes into two groups, namely higher performance and lesser performance by using the Chinese Whisper clustering technique. The Chinese Whisper Clustering method uses Ruzicka similarity between the nodes according to the node's leftover energy and bandwidth use. The selected energy-efficient nodes are used for data delivery and enhance the network lifespan by minimizing energy consumption.
- To shorten the end-to-end delay, source node finds the neighboring sensor nodes with higher signal strength than the other nodes in the network.
- Finally, to validate effectiveness of the IoT-CWJSBNC technique, a series of simulation tests are conducted using different metrics and existing routing methods. The simulation's output and analysis show superior performance to traditional routing techniques.

1.2 Organization of Paper

The remaining of the paper is structured into different sections like this: In section 2, the related work in areas of cluster and energy-efficient routing is discussed. In section 3, the proposed IoT-CWJSBNC developed and explained. The proposed job is simulated in section 4, and section 5 offers an appropriate comparison analysis. Section 6 brings the paper to a conclusion.

2. RELATED WORKS

A Reliable Cluster-based Energy-aware Routing (RCER) protocol was introduced in [11] to provide enhanced data delivery performance in conjunction with network reliability. But the clustering performance did not increase. New energy-aware and reliable routing protocols were developed in [12] to extend the lifespan of the network by using multi-hop routing methods. However, no delay-aware routing was carried out.

For WSN-based IoT applications, an energy-efficient routing protocol was devised in [13] to increase packet delivery ratio and reduce delay. But it declined to use the efficient algorithm to enhance the routing QoS parameters. An ant colony optimization for multi-agent path finding routing protocol was introduced in [14]. The designed protocol only considers the energy but it failed to find the efficient node with lesser bandwidth consumption and higher signal strength for reliable data delivery. Cluster-Tree based Energy Efficient Data Gathering (CTEEDG) protocol was introduced in [15] for enhancing the lifetime and throughput. On the other hand, packet loss rate was not reduced.

A novel energy-efficient centroid-based routing protocol (EECRP) was introduced in [16] for WSN-assisted IoT to enhance network performance. However, the delay of data transmission was not effectively reduced. To minimize the delay, dynamic Multi-Hop Energy Efficient Routing Protocol (DMEERP) was developed in [17] to improve the reliability of packet delivery ratio with lesser energy consumption. But packet loss rate was not minimized.

An efficient cluster head election method was introduced in [18] based on residual energy and improves the network lifetime. But it failed to perform an efficient clustering process with nodes changing their position frequently. An energy-efficient and reliable routing method was devised in [19] in order to increase data transfer and reduce packet loss. But the method failed to focus on the routing optimization method to increase performance of network. Joint clustering and routing (JCR) protocol was introduced in [20] for collecting data in a reliable and effective manner in WSN. But, the packet delivery ratio was not enhanced.

3. PROPOSAL METHODOLOGY

A WSN is a self-organizing wireless network that includes numerous low-cost sensor nodes and collectively performs sensing, processing, and communication. The sensor node senses and brings in the information from environments and delivers it to a central location (i.e. base station) via sink node. During communication, energy-efficient routing is a major challenging task. WSN is employed in the healthcare domain to monitor the patient's health condition through IoT devices i.e. sensor nodes for sensing, data processing and to perform efficient data communication. During medical data transmission, energy is needed within IoT-based sensor networks for communication to improve the network lifetime. Many techniques were introduced on energy-efficient routing for WSN. Improved-Adaptive Ranking based Energy-efficient Opportunistic Routing protocol (I-AREOR) was introduced in [21] to lessen the energy depended on the regional density, relative distance, and remaining energy. However, it failed to consider the machine learning algorithms. But, the network lifetime was not improved. In order to deal with these issues, a cutting-edge machine learning technique known as (IoT-CWJSBNC) is introduced for performing energy-efficient routing in WSN.

3.1 System Model

Here, a proposed system model of IoT-CWJSBNC is designed. The number of sensor nodes $S_i = Sn_1, Sn_2, Sn_3 \dots Sn_n$ are positioned across squared area '$n * n$' within the transmission range 'T_R'. Each node in the network collects information from environment. The source node (SN) routes the collected information or data packets $dp_i = dp_1, dp_2, \dots, dp_n$ to sink node 'S' through energy-efficient neighboring nodes $NN_i = NN_1, NN_2, \dots, NN_n$ to enhance the network lifetime in WSN.

Figure 1 depicts architecture of a wireless sensor network consisting of sensor devices $S_i = Sn_1, Sn_2, Sn_3 \dots Sn_n$, sink node '$S$' and base station (BS).

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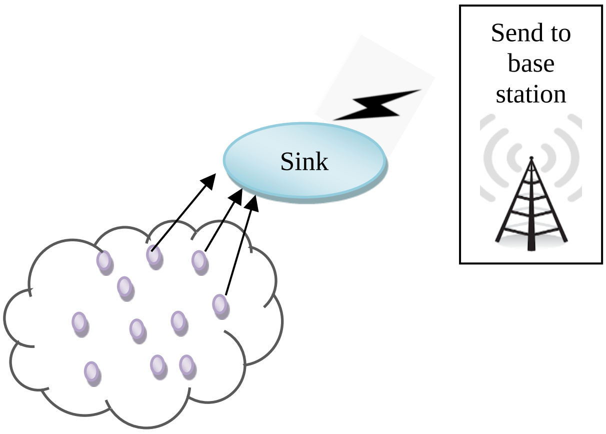

Figure 1 Architecture of wireless sensor network

IoT devices serve as sensor nodes to sense and gather patient data from a distance. After the data collection process, sensor nodes are grouped together into two on basis of energy and bandwidth during the routing process. The sensor node clustering is performed using Jensen-Shannon Boost Node Clustering technique. The designed technique is an ensemble technique to amplify the performance of the machine learning algorithm by converting the weak learner into a strong one. The weak learner is a base clustering technique that lacks of providing precise clustering outcomes. On the contrary, an ensemble technique provides accurate clustering results by combining the weak learners.

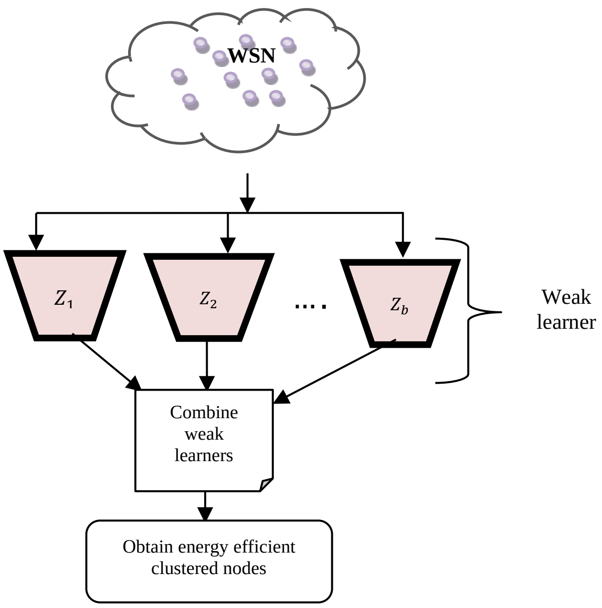

Figure 2 Structure of Jensen-Shannon Boost Node clustering technique

Figure 2 shows the structure of a Jensen-Shannon Boost Node clustering technique to determine which sensor nodes are energy-efficient in the network for data communication in WSN. The ensemble clustering uses a training set $\{(S_i, Y_i)\}$ where 'S_i' denotes the number of sensor nodes $S_i = Sn_1, Sn_2, Sn_3 \dots Sn_n$, '$Y$' denotes an ensemble clustering outcome. As shown in figure 2, at first using an ensemble technique, constructs 'b' weak learners $Z_1, Z_2, Z_3, \dots Z_b$. The proposed IoT-CWJSBNC technique uses a Chinese Whisper Clustering technique as a weak learner.

The main advantage of Ruzicka Chinese whispers algorithm is capable of identifying similar nodes in a network very fast. For this reason, this algorithm is good to analyze large networks using a graph with large number of nodes. An improved clustering and routing (ICR) protocol was developed in [22] for a large-scale network with IoT. The designed clustering method failed to provide efficient routing solutions. A Chinese Whisper Clustering algorithm is an undirected graph-based clustering technique. A WSN represented by an undirected graph '$G = (v, e)$' where 'v' denotes sensor nodes $S_i = Sn_1, Sn_2, Sn_3 \dots Sn_n$' and '$e$' denotes edges i.e. links between the nodes. The sensor nodes in this instance are arranged into various clusters. Then the algorithm initializes the iterations and the number of clusters. Then the node moves to the cluster to which the given node connects with the most links.

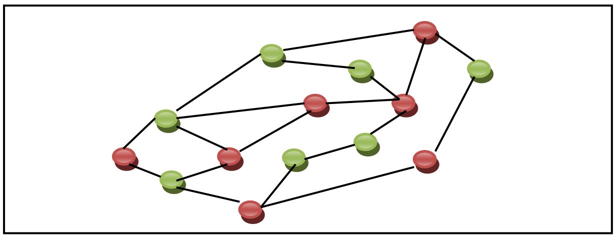

Figure 3 Undirected graphical structures

Figure 3 illustrates the undirected simple graph with multiple nodes that are represented by different colors. For each node in the network $S_{n1} \in N$, we have to find a certain amount of resources (energy, bandwidth) for assigning the nodes into the clusters. The designed model performs the link mapping. In link mapping, nodes are linked based on energy and bandwidth. An energy-efficient geographic (EEG) routing protocol was developed in [23] to enhance energy consumption. However, it failed to strengthen the data delivery ratio.

The mathematical formulation for the sensor node's energy is provided below.

$$e = p * t \tag{1}$$

Where 'e' stands for the energy of the sensor nodes, p for power measured in watts, and t for time measured in seconds (Sec). Each sensor node's energy is expressed in terms of joules (J). During the sensing process, sensor's energy level degrades. Therefore, the node's residual energy is quantified as given below,

$$e_R = [T_e] - [T_c] \tag{2}$$

In (2),e_R symbolizes residual energy of sensor node, T_e is total energy (i.e. initial energy) of sensor nodes, T_c is consumed energy. The bandwidth consumption of device is estimated as given below,

$$Bw_{con} = [Bw_t] - [Bw_a] \tag{3}$$

Where, Bw_{con} describes a bandwidth consumption, Bw_t represents a total bandwidth, Bw_a denotes an available bandwidth. Link-state routing protocol with hybrid multipath energy and quality of service (QoS) awareness was designed in [24] to improve the QoS and cuts down energy cost on each packet. But this protocol failed to enhance the performance using multi-hop wireless networks scenarios. Then the Ruzicka similarity is measured between the nodes based on the estimated resource as given below,

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$$\varphi = \frac{Sn_i \cap Sn_j}{\sum Sn_i + \sum Sn_j - Sn_i \cap Sn_j} \qquad (4)$$

Where φ indicates a similarity coefficient, Sn_i, Sn_j denotes a sensor nodes $Sn_i \cap Sn_j$ is a mutual dependence between the nodes, $\sum Sn_i$ is the sum of S_i score based on resource, $\sum Sn_j$ is the sum of Sn_j score based on the resource. The output ranges of the similarity coefficient are between 0 and +1. The nodes with similar characteristics belongs to one cluster at a given moment. In other words, the weak learner performs hard partitioning to assemble the sensor nodes into a specific cluster at a particular instant. In this way, every sensor node assigns to the more suitable cluster.

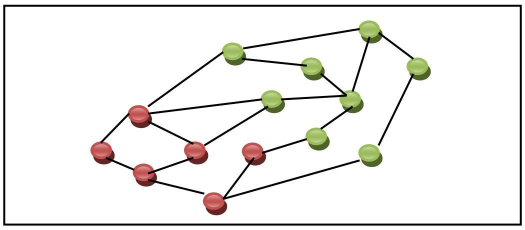

Figure 4 Ruzicka Chinese whispers clustering algorithm

Figure 4 shows the Ruzicka Chinese whispers clustering algorithm to partition the network into different clusters. Enhanced Energy Proficient Clustering (EEPC) was introduced in [25] for decreasing the energy consumption. But, the data loss was not minimized. As shown in figure 4, two different clusters are obtained and represented by green and red colors. The clustering procedure contains some training errors for the weak learner. Therefore, the ensemble technique provides strong clustering outcomes by combining the weak learners.

$$Y = \sum_{i=1}^{n} z_i(x) \qquad (5)$$

Where, Y symbolizes the output of the strong results, $z_i(x)$ indicates a weak learner's output. After that, each weak learner is allocated weight.

$$Y = \sum_{i=1}^{n} \delta_t z_i(x) \qquad (6)$$

Where, δ_t indicates a weight of the weak learner. After assigning a weight, the Jensen-Shannon (JS) divergence is applied for each weak learner to measure the dissimilarity between the two clusters. This helps to minimize the error during the clustering process. The divergence is measured as given below,

$$D = \frac{1}{2} \|C_1 - C_2\| \qquad (7)$$

Where D denotes a divergence, C_1 and C_2 denotes two different clusters. The Shannon divergence D provides the value between $0 \le D \le 1$. The higher divergence between the clusters has a lesser error. Otherwise, the minimum divergence between the clusters has a higher error. The initial weight of the weak learner is modified in light of the incorrect value. The initial weight raises when the weak learner has a higher error. The initial weight gets degraded when the weak learner has a minimum error. Therefore, the ensemble technique identifies the weak learner which has least amount of error.

$$Y = \arg\min E\,(z_i(x)) \qquad (8)$$

Where $arg\,min$ is an argument of minimum function and 'E' denotes error of the weak classifier. The ensemble technique accurately clusters the sensor nodes as higher performance or lesser performance. After finding the higher performance sensor node, patient data transmission is performed along with high performance nodes. The source node finds the neighbouring sensor nodes which have higher signal strength. An Optimize GA for Cluster Head Selection protocol was developed in [26] to enhance the energy consumption of the network. Also, multiple movable sinks are used up to the transmission distance among the sink and CH through data communication. However, the received signal strength was not computed. The sensor node's received signal strength is measured as shown below in order to resolve the problem,

$$R_{sp} = T_{sp} * \frac{G_t * G_r * v_t^2 * v_r^2}{d^4} \qquad (9)$$

Where R_{sp} stands for node's received signal strength, S_t is node's transmitted signal power G_t, G_r denotes node's receiver antenna gain, v_t^2 for transmitter antenna height, v_r^2 indicates a receiver antenna height, d for node's distance from transmitter and receiver. Therefore, the source node selects the neighbouring node which has higher signal strength to forward the patient data. This facilitates better data transfer and cuts down on delay. The following is a description of the IoT-CWJSBNC algorithmic procedure.

//Algorithm 1: IoT based Chinese Whisper Jenson –Shannon Boost Node Clustering

Input: Sensor nodes S_i=Sn_1,Sn_2,Sn_3...Sn_n, Patient Data dp_i = dp_1,dp_2,...dp_n

Output: Improve routing with minimum delay

```
Begin
    For each Sni
        Calculate energy and bandwidth
        Construct 'b' weak learners
        Initialize the two clusters
        Measure the similarity between the nodes 'φ'
        Nodes are clustered as high performance
            or low performance
    End for
    Combine all weak learners Y = ∑_{i=1}^{n} z_i(x)
    For weak learners z_i(x)
        Initialize a weight 'δ_t'
        Compute the Jenson-Shannon divergence 'D'
        Find the error 'E'
        Update the weight α_t'
        Find weak learner with minimum error
            arg min E (z_i(x))
        Obtain strong clustering results
    End for
    For each high-performance node
        Measure received signal strength 'R_sp'
        If ( argmax R_sp ) then
            Source node finds a neighbouring node
        else
            Source node finds another neighbouring node
        End if
        Source node sends patient data 'dpi'
            via neighbouring node s
    End For
End
```

The sequential method for enhancing data transmission in WSN is described in Algorithm 1. For each sensor node, residual energy and

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bandwidth consumption are measured. The ensemble strategy creates the group of weak learners. By applying the Ruzicka Chinese whispers algorithm, number of clusters are initialized. For each sensor node, the similarity is measured between the sensor nodes. Based on a similarity measure, the nodes are grouped into different clusters. Once the weak learners have been combined, each sensor node's weight is assigned using the ensemble technique. Followed by, the Jensen-Shannon (JS) divergence is applied for each weak learner to assess the dissimilarity among the two clusters. Based on the divergence value, error rate is measured. Then the proposed ensemble technique locates the weak learner with least amount of error. The result is the higher performance energy efficient nodes are chosen for routing the patient data. The source node finds the neighboring node with higher signal strength for efficient data delivery with minimum delay.

4. SIMULATION SETUP

The NS2.34 simulators is used to simulate the proposed IoT-CWJSBNC method as well as the already-in-use SEEP [1] and I-SEP [2] approaches. Totally 500 sensor nodes are distributed over the region of A^2 (1100 m * 1100 m). The Random Waypoint is utilized as a node mobility model. The DSR protocol is implemented to route patient data from source to destination that is energy-efficient. 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, patient health information, and so on. This information is sent from sender to receiver with minimum time. The set simulation time is 300 sec. Energy-efficient data delivery between the source and destination is made possible by the use of DSR protocol. Table 1 lists the simulation parameters and their associated values.

Table 1 Simulation Parameters

Simulation Parameter	Value
Simulator	NS 2.34
Network area	1100m * 1100m
No. of mobile nodes	50,100,150,200,250,300,350,400,450,500
Protocol	DSR
Simulation Time	300Sec
Mobility Model	Random Way Point Model
Nodes Speed	0-20m/s
Data Packets	100,200,300,400,500,600,700,800,900,1000
Number of Runs	10

5. PERFORMANCE RESULTS AND DISCUSSION

Various factors including energy consumption, packet delivery ratio, packet loss rate, and end-to-end delay, are reviewed in this part to compare the performance of the proposed IoT-CWJSBNC technique with that of the existing methods SEEP [1] and I-SEP [2]. The simulation results of different parameters are tabulated and graphical results are shown.

Energy consumption is measured as quantity of energy used by sensor nodes to transfer patient data from the source to destination node. The energy consumption is formulated as given below,

$$Con_E = n * Con_E\ (single\ sensor\ node) \quad (10)$$

Where, Con_E symbolizes energy consumption, 'n' denotes number of sensor nodes. It is measured in the unit of joule (J).

Packet delivery ratio is calculated as amount of patient data (i.e. data packets) received at the destination divided by the quantity of data packets transmitted. There is a formula provided for estimating the packet delivery ratio,

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

Where, R_{PD} denotes a packet delivery ratio, NPR denotes the number of packets received, NPS denotes the number of packets sent. It is measured in terms of percentage (%).

Packet loss rate is calculated as the quantity of patient data lost in relation to the total quantity of data packets sent from the source node. This leads to the loss rate being calculated as follows,

$$R_{PD} = \left[\frac{NPL}{NPS}\right] * 100 \quad (12)$$

In (12), R_{PL} represents the packet loss rate, NPL denotes the number of packets lost, NPS denotes the number of packets sent. It is evaluated in regards of percentage (%).

End-to-end delay is measured based on the expected time of arrival of the patient data and the actual time of arrival of the patient data at the destination end. The overall delay is formulated as given below,

$$Delay_{EE} = [t_{act}] - [t_{ex}] \quad (13)$$

Where, '$Delay_{EE}$' symbolizes the end to end delay, t_{act} denotes an actual time of arrival t_{ex} denotes an expected time of arrival. Milliseconds (ms) are used to estimate the overall delay.

The simulation results of energy usage for various sensor node counts are presented in Table 2. For determining the energy consumption, the proposed IoT-CWJSBNC and existing two methods SEEP [1] and I-SEP [2] are implemented in a network simulator. The performance of the suggested IoT-CWJSBNC technique is evaluated by comparing the results to the established works [1] and [2]. Let us consider the count of sensor nodes is 50 and energy level is set to each sensor node 0.5$Joule$. Sensor node energy levels degrade as a result of the sensing and transmitting operation. Therefore, the energy consumed by the single sensor node using IoT-CWJSBNC is 0.26 $Joule$ and the overall energy utilization of 50 sensor nodes is 13$Joule$. By applying the SEEP [1] and I-SEP [2], energy consumption is observed as 18$Joule$ and 20 $Joule$ respectively. Similarly, various conclusions are drawn by applying varied number of sensor nodes. The observed outcomes of the suggested IoT-CWJSBNC technique are contrasted with those of existing techniques. The average of ten companion outcomes shows that the energy consumption using the suggested IoT-CWJSBNC approach is significantly reduced by 11% and 18% in contrast to

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other works SEEP [1] and I-SEP [2]. Energy consumption is displayed graphically in figure 5.

Table 2 Comparison of energy consumption

Number of sensor nodes	Energy consumption (Joule)		
	IoT-CWJSBNC	SEEP	I-SEP
50	13	18	20
100	20	25	28
150	23	27	30
200	25	28	32
250	28	30	34
300	30	32	35
350	32	34	36
400	34	36	38
450	36	38	40
500	39	42	44

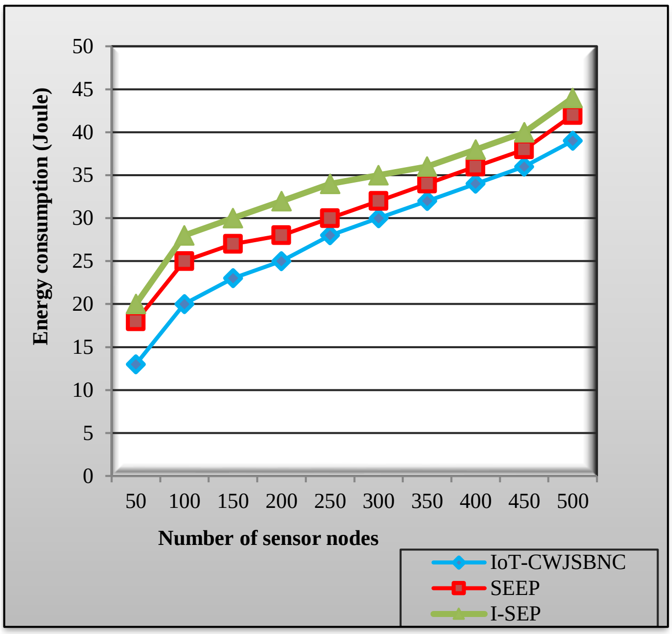

Figure 5 Graphical illustration of energy consumption

Figure 5 depicts the simulation results of energy consumption measured in the vertical axis for a different quantity of sensor nodes considered around 50 to 500 in the horizontal axis. The graphical illustration infers a result of energy consumption gets increased with the increase in the number of sensor nodes. However, the numerical and graphical plot inferred that energy consumed using IoT-CWJSBNC approach is comparatively better than [1] and [2]. The use of clustering energy-efficient nodes for enhanced communication is what has caused the improvement. The ensemble technique uses the Chinese Whisper clustering algorithm as a weak learner.

This algorithm partitions the sensor nodes according to energy and bandwidth. The weak learners are combined using the ensemble technique which yields excellent clustering outcomes. Based on the clustering results, the higher performance nodes are selected to perform routing and to minimize energy consumption.

Table 3 Comparison of packet delivery ratio

Number of Patient data	Packet Delivery Ratio (%)		
	IoT-CWJSBNC	SEEP	I-SEP
100	90	86	83
200	91	89	85
300	90	88	82
400	92	86	84
500	91	87	83
600	90	88	85
700	91	87	84
800	93	88	85
900	92	89	86
1000	90	88	85

Table 3 given above illustrates the performance data delivery ratio concerning 10 different runs. As shown in table 3, delivery ratio results are observed for three different methods IoT-CWJSBNC, SEEP [1] and I-SEP [2]. 10 different runs are performed for different patient data. The findings indicate that IoT-CWJSBNC technique has an increased ratio of deliveries than traditional methods. The simulation is conducted with 100 patient data originating from the source node, 90 data are correctly received at destination and the 90% delivery ratio was discovered using IoT-CWJSBNC, 86% with the support of [1] and 83% with [2]. This outcome implies that the IoT-CWJSBNC approach results in a superior data delivery ratio and average of ten findings shows that in comparison to traditional routing strategies the data delivery ratio has significantly risen by 4% and 8%.

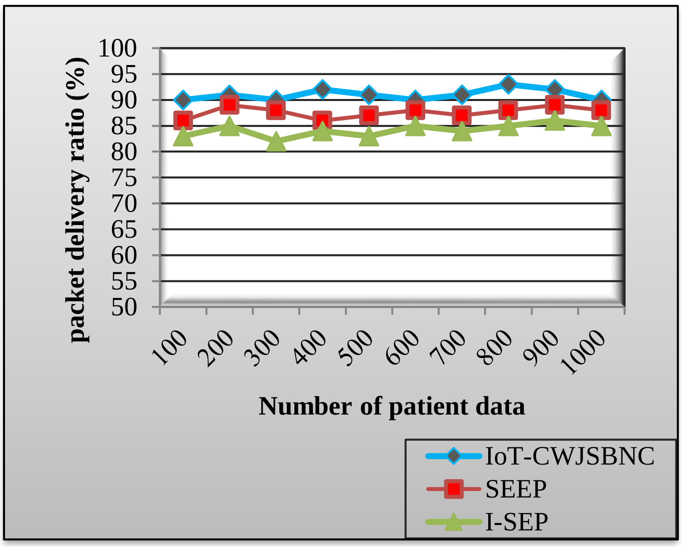

Figure 6 Graphical illustration of data delivery ratio

Figure 6 given above illustrates the performance evaluation of the data delivery ratio in relation to the quantity of data packets captured between 100 to 1000. As shown in figure 5, number of data packets is counted along horizontal axis with the delivery ratio being measured along vertical axis. The pictorial plot shows that compared

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to other two ways currently in use, the IoT-CWJSBNC technique boosts data delivery ratio. This is because of the reason, that the IoT-CWJSBNC technique uses the Chinese Whisper Jensen-Shannon boost clustering to locate the high-performance nodes depending on energy and bandwidth. With selected high-performance nodes, the data transmission is performed. As a result, a higher ratio of delivered packets is achieved.

Table 4 Comparison of packet loss rate

Number of patient data	Packet loss rate (%)		
	IoT-CWJSBNC	**SEEP**	**I-SEP**
100	10	14	17
200	9	11	15
300	10	12	18
400	8	14	16
500	9	13	17
600	10	12	15
700	9	13	16
800	7	12	15
900	8	11	14
1000	10	12	15

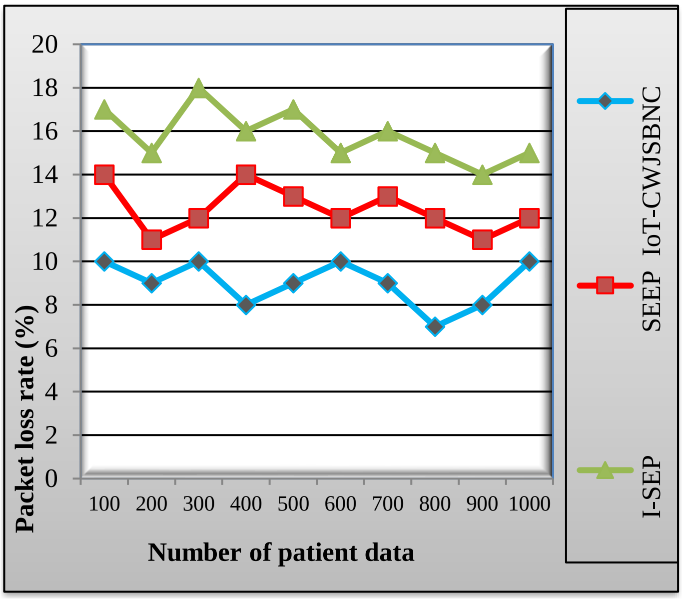

Figure 7 Graphical illustration of packet loss rate

The packet loss rate is displayed in Table 4 above in proportion to the range of data packets taken, from 100 to 1000. The quantity of patient data lost during transmission serves as a proxy for the packet loss rate. The tabulated results show that compared to the other technologies now in use, IoT-CWJSBNC technique significantly lowers the packet loss rate. Let us consider 100 data packets being originated from the source node, 10 data packets are lost at destination using the IoT-CWJSBNC and rate of loss of proposed and traditional methods, SEEP [1] and I-SEP [2] are 10%, 14% and 17% respectively. The observed statistical findings of IoT-CWJSBNC method are contrasted with packet loss rate of present techniques. In comparison to current practices [1] and [2], the average comparative studies indicate that IoT-CWJSBNC minimizes packet loss rate by 27% and 43% respectively.

In Figure 7 the graphical illustration of packet loss rate versus number of patient data being transmitted from source to destination. According to the figure, the packet loss rate of three approaches namely IoT-CWJSBNC and existing methods SEEP [1] and I-SEP [2] are depicted by three distinct colors like blue, red and gray. From the visual illustration, the loss rate of IoT-CWJSBNC technique is minimized than the other two currently used methods. The significant reason for this improvement is to apply the Jensen-Shannon Boost method to discover the energy and bandwidth-efficient nodes for transferring the patient data from source to destination. Besides, source node finds neighbouring node which has higher signal strength for better data delivery with a minimum loss rate.

Table 5 Comparison of end to end delay

Number of patient data	End to End delay (ms)		
	IoT-CWJSBNC	**SEEP**	**I-SEP**
100	15	18	21
200	17	20	23
300	18	21	24
400	21	23	26
500	24	26	29
600	27	29	32
700	31	33	36
800	35	37	41
900	38	40	44
1000	42	45	48

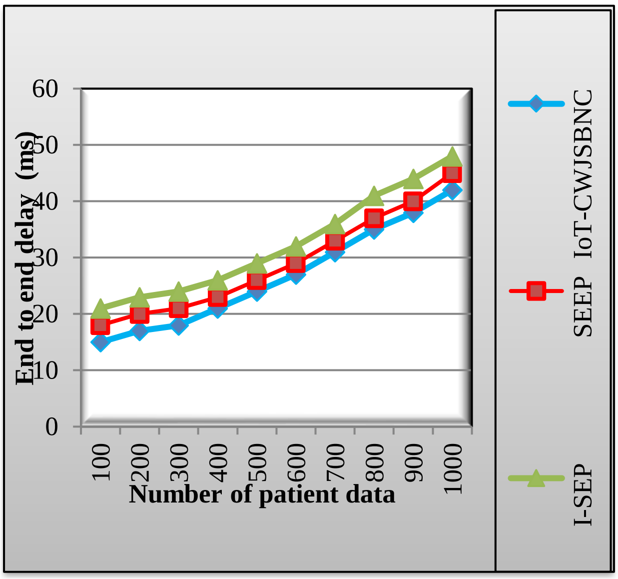

Figure 8 Graphical illustration of end to end delay

Table 5 and figure 8 depicts performance analysis of end-to-end delay versus a number of data in the ranges from 100 to 1000. The graphical representation demonstrates the end-to-end delay of various approaches which are seen in the vertical axis for a variety of data packet counts (i.e. patient data) taken into account in the

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horizontal direction. According to the graphical representation, end-to-end transmission delay of the data grows with the number of data packets. However, with the simulation is conducted for 100 data packets, end to end delay of data transmission is '$15ms$' using the IoT-CWJSBNC while the overall delay using SEEP [1] and I-SEP [2] were found to be $18ms$ and $21ms$.The remaining nine results are performed similarly with input counts from 200,300...1000. The observed outcomes of the suggested technique are contrasted with those of currently used approaches. According to the average comparative data, the overall end-to-end delay employing IoT-CWJSBNC approach is dramatically reduced by 9% in comparison to SEEP [1] and 19% when contrasted to I-SEP [2]. The rationale for the improvement is to find the neighbouring node with higher signal strength. The source node finds the neighbouring sensor nodes to distribute the patient data to destination. The higher signal strength of the node quickly delivers the data to other nodes resulting in minimal delay of data delivery.

6. CONCLUSION

By addressing the issue of Cluster formation, which is based on energy and bandwidth consumption, a unique energy efficient cluster-based routing technique called IoT-CWJSBNC is developed in this study to control the energy of WSN assisted IoT. The IoT-CWJSBNC also introduced a Chinese Whisper Jensen-Shannon Boosting technique for cluster formation. The ensemble technique uses the Chinese Whisper graph-based clustering technique to choose the high performing sensor nodes based on how much energy and bandwidth they use. The boosting technique combines the outcomes of weak learners to improve the clustering performance for efficient routing in WSN-assisted IoT. Then the source node finds the neighboring sensor nodes which have higher signal strength to efficiently deliver the data packets with minimum delay. Simulation is made available to analyze the effectiveness of the IoT-CWJSBNC with the traditional routing techniques through several metrics such as energy consumption, packet delivery ratio, packet loss rate, and an end-to-end delay. The observed outcomes facilitate that suggested IoT-CWJSBNC technique is more efficient for providing energy-efficient routing than the earlier ones, having an increased delivery rate, a decreased loss rate, delay and energy usage.

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