



INTELLIGENT DEEP LEARNING AND SOFTMAX ROUTING FOR ENERGY-EFFICIENT WIRELESS SENSOR NETWORKS IN PUBLIC SPACE DESIGN

MENGMENG CHANG*

Abstract. The increasing usage of several nodes to transfer the massive volume of data to the remotes in wireless sensor networks is a challenging task to reduce the loss. The high volumes of data transmission in wireless sensor networks (WSN) can surpass their capacity, resulting in congestion, latency issues, and packet loss. However, computational intelligence (CI) models can aid in managing and creating intelligent networks in WSN. The WSN congestion issues result in information loss and increased energy usage. CI-based models have been used to resolve this issue, reducing the latency. This paper proposes SoftMax Routing with Deep Neural Network (SRDNN) for efficient routing in WSN. This will route the data packets by choosing the high energy and lower load. It consists of two parts, such as the construction of the routing path, which determines the residual energy of the node. It is analyzed using SoftMax routing to decide whether the node is efficient in energy. The route request and reply established various paths between the source and destination. The path with minimum buffer space and maximum bandwidth is chosen in the optimal routing. The simulation results under the metrics such as energy consumption, data loss rate, throughput, and delay show the proposed model performance.

Key words: Wireless Sensor Networks, routing, SoftMax, Deep neural network, Deep learning, energy efficiency.

1. Introduction. WSNs are a significant technological improvement enabling sensors to gather data from various environmental sensing devices [14, 2]. It has been used for intelligent data processing and decision-making [34]. In WSN, a more significant number of Sensor nodes (SN) since the data is processed in a self-organizing manner with the sink [13]. The SN transfers the gathered data to the sink, which will integrate, process and upload the data to the respective server [7]. The WSN has various advantages, including high reliability, deployment, and reduced power consumption [16]. Due to these reasons, it has been widely used in medical care, environmental monitoring, and other fields [29, 9].

However, the constrained power and the capacity to process the SNs reduce the WSN lifetime [18]. In general, WSN sensors are equipped with limited battery power that is not changeable during the deployment. Hence, energy is the primary concern in WSN, and energy-efficient approaches can prolong the network lifetime [31]. Identification of the load balancing model that efficiently utilizes the limited resources and increases the network lifetime. Specifically, the energy-efficient routing methods significantly reduce the energy of the WSN and increase its survival rate [4].

Traditional routing approaches focused on the clustering-based model for data flow control to extend the WSN lifetime [5]. The low energy adaptive clustering hierarchy (LEACH) routing [10] categorizes the SN into various clusters and uses the hierarchical cluster head to process the sensed data. In [8], forwarding the data is separated from data transmission to assist the node in avoiding premature death of the nodes. These approaches have some issues, such as difficulty in formulating it, which consumes large amounts of energy and needs to be adaptable to various network structures. Therefore, adopting new strategies to solve these issues is necessary.

In [3], The network on chip (NoC) structure was developed for efficient data transmission. It performs on-chip antenna usage among the long-distance nodes to reduce the latency. However, the EE still needed to be improved. In [20], opportunistic routing (OR) was introduced for multiple input multiple output WANs. It also fails to reduce the latency. In [30], Softmax Regressed Tanimoto Reweight Boost Classification (SRTRBC) method was developed to reduce energy utilization with reduced latency. This model identifies the underloaded EE nodes for data transmission. To solve the issues such as increased packet loss, reduced packet delivery, increased latency, and high computational cost, this paper contributes the following:

*Department of Art Design Taiyuan Normal University, Jinzhong, Shanxi, 030619 Chin (mengmengchang1@outlook.com)

1. This paper developed an energy-efficient congestion-aware routing scheme for WSN by identifying underloaded energy-efficient nodes for data transmission.
2. The Model comprises two parts: routing path construction using Softmax regression routing and congestion-aware routing using DNN.
3. The softmax routing identifies the residual energy (RE) of the node by examining whether it is an efficient or inefficient node through multiple paths from source to destination.
4. Based on the buffer space and the bandwidth, DNN performs the congestion-aware classification of the node with increased bandwidth and reduced buffer space for optimal routing path selection.
5. The proposed SRDNN experiments in the simulation environment and the congestion-aware scheme reduce packet loss, energy, and latency.

The remaining section of this paper is as follows: Section 2 discusses the related literature on energy-efficient approaches. Section 3 introduced the proposed network model with materials for energy-efficient routing. Section 4 addressed the simulation results and comparison of numerical outcomes. Section 5 concludes the proposed model's merits and future direction.

2. Related work. The article[12] highlights the importance of big data in surveillance applications and introduces a novel object-tracking approach using graph-based modeling and multilevel fusion. The performance evaluation results indicate the effectiveness of the proposed method [12]. The wireless multimedia sensor node (WMSN) [11] with video and audio capabilities that fuses object recognition results to improve performance and reduce data transmission size in a WMSN. The performance test results indicate that the proposed approach can significantly enhance object recognition capability while maintaining low overhead for auditory data processing. The article[26] presents a new congestion-aware routing algorithm that combines global and local routing algorithms to reduce average packet latency without increasing system power. The experimental results demonstrate better performance than DyAD, CATRA, and ERCA algorithms under various traffic conditions.

The paper [17] proposes a new method for layer-wise training of deep residual-like networks with statistical guarantees on multi-class classification tasks. The proposed method uses functional gradient boosting and shows global convergence under a standard margin assumption, eliminating a worse dependence on network depth in a generalization bound. The paper[21] proposes an enhanced routing mechanism for sensor networks that considers congestion and uses fuzzy rule sets to make decisions. Fuzzy rule sets may only sometimes provide the most accurate or optimal results, as they rely on imprecise linguistic descriptions rather than precise mathematical models. The computational complexity of fuzzy rule [1] sets can be high, making it difficult to scale to large sensor networks with many nodes. Wireless Sensor Networks (WSNs) can suffer from congestion due to many nodes and limited network resources. Technique[6] congestion and clustering control mechanism is used to mitigate congestion. Also, the article uses a hybrid multi-objective approach to improve the network performance in congestion [23]. By using bidirectional communication between[22] the ground control station and the drones, the protocol can dynamically adjust the data rate and prioritize data transmission based on network conditions. This helps to mitigate congestion and improve the overall performance and reliability of the Internet of drones.

The paper [33] employs a centralized controller to manage network congestion using multiple metrics, allowing for optimized routing decisions that minimize packet loss and energy consumption in low-power and lossy networks. A mechanism that improves congestion control in CoAP (Constrained Application Protocol) [25] observes group communication by dynamically adjusting the data transmission rate and considering the reliability of network paths. The approach in [19] utilizes fuzzy logic and sliding mode control to regulate congestion in wireless sensor networks by jointly considering network layer and physical layer parameters to optimize data transmission while minimizing energy consumption. The author in [24] uses a protocol that combines rate-based congestion control and energy-aware routing to reduce energy consumption in wireless sensor networks by adjusting data rates and routing paths based on the energy levels of individual nodes.

To optimize congestion control in wireless sensor networks by considering traffic patterns and energy consumption, protocol [32] dynamically adjusts data rates and routes based on network traffic. The energy levels of individual nodes are supposed to minimize congestion and energy consumption. The protocol in the paper [15] employs clustering techniques to group sensor nodes and uses a congestion control mechanism to regulate data transmission while considering the sinks' mobility. By optimizing the routing of data and reducing the

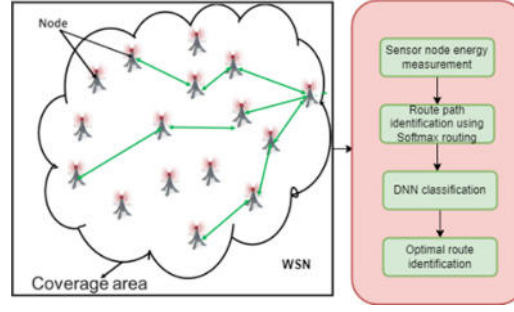


Fig. 3.1: Proposed system model

energy consumption of individual nodes, this protocol can extend the lifetime of the WSN and improve overall network performance.

The above literature review shows more congestion control and energy management techniques in WSN. However, deep learning techniques are very limited in this process. This research presents an attractive deep-learning model for conserving the energy in the WSN model.

3. Proposed Model. WSN consists of sensor nodes that sense the data and transfer it into the sink node. Fig 3.1 illustrates the proposed optimal routing path identification model that performs the routing identification that enhances data delivery and reduces the latency. It computes each distributed sensor node energy. Next, the route path between the source and destination is identified using the request and reply message. The minimum route between the sender and receiver is selected for transmission using the proposed Softmax routing with the DNN-based routing model. This congestion-awake routing scheme reduces the network latency and congestion.

The proposed system network model consists of the sensor nodes called S_i , $i = 1, 2, 3, \dots, N$ distributed in the $N \times N$ area within the transmission range T . The sensor nodes are independently located and gather the data from the environment. The gathered data packets called P_i , $i=1, 2, 3, \dots, M$ are forwarded to the destination node d through the congestion awake nodes called C_i , $i=1, 2, 3, \dots, N$ to increase the WSN lifetime with the optimal routing.

3.1. Construction of Route path using Softmax routing. The SRDNN has been used to find the optimal route path classification among the sensor nodes using the softmax routing analysis. It is an ML model that finds the relationship among the dependent and independent variables. The SR observes the energy of the SN. For each SN, the energy is computed, and at the initial stage, all SN have the same energy and is reduced during the sensing procedure. The energy of SN is calculated as the multiplication of time and power as shown in Eqn 3.1. The RE of the node is computed using Eqn 3.2

$$E_S(\text{Joule}) = \text{Power (watts)} \times \text{Time (seconds)} \quad (3.1)$$

$$RE_{E_S} = \text{Total}_{E_S} - \text{Consumed}_{E_S} \quad (3.2)$$

where, RE denotes the residual energy of SN, Total declares the SN total energy and consumed energy of SN is declared as Consumed_{E_S} . The SR examines the predicted SN energy and finds the energy-efficient node. This activation function can categorize the SN over the predicted output as formulated in Eqn 3.3

$$SR = \frac{e^{RE_i}}{\sum_{k=1}^p e^{RE_k}} \quad (3.3)$$

where, RE_i is the residual energy of SN i that ranges from 0 to p . The SR output ranges from 0 to 1. While SR is analyzed with regression then the values ranges categorized as follows

$$= \begin{cases} \text{Non energy - efficeint node} & \text{if } 0 \leq SR < 0.5 \\ \text{Energy efficeint node} & \text{if } 0.5 \leq SR \leq 1 \end{cases} \quad (3.4)$$

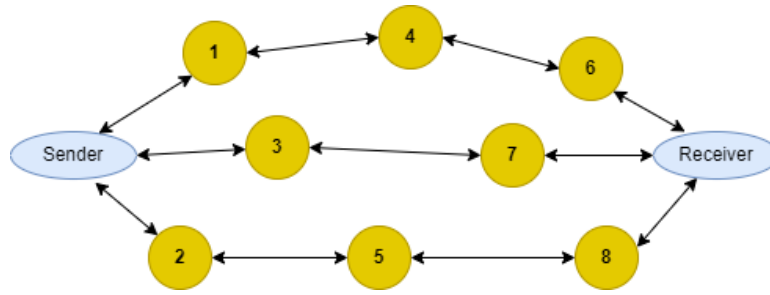


Fig. 3.2: Construction of Routing path

Once the nodes are categorized, the SN with a higher SR is chosen to construct the routing path. The sender distributes the request to the receiver through the intermediate nodes. The path between the sender and receiver is constructed using these two control messages, such as route request A_{req} and route reply A_{rep} .

$$Sender \xrightarrow{A_{req}} \sum_{j=1}^d (I_j) \xrightarrow{A_{req}} Receiver \tag{3.5}$$

The sender node transfers the request for a route to the sink node via intermediate node I. Once, the request messages are collected, the receiver replies to the sender as follows

$$Sender \xleftarrow{A_{rep}} \sum_{j=1}^d (I_j) \xleftarrow{A_{rep}} Receiver \tag{3.6}$$

The multiple paths among the sender and receiver using SR are demonstrated in Fig 3.2. Once the routing path is constructed, the possible route from sender to receiver is [S,1,4,6,R], [S,3,7,R] and [S,2,5,8,R]. These three routes with the intermediate nodes are the possible paths from the sender to the receiver.

3.2. DNN based classification . The DNN structure is illustrated in Fig 3.3 which consists of input, output, and various hidden layers. The output layer classifies the routing path as a congestion-aware and non-congestion-aware path. DNN is a kind of feed-forward network with multiple layers that increase the network capability [28]. Let X be the input with the selected routing path and Y is the output layer that classifies the path into two categories which range the value as 0 to 1. The output computation of each hidden layer h is denoted in Eqn 3.7

$$h_i(X) = \sigma(W_i^T(X) + b_i) \tag{3.7}$$

Where σ is the activation function called ReLU used in hidden layer and Softmax function used in output layer, W is the weight and b is the bias. The activation functions are denoted in Eqn 3.8 and 3.9.

$$\sigma_{ReLU}(X) = \max(0, X) \in [0, \infty] \tag{3.8}$$

$$\sigma_{sigmoid}(X) = \frac{1}{1 + e^{-X}} \in (0, 1) \tag{3.9}$$

This paper considers the DNN with the input of three layers to represent the selected routing path. The dense layers with 2^{10} , 2^8 and 2^6 with the sigmoid function represent the output as congestion aware route or not. Once it is classified, the weak learners are grouped to form the strong one as in Eqn 3.10

$$WL = \sum_{k=1}^m \omega_k \tag{3.10}$$

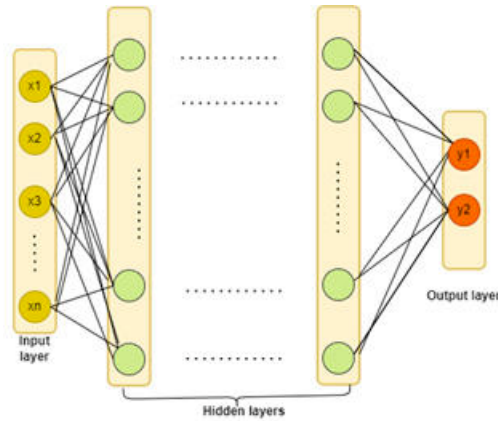


Fig. 3.3: DNN

Table 4.1: Energy Efficiency (%) comparison

No. of SN	NoC structure-based routing	Opportunistic routing (OR)	RL-AR	Proposed SRDNN
200	88.7	91.3	96.2	98.4
400	90.2	92.4	94.1	97.6
600	88.9	91.3	97.8	98.9
800	88.3	90.8	96.8	98.8
1000	84.5	93.4	94.6	97.4
Avg performance	88.12	91.84	95.9	98.22

where WL denotes the weak classifier output and ω_k declares the number of weak learners. In order to reduce the network loss constraint, the binary cross entropy loss function [27] is used as in Eqn 3.11

$$Loss = L(\omega, b) + L_{const} \quad (3.11)$$

$$L(\omega, b) = \frac{1}{n} \sum_{i=1}^n -[Y(i) \ln(Y_L(i)) + (1 - Y(i)) \ln(1 - Y_L(i))] \quad (3.12)$$

Where $Y(i)$ denotes the actual output and $Y_L(i)$ denotes the DNN output.

4. Simulation results. The simulation of proposed SRDNN is experimented using MATLAB. The simulation environment consists of 1000 sensor nodes and it is experimented for 10 runs. The proposed and existing approaches such as network on chip structure [3], opportunistic routing [20] and RL based adaptive routing [30] are compared. It is evaluated using the metrics such as energy, data delivery and data loss rate, latency and throughput.

4.1. Analysis in terms of Energy Efficiency (EE). EE: It is the proportion of output and input energy which is determined as in Eqn 4.1. The performance comparison of EE of the proposed and existing methods is shown in Table 4.2.

$$EE (\%) = \frac{E_{output}}{E_{Input}} \times 100 \quad (4.1)$$

From table 4.1, the developed routing and existing approaches EE are compared. Among the state of the art approaches, the proposed SRDNN model outperforms with the increased EE. For instance, 600 number of SNs,

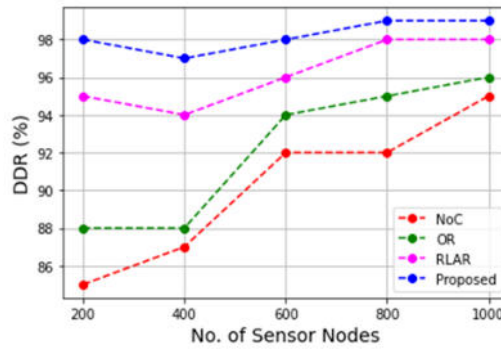


Fig. 4.1: DDR comparison

the EE of proposed model is 98.9%. Whereas, the other approaches such as NoC secured 88.9%, OR obtained 91.3% and RL-AR secured 97.8%. Due to the transmission process, the EE of SNs are reduced while increasing the number of SNs. As an average, the performance of the proposed model is superior to other approaches. Comparatively, the SRDNN is improved by 10.1% than NoC, 7.6% than OR and 2.32% than RL-AR because of the efficient routing and classification model.

4.2. Analysis in terms of Data delivery rate (DDR): . It is computed as the ration between the correctly delivered number of packets and total count of sent packets which is formulated as in Eqn 4.2

$$DDR = \frac{\text{No.of correctly delivered packets}}{\text{Total no.of packets sent}} * 100 \quad (4.2)$$

Fig 4.1 illustrates the DDR comparison among the proposed and existing approaches. The X axis denotes the No of sensor nodes transfer the data packets. The Y axis denotes the DDR of four approaches in terms of %. The illustration of this graph promotes the performance of the proposed model with increased DDR than other approaches. Due to the implementation of the softmax routing to find the residual energy, the node that is congestion aware is identified efficiently using DNN. For instance, 1000 number of SNs, the DDR of proposed model is 99% which is superior to other models such as NoC (95%), OR (96%) and RLAR (98%). The average performance of the proposed model is increased by 8% than NoC, 6% than OR and 2% than RLAR.

4.3. Analysis in terms of Latency. :

It is the variation between the expected and actual arrival time of the data packets and it is denoted in Eqn 4.3

$$L (ms) = \text{Actual}_{AT} - \text{Expected}_{AT} \quad (4.3)$$

Fig 4.2 illustrates the latency comparison among the proposed and existing approaches. The X axis denotes the No of sensor nodes transfer the data packets. The Y axis denotes the latency of four approaches in terms of milliseconds. The illustration of this graph promotes the performance of the proposed model with reduced latency than other approaches. Due to the implementation of the softmax routing to find the residual energy, the node that is congestion aware is identified efficiently using DNN. For instance, 600 number of SNs, the latency of proposed model is 24ms which is lesser than other models such as NoC (47ms), OR (38ms) and RLAR (35ms). The average performance of the proposed model is reduced by 21.2% than NoC, 13.2% than OR and 8.4% than RLAR.

4.4. Analysis in terms of Data loss rate (DLR). It is the ratio between the count of data packets that are correctly delivered and total number of transmitted packets which is denoted in Eqn 4.4

$$DLR = \frac{\text{No of data packet delivered}}{\text{No of data packet sent}} * 100 \quad (4.4)$$

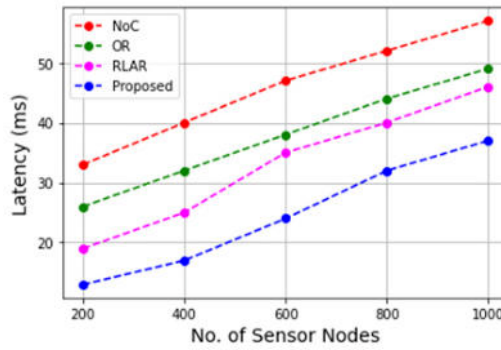


Fig. 4.2: Latency comparison

Table 4.2: DLR (%) comparison

No. of SN	NoC structure based routing	Opportunistic routing (OR)	RL-AR	Proposed SRDNN
200	15	12	10	4
400	13	12	8	3
600	8	6	5	3
800	8	5	5	2
1000	5	4	4	2
Avg performance	9.8	7.8	6.4	2.8

Table 4.2 represents the DLR comparison of proposed SRDNN model and existing approaches such as NoC, OR and RL-AR. The results show that the performance of the proposed model with reduced DLR than other approaches. Due to the implementation of the softmax routing to find the residual energy, the node that is congestion aware is identified efficiently using DNN. As an average, the proposed model secured the reduced DLR of 2.8% than other approaches such as NoC (9.8%), OR (7.8%) and RLAR (6.4%). The average performance of the proposed model is reduced by 7% than NoC, 5% than OR and 3.6% than RLAR.

4.5. Analysis in terms of Throughput. It is the amount of data packets that are broadcasted from the SN at a particular time interval which is measured using Eqn 4.5

$$\text{Throughput (bps)} = \frac{\text{No. of transmitted packets}}{\text{Time interval}} \quad (4.5)$$

Fig 4.3 illustrates the Throughput comparison among the proposed and existing approaches. The X-axis denotes the No of sensor nodes to transfer the data packets. The Y axis denotes the throughput of four approaches in terms of bits per second (bps). The illustration of this graph promotes the performance of the proposed model with reduced throughput than other approaches. Due to the implementation of the softmax routing to find the residual energy, the node that is congestion aware is identified efficiently using DNN. For instance, 1000 SNs, the throughput of the proposed model is 890bps which is lesser than other models such as NoC (924bps), OR (954bps), and RLAR (978bps). The average performance of the proposed model is reduced by 4.8% than NoC, 7.11% than OR and 14.9% than RLAR.

The computational complexity of the proposed SRDNN model can be considered to be normal when compared with existing efficiency. Therefore, the computational complexity of the proposed SRDNN model for each run can be estimated to be in the order of $O(n^2 * r)$, where r is the number of iterations required for convergence during the training process. Assuming a moderate number of iterations required for convergence, the computational complexity of the proposed SRDNN model for 10 runs can be estimated to be in the order of $O(n^2 * r * 10)$.

The limitations of the research are as follows,

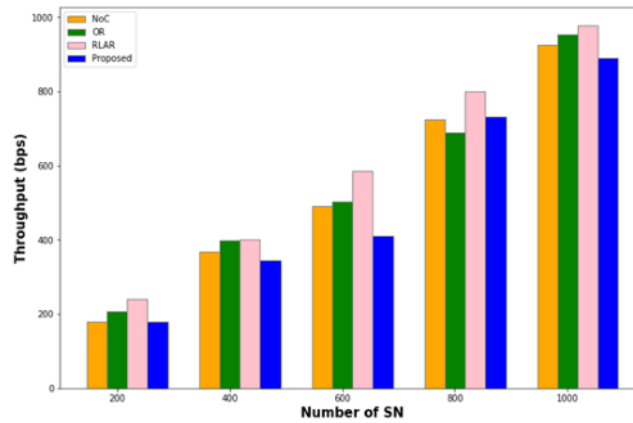


Fig. 4.3: Throughput comparison

- The study does not consider the effects of external interference or signal jamming, which can successfully test the performance of the proposed model. so it can be considered in future work.
- The proposed model relies heavily on the energy levels of the nodes in static, which may not be accurate in dynamic network conditions where node energy levels fluctuate frequently.

Applications

The proposed SoftMax Routing with Deep Neural Network (SRDNN) method for efficient routing in wireless sensor networks (WSN) has practical applications in various fields, including environmental monitoring, healthcare, and industrial control.

1. In environmental monitoring, the SRDNN method can be used to route data from sensors monitoring parameters such as temperature, humidity, and air quality. The proposed method can ensure efficient routing of data while reducing energy consumption, minimizing packet loss, and increasing throughput. This can improve the accuracy and reliability of environmental monitoring data, allowing for better decision-making regarding resource management, urban planning, and pollution control.
2. In healthcare, the SRDNN method can be applied to WSNs used for patient monitoring, such as monitoring vital signs, medication adherence, and activity levels. The proposed method can ensure timely and efficient delivery of data while minimizing data loss and reducing energy consumption. This can improve patient outcomes by enabling better decision-making by healthcare providers, leading to improved patient care and reduced hospital readmissions.
3. In industrial control, the SRDNN method can be used to route data from sensors used to monitor and control industrial processes such as manufacturing, oil and gas production, and power generation. The proposed method can ensure efficient and reliable delivery of data while minimizing energy consumption and reducing packet loss. This can lead to improved process control and optimization, resulting in increased efficiency and reduced costs.

The potential impact of the proposed method in these fields is significant, as it can lead to improved data collection, analysis, and decision-making. This can improve efficiency, reduce costs, and enhance safety in various industries. Additionally, the proposed method can enable the deployment of larger and more complex WSNs, leading to the development of new applications and use cases.

5. Conclusion. This paper introduced the efficient routing and classification scheme using SRDNN for congestion-aware data transmission over WSN. This model constructs the routing path using the SN residual energy. This residual energy identifies the EE and non-EE nodes. The multiple path from sender to receiver is constructed using the intermediate nodes. The DNN classification performs the classification of congestion aware routing with reduced latency and data loss during the data transfer through WSN. The simulation and numerical results show that the proposed SRDNN outperforms other existing approaches in terms of EE,

data delivery and data loss rate, latency, and throughput. The SRDNN secured improved delivery and EE rates and reduced latency, data loss and throughput. In the future, the proposed model will be updated with Meta-heuristic algorithms to optimize the usage of energy and increase the data delivery rate for a dynamic environment. Also, network interference will be considered in future system design.

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