QUANTILE REGRESSIVE FISH SWARM OPTIMIZED DEEP CONVOLUTIONAL NEURAL LEARNING FOR RELIABLE DATA TRANSMISSION IN IOV

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ABSTRACT

Route path identification on the Internet of Vehicles (IoV) is complicated due to the nature of high dynamic mobility, bandwidth constraints, and traffic load. A vehicle present on the IoV communicates with each other to find the status of the road and location of other vehicles for reliable data transmission. However, the existing routing algorithm does not effectively improve the packet delivery ratio and reduce the delay. To resolve these issues, A Quantile Regressive Fish Swarm Optimized Deep Convolutional Neural Learning (QRFSODCNL) technique is introduced reliable data transmission with minimum end to end delay in IoV. The Deep Convolutional Neural Learning uses multiple layers such as one input layer, three hidden layers, and one output layer for vehicle location identification and optimal route path discovery. The different node characteristics of vehicle nodes are analyzed in the hidden layers using the quantile regression function. Depends on the regression analysis, the neighbouring node is identified with minimal time. To improve the throughput and reduce the packet loss rate, the artificial fish swarm optimization technique is applied to choose the best route among the population based on the fitness function. Simulation is carried out to analyze the performance of QRFSODCNL technique and existing methods with different metrics such as packet delivery ratio, packet loss rate, average end to end delay, and throughput. The discussed outcome proves that the QRFSODCNL technique outperforms well as compared to the state-of-the-art methods.

KEYWORDS

IoV, Deep Convolutional Neural Learning, neighbouring location identification, Quantile Regression, multicriteria artificial fish swarm optimization, optimal route path identification

1. INTRODUCTION

With the development of a transportation system, I have emerged to facilitate more convenient and fast services. I adopt a communication network to realize the intercommunication and coordination between vehicles. It is designed to cater to the needs of the automotive industry and has become a popular and crucial platform with information interaction among vehicles, pedestrians, drivers, and city infrastructure. IoV permits vehicles to exchange information with infrastructures using Vehicular Ad Hoc Networks (VANETs). This generates a network with intelligent devices as participants. It observes driving habits and gives recommendations, notifications of problems, or emergency alerts to the driver. However, there is a need for improving the communication speed between the vehicles. The optimal route path identification is incorporated to avoid route path failure which plays a major role in IoV. Deep learning is implemented to improve vehicle communication with minimum loss and delay.

The community aware mechanism [1] on the Internet of vehicles (CVs) was developed to perform the data communication between the vehicles. Though the mechanism minimizes the

DOI: 10.5121/ijcnc.2021.13205

delay, the higher packet delivery ratio was not achieved. The quality of service-aware routing algorithm (QRA) [2] is proposed to identify the optimal path. However, the designed QRA algorithm failed to perform reliable data communication.

To distribute data packets based on bandwidth constraints, an Energy Efficient Multicast routing protocol based on Software Defined Networks and Fog computing for Vehicular networks (EEMSFV) was proposed [3]. The method failed to improve network throughput.

An Identical Destination Based C ommunity [4] on the Internet of Vehicles (IDCIoV) was developed to find the optimal route path. The method failed to reduce the end-to-end delay while performing the data communication. A distributed replication-based data dissemination algorithm [5] was proposed for efficient data transmission between the vehicles. But the performance of the packet loss rate was not reduced. A metaheuristic dragonfly-based clustering algorithm was introduced [6] for cluster-based packet route optimization to improve the transmission. But the performance of the algorithm was not improved for mobility awareness.

A grey wolf optimization-based clustering algorithm [7] was developed for reliable data transmission. The designed algorithm failed to consider the bandwidth constraints for efficient data transmission. The Ant colony optimization (ACO) and Particle swarm optimization (PSO) Algorithms were introduced in [8] for increasing the data communication between the vehicles. But it failed to analyze the node characteristics for neighbouring node identification. An enhanced intelligent hybrid routing protocol using improved fuzzy and cuckoo algorithms was developed [9] to discover the stable path between a source and destination. But effective neighbouring node location identification remained unaddressed. A Software-Defined Cognitive Network for IoV (SDCIV) was introduced [10] for efficient data communication. The designed method did not use any optimization method for optimal route path identification.

The objective of the proposed QRFSODCNL technique is summarized as follows,

- To improve reliable data packet delivery in IoV, the QRFSODCNL technique is introduced by identifying the neighbouring location and optimal path discovery using different layers. In the hidden layers, the different characteristics of the vehicle nodes such as distance, signal strength, direction, and energy are analyzed using the quantile regression function. Based on the regression analysis, the neighbouring nodes are identified. Then the multiple route paths between the source and destination are constructed for reliable data transmission. This helps to minimize the end-to-end delay.
- To improve the network throughput and minimize the packet loss, an artificial fish swarm optimization technique is introduced with multicriteria such as path length and bandwidth availability. The optimization technique selects the best route and obtains the results at the output layer for data transmission among the population based on the fitness function.

The structure of the article is ordered as follows: Section 2 reviews the related works. Section 3 describes the proposed methodology. The simulation settings are provided in section 4. The results and discussion are provided in section 5. Section 6 concludes the paper.

2. RELATED WORK

A bio-inspired unicast routing protocol was introduced in [11] to select the next hops for data transmission between the vehicles. Though the designed protocol reduces delay, the delivery ratio was not improved. A micro artificial bee colony (MABC) algorithm was designed [12] to enhance the network lifetime and reduce delay cost. The designed algorithm failed to analyze the various metrics such as packet delivery and loss rate.

A Path Transmission Costs-based Multi-lane Connectivity Routing protocol (PTCCR) was developed [13] for finding the neighbour location and optimal path. However, it failed to use the swarm intelligence for packet transmission with minimum delay. A statistical framework method was developed [14] for optimizing the routing parameters to improve vehicle communication. But the designed model did not perform the relay node selection to evaluate the quality of the link connection.

A hybrid relay node selection technique was developed [15] for message distribution with minimum delay. However, the multiple characteristics of the relay nodes were not considered. The clustering and position-based broadcast approaches were introduced in [16] for data transmission with lesser delay. But the network throughput was not improved. A reliable emergency message dissemination protocol was proposed [17] with less end to end delay. But the packet delivery ratio was not improved.

A coalitional game theory-based clustering algorithm was designed [18] to improve the data packet communication. Though the algorithm minimizes the delay, the packet loss rate was not minimized. An ant colony optimization was developed [19] to improve the accuracy of path identification and also minimize the packet loss. The energy-aware path identification remained unaddressed.

A Heterogeneous IoV Architecture was introduced [20] for transmitting the data packets. The neighbouring node identification was not performed. A hybrid emergency message transmission (HEMT) method was developed [21] for improving the transmission efficiency. The method failed to consider energy-aware message transmission.

A road aware approach was designed [22] to forward packets among source and destination. In the proposed approach, roads are partitioned into segments depends on an intersection with unique ids. Vehicles share their information via the hello beacons to discover the best path among source and destination. But, the delay was more. In [23], two member-centric protocols were introduced to ensure the reliability of data forwarding for multiple-source to single-destination. A novel Heterogeneous architecture was presented in [24] for data transmission from vehicle to infrastructure (V2I).

3. PROPOSED SYSTEM

The Quantile Regressive Fish Swarm Optimized Deep Convolutional Neural Learning (QRFSODCNL) is introduced for improving the reliable data transmission in IoV with minimum delay. Probit Regressive Chaotic Bio-inspired Grey Wolf Optimization (PRCBGWO) technique enhances data transmission although the energy-aware neighbour location identification techniques are not used to decrease the packet loss and delay. Hence, the QRFSODCNL technique is proposed for identifying the neighbouring location by considering the energy parameters. In the proposed QRFSODCNL technique, deep convolutional neural learning is used to achieve efficient data transmission by selecting an optimal route path based on the fitness measurement. Deep convolutional neural learning (DCNL) is a machine learning algorithm, it includes multiple layers to extract features from input data, and better results are attained in deeper architectures where each layer is pre-trained with an unsupervised learning algorithm. It is a type of machine learning algorithm that utilizes the quantile regression algorithm for neighbouring node identification. DCNL assigns importance to each data in input and can differentiate one from the other. DCNL was inspired by the Neurons in the Human Brain. The role of DCNL is to reduce the vehicle data which is easier to process, without losing features to attain good prediction. At first, DCNL creates the number of neurons and assigns random numerical values (i.e., Weights). If the network did not accurately analyze the node characteristics, an algorithm would adjust the weights.

The IoV enabled vehicle nodes are organized in an undirected graph $g(V_t, L_n)$where the vehicle nodes $v_1, v_2, v_3, \ldots. v_n$are represented by V_t which are distributed over a squared area of '$m * m$' and 'L_n' denotes a connection between the pair of nodes. To initiate the data transmission, the source node (SV) finds one-hop neighbours $Nn_1, Nn_2, Nn_3,, \ldots. Nn_n$ towards the destination node (DV).After that, multiple route paths$\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots\ldots, \mathrm{p}_n$are established between the SV and DV. Subsequently, an optimal path($\mathrm{P_{th}}$) among the multiple paths is identified to improve the data transmission in IoV. With the help of the above system model, the proposed QRFSODCNL technique is designed.

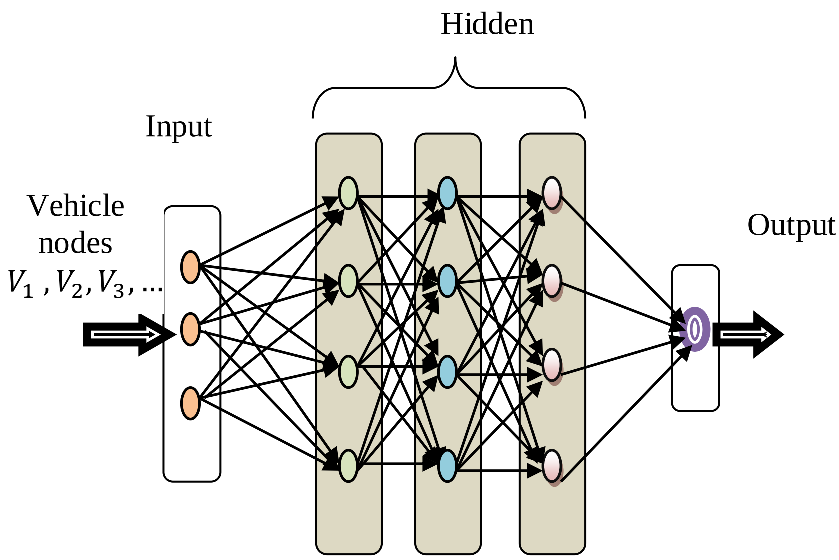

Figure 1. Structure of Deep Convolutional Neural Learning

Figure 1 illustrates the structure of the deep convolutional neural learning with one input layer, three hidden layers, and one output layer. The vehicle nodes are given to the input layer$v_1, v_2, v_3, \ldots. v_n$ at the time. Deep neural learning comprises the neurons-like nodes that are fully connected to the deep convolution layers with the adjustable weights used to learn the features. Then, the inputs are transferred into the first hidden layer. In that layer, the node characteristics are analyzed to find the neighbour location for data transmission. Let us consider the number of vehicle nodes $v_1, v_2, v_3, \ldots. v_n$and defines the source vehicle (SV)and destination vehicle (DV).

3.1. Neighbouring node location identification

The neighbouring node location identification is performed using different characteristics such as distance, signal strength, angle of direction, and energy.

- **Distance**

The distance is measured based on the time of arrival which is the time difference between the beacon message transmission and beacon message reception between the source vehicle and the other vehicles in the network.

$$d = (\mathrm{T_B} - \mathrm{T_r})(1)$$

Where d represents a distance between the vehicle nodes, $\mathrm{T_B}$ represents a time for beacon message transmitted from source to other nodes, and $\mathrm{T_r}$denotes a reply message arrival time from the other nodes.

- **Received signal strength**

After finding the distance, the received signal strength of the mobile node is calculated as follows,

$$R_{ss} = 10 * log_{10}\left(\frac{P_T}{P_R}\right) \quad (2)$$

Where R_{ss} represents a received signal power of the vehicle node, P_T represents a measured power, P_R denotes a reference power.

- **Angle of direction**

The angle of direction is used to find the direction of the movable vehicle nodes from the source node. Let us consider, the coordinate of the source and the other vehicle nodes are $(\mathrm{u_1}, \mathrm{v_1})$ and $(\mathrm{u_2}, \mathrm{v_2})$. The angle of direction is computed using the following mathematical equations,

$$\alpha = \tan^{-1}\left(\frac{u_2 - u_1}{v_2 - v_1}\right) \quad (3)$$

Where α represents the angle between the two vehicles.

- **Energy**

Energy is the major characteristics of the vehicle nodes to improve the transmission. Therefore, the energy of the vehicle node is measured as the product of the power and the time.

$$E = P_{power} * T_{time} \quad (4)$$

Where E denotes energy, P_{power} represents the power, T_{time} denotes a time. The residual energy of the vehicle node is calculated as a difference between the total energy of the vehicle node and the consumed energy.

$$E_{res} = E_t - E_{cd} \quad (5)$$

Where E_{res} represents the residual energy, E_t denotes total energy, E_{cd} is the consumed energy. With the above-said characteristics

$$W = d_i < d_j \&\& R_{ssi} < R_{ssj} \&\& Samedirection \ \&\& E_{res} > E_{th}(6)$$

Where denotes a function which identifies the neighbouring location based on the comparison. The quantile regression is a statistical technique to analyze the node characteristics as follows.

$$y = Q(V_1, V_2, V_3, \ldots. V_n|W) = x_t * W \qquad (7)$$

Where $y$denotes a regression output, Q denotes a condition of the Quantile of the dependent variable (y), x_t denotes independent variables (i.e. Nodes), W denotes a vector of parameters (i.e. W). The Quantile regression analyses the nodes with their characteristics and returns the values (0, 1). If the result is higher than the threshold, then the node is chosen as the neighbouring node. Subsequently, all the neighbouring locations are identified from source to destination vehicles. After finding the neighbouring nodes, the route paths from source to destination are established at the second hidden layer by distributing the two control messages namely request (req) and reply(rep). The source node distributes a request to the selected neighbouring nodes and the destination vehicle node. After receiving the request messages, the node sends reply messages back to the source node. In this way, the multiple route paths from source to destination are created.

3.2. Optimal route path identification

The output of the second hidden layer is transferred as input into the third hidden layer to find the best optimal route path for reliable data transmission. The optimal route path identification is performed using Multi-criteria Artificial Fish Swarm Optimization. The Fish Swarm Optimization is a swarm intelligence that worked based on the population and stochastic search. Swarm Intelligence is defined as the collective behavior of living mammals like birds, fishes, ants, and so on. The behavior of the animal is to find their food source (i.e. prey). On the contrary to the existing optimization algorithm, the proposed optimization algorithm is to provide the best approach which has a higher convergence speed, flexibility, and higher accuracy. Artificial fish swarm is a metaheuristic technique that works based on different behaviours like prey, swarm, and follows. Here the Artificial fish swarm is related to the multiple paths$\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots\ldots \mathrm{p}_\mathrm{n}$ and multi-criteria referred to the multiple objective functions such as path length i.e. distances, bandwidth availability, node buffer capacity. Based on the multi-criteria, an optimal route path (i.e. artificial fish) is selected among the population.

By applying the meta-heuristic artificial fish swarm optimization, the population of ‘n’ artificial fish swarms (i.e. available paths) is randomly distributed in the search space.

$$V = \mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots\ldots \mathrm{p}_\mathrm{n} \quad (8)$$

After the initialization, the fitness is calculated for each fish swarm in the current population. The fitness is calculated based on multiple objective functions such as path length, bandwidth availability, and node buffer capacity.

The path length is measured based on distance from the source to the destination. Let us consider the coordinate of the two source vehicle and destination vehicles are $(\mathrm{x}_1, \mathrm{y}_1)$ and $(\mathrm{x}_2, \mathrm{y}_2)$ respectively. The distance between two points is estimated as

$$D = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2} \qquad (9)$$

Where $D$is the distance between the source vehicle and destination vehicle?. Then the available bandwidth is calculated as follows,

$$bw_a = (bw_{tt} - bw_u) \quad (10)$$

Where, bw_adenotes an available bandwidth of the route path from source vehicle to destination vehicle, bw_{tt}denotes a total bandwidth, bw_udenotes a utilized bandwidth.

The node buffer capacity is computed for determining the node status. To calculate network load, the maximum buffer queue length is taken to lessen packet drops due to collision in the receiver node.

$$B_i\,(t) = \frac{B_{max} - B_n\,(t)}{B_{max}} \qquad (11)$$

From (11), $B_i\,(t)$ is an average buffer capacity, B_{max} is a maximum buffer size, $B_n\,(t)$ denotes the number of packets in buffer queue at the time. If the buffer queue length is higher than the threshold, the node buffer size is full. In this case, the other alternative the node is chosen to forward the data packet depends on the fitness function. If the node buffer size is empty, it lessens routing to load that results in the master node lessen network traffic and enhances packet delivery. Then the fitness is measured based on these three objective functions.

$$F(x) = \{(\min D)\ \&\&(bw_a > \ \delta)\&\&\ \ (B_i\,(t) < B_t)\} \qquad (12)$$

Where $F(x)$denotes a fitness function, δ denotes a threshold for the bandwidth availability. B_t refers to the threshold for buffer capacity. Based on the fitness value, three different behaviours of the fish such as search or prey, swarm, and follow are analyzed to identify the global best solution.

Search or prey behaviour

Prey is a fundamental behavior of the artificial fish that is used to find the food source (i.e multiple objective functions) in the search space. Generally, the fish identify the food source in the water is based on their vision or sense. Let us consider the current position of the fish is $F_i$and the updated position is$F_i(t+1)$. If the fitness of one fish is higher than the other i.e. $F(x_a) < \ F(x_b)$, then the search or prey behavior is executed and then the position updates are expressed as follows

$$F_i(t+1) = F_i(t) + R * S * \left(\frac{(F_b - F_a)}{\|F_b - F_a\|}\right) \quad (13)$$

Where $F_i(t+1)$ represents an updated position of artificial fish, F_i represent the current position of the artificial fish, $R$is a random number $(0 < R < 1)$, S that represents a moving step of the artificial fish that is a random positive number, $\|F_b - F_a\|$ is the visual distance between the position of the ‘b’ fish and the position of the ‘a’ fish.

Swarm behaviour

In swarm behavior, the artificial fishes are moved in the form of a group for avoiding the risks. Let us consider the current position of the artificial fish isF_i, the center position of the several fish is represented by $\mathrm{F_c}$. The swarm behavior of the fish is executed.

$$F(x_c) < \ F(x_a)\&\&\left(\frac{N_b}{N} < \tau\right) \ (14)$$

Where $F\,(x_c)$ is the fitness of artificial fish at the center position, N_b denotes the number of companions within the current neighbourhood, N denotes a total number of artificial fishes, τ denotes a crowd factor $(0 < \tau < 1)$. Therefore, the position of artificial fish is updated as follows,

$$F_i(t+1) = F_i\,(t) + R * S * \left(\frac{(F_c - F_a)}{\|F_c - F_a\|}\right)(15)$$

Where $F_i(t+1)$ represents an updated position of artificial fish, $F_i\ (t)$ denotes a current position, R represents a random number $(0 < R < 1)$, Sdenotes a movement steps of the fish which is a random positive number, $\|F_c - F_a\|$ is the visual distance between the central position of the fish and the current position of the fish.

Follow behaviour

Due to the movement of the fish swarm, when a single fish or group of fishes discovers their food, the neighbourhood trails and reaches the food in a fast manner. Let $F_i$be the current position, and it uses the companion $\mathrm{F_j}$in the neighbourhood. If$(x_b) > F(x_a)$&&$\left(\frac{N_b}{N} < \tau\right)$, then the following behavior of the artificial fish is executed which indicates that the companion x_b the state has maximum food concentration (i.e. higher fitness value). The position update is given below,

$$F_i(t+1) = F_i(t) + R * S * \left(\frac{(F_{max} - F_a)}{\|F_{max} - F_a\|}\right) \quad (16)$$

Where $F_i(t+1)$ represents an updated position of artificial fish, $F_i\ (t)$ is the current position,F_{max} denotes a position having the best fitness inside the visual, $R$is a random number$(0 < R < 1)$, Srepresents a moving step of the artificial fish which is a random positive number, $\|F_{max} - F_a\|$ is the visual distance between the central position of the fish having the maximum fitness function and the position of the 'a' the fish. Finally, the old artificial fish is replaced with a new optimal one based on their fitness. This process is iterated until it reaches the maximum iteration. The hidden layer output is indicated as '$H(t)$'.

$$H(t) = \omega_1 * x_t + \omega_h * H\ (t-1) \qquad (17)$$

Where $H(t)$represents an output of a hidden layer. $H\ (t-1)$' indicates output from hidden layer 2 and 'ω_h'is a weight of the hidden layer, $\omega_1$is a weight among input and the hidden layers are the input. In equation (16), the symbol $'*'$ denotes a convolution operator. Finally, the optimal route path is obtained at the output layer. Then the source node transmits the data packets along the path to improve the packet delivery and minimizes the packet loss. The algorithmic process of deep learning is described as follows,

Input: Number of vehicle nodes$V_1, V_2, V_3, \ldots. V_n$,
Output: Improve data transmission
Begin
Give V_i to the input layer with the weight ω_1 \\ **Input layer**
For each vehicle nodesV_i \\ **First hidden layer**
Find the $d, R_{ss}, \alpha, \mathrm{E_{res}}$
Perform quantile regression analysis $Q(V_1, V_2, V_3, \ldots. V_n | W)$
If $(y > th)$ **then**
Identify the neighboring node
end if
end for
SV sends requests to DV via neighboring nodes \\ **Second hidden layer**
DVsends a reply to the source node
Construct multiple route paths$\mathrm{p_1, p_2, p_3, \ldots. p_n}$ between SV and DV
Initialize the population of route paths$\mathrm{V} = \mathrm{p_1, p_2, p_3, \ldots. p_n}$\\ **third hidden layer**
for each $\mathrm{p_i}$ in V
Calculate the fitness $\mathrm{F(x)}$
While (T< max_ iter)

if $\left(F(x_a) < F(x_b)\right)$ **then**
Updates the position $F_i(t+1) = F_i(t) + R * S * \left(\frac{(F_b - F_a)}{\|F_b - F_a\|}\right)$
else if $\left(F(x_c) < F(x_a) \&\& \left(\frac{N_b}{N} < \tau\right)\right)$ **then**
Updates the position $F_i(t+1) = F_i(t) + R * S * \left(\frac{(F_c - F_a)}{\|F_c - F_a\|}\right)$
else if $\left(F(x_b) > F(x_a) \&\& \left(\frac{N_b}{N} < \tau\right)\right)$ **then**
Updates the position $F_i(t+1) = F_i(t) + R * S * \left(\frac{(F_{max} - F_a)}{\|F_{max} - F_a\|}\right)$
end if
Replace the old path into the current best
T= T+1
end while
end for
Obtain the best optimal path \\\\ **output layer**
SV transmits the data packets to DV via optimal route path
End

Algorithm 1. Quantile Regressive Fish Swarm Optimized Deep Convolutional Neural Learning

The above-said algorithm clearly describes that the proposed technique effectively finds the route path for reliable data transmission in IoV. In the future, the bandwidth of the node is considered for neighbouring node identification.

4. SIMULATION SETTINGS

The simulation of the proposed QRFSODCNL technique and existing routing algorithms namely CIoVS [1], QRA [2], EEMSFV [3], IDCIoV [4], Heterogeneous architecture [24],PRCBGWO technique are implemented using NS2.34 network simulator. For the simulation purposes, 500 vehicle nodes are distributed over a squared area of $(1100m \; x \; 1100m)$. Random Waypoint is employed as a mobility model. The simulation time is set as 300 sec. The Number of vehicle nodes and the number of data packets is considered in the range of 50 to 500 and 30 to 300 respectively. The Size of data packets is 10KB-100KB. The node speed ranges from 0-20 m/s. The DSR routing protocol is used to perform optimal route path selection for data transmission in IoV. The simulation parameters and the values are listed below

Table 1. Simulation parameters

Simulation Parameters	**Values**
Simulator	NS2.34
Simulation area	1100 m * 1100 m
Number of vehicle nodes	50,100,150,200,250,300,350,400 ,450,500
Number of data packets	30,60,90,120,150,180,210,240, 270,300
Size of data packet	10KB-100KB
Mobility model	Random Waypoint model
Speed of nodes	0 – 20 m/s
Simulation time	300sec
Routing protocol	DSR
Number of runs	10

5. COMPARATIVE RESULTS ANALYSIS

The results of QRFSODCNL technique and existing CIoVS [1], QRA [2], EEMSFV [3], IDCIoV [4], Heterogeneous architecture [24], PRCBGWO technique are evaluated with metrics namely packet delivery ratio, packet loss rate, end to end delay and throughput. The various results of proposed and existing are discussed with the help of table format and graphical illustration.

5.1. Packet delivery ratio

The packet delivery ratio is referred to as the ratio of several packets received to the total number of packets sent. PDR is expressed as follows,

$$PDR = \left(\frac{N_{DPR}}{N_{DPS}}\right) * 100 \quad (18)$$

Where PDR indicates packet delivery ratio, N_{DPS} indicates the number of data packets sent, N_{DPR} indicates the number of data packets received. PDR is calculated in percentage (%).

Table 2 illustrates the results of the Packet delivery ratio with the number of data packets. For conducting a simulation, 30 to 300 data packets are taken as input. The reported results prove that the packet delivery ratio of the QRFSODCNL technique is compared to CIoVS [1], QRA [2], EEMSFV [3], IDCIoV [4], Heterogeneous architecture [24], PRCBGWO technique.

Table 2. Packet delivery ratio

No. of data packets	Packet delivery ratio (%)						
	CIoVS	**QRA**	**EEMSFV**	**IDCIoV**	**Heterogeneous Architecture**	**PRCB GWO**	**QRFSO DCNL**
30	70	77	73	80	81	83	87
60	75	80	78	83	82	87	90
90	76	81	80	84	83	88	91
120	80	83	82	86	87	91	92
150	81	84	83	87	88	92	93
180	83	86	85	89	90	93	94
210	84	88	87	90	92	94	95
240	85	89	88	91	93	95	96
270	87	90	89	92	93	96	97
300	88	91	90	93	95	97	98

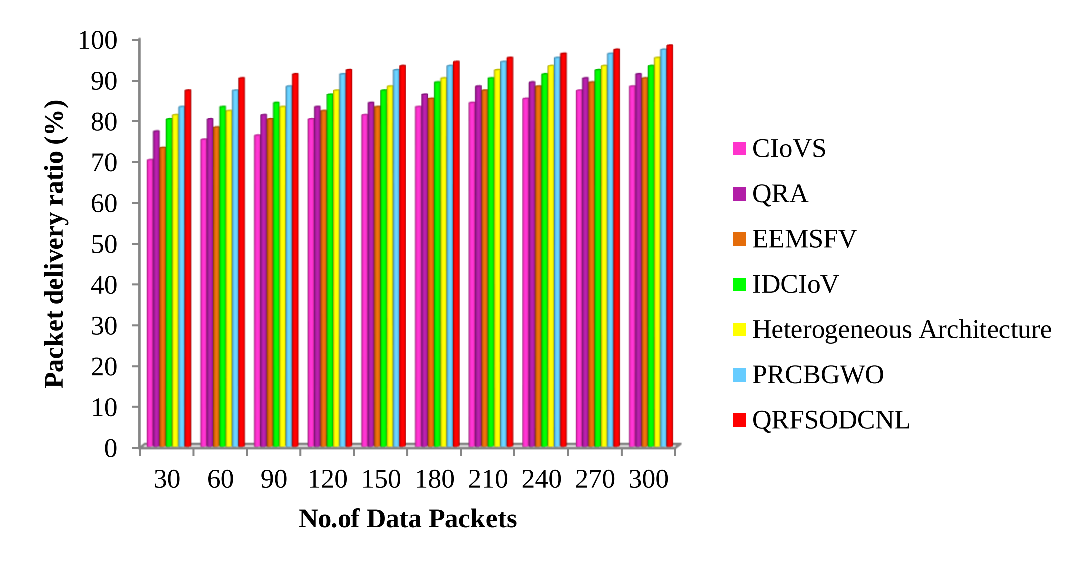

Figure 2. Simulation results of packet delivery ratio

Figure 2 shows the impact of the packet delivery ratio versus the number of data packets sent from the source node. As shown in the above graphical results, the number of data packets taken as input in the horizontal axis, and the results of the packet delivery ratio is obtained at a vertical axis. The graphical results show that the QRFSODCNL technique achieves a higher packet delivery ratio than the other routing methods. This is because the QRFSODCNL technique uses the deep learning concept for neighbour node discovery and the optimal route path identification. The quantile regression function is applied for analyzing the different characteristics and identifying the neighbouring nodes from source to destination. Then the multi-criteria optimization technique is applied for finding the route path and the source node transmitting the data packets to the destination. This, in turn, improves reliable data packet delivery. Ten simulation results of packet delivery ratio are obtained with various input data packets. The average of ten simulation results proves that the packet delivery ratio using QRFSODCNL technique is significantly improved by 16%, 10% and 12% when compared to CIoVS [1], QRA [2], EEMSFV [3] and 7%, 2%, and 6% as compared to IDCIoV [4], PRCBGWO, Heterogeneous architecture [24].

5.2. Packet loss rate

PLR is referred to as the ratio of the number of packets dropped at the destination end to the total number of packets sent. The packet loss rate is measured using the following mathematical equation,

$$PLR = \left(\frac{N_{DPD}}{N_{DPS}}\right) * 100 \quad (19)$$

Where PLRrepresents the packet loss rate, N_{DPS} denotes the number of data packets sent, N_{DPD} denotes the number of data packets dropped. The packet loss rate is measured in terms of percentage (%).

Table 3. Packet Loss rate

No.of Data packets	**Packet Loss rate (%)**						
	CIoVS	**QRA**	**EEMSFV**	**IDCIoV**	**Heterogeneous Architecture**	**PRCBGWO**	**QRFSODCNL**
30	30	23	27	20	19	17	13
60	25	20	22	17	16	13	10
90	24	19	20	16	15	12	9
120	20	17	18	14	13	9	8
150	19	16	17	13	12	8	7
180	17	14	15	11	10	7	6
210	16	12	13	10	9	6	5
240	15	11	12	9	7	5	4
270	13	10	11	8	5	4	3
300	12	9	10	7	4	3	2

PLR Results of different methods are portrayed in table 3 with the number of the data packet. The various results of the packet loss rate of the different data packets are shown in Figure 3.

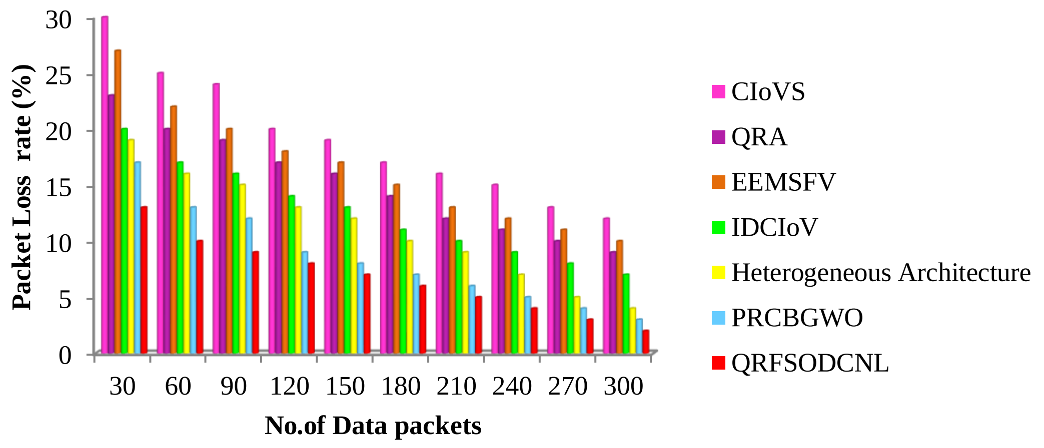

Figure 3. Packet loss rate

Figure 3 depicts the PLR with the number of data packets using different methods. As shown in the above graphical representation, the proposed QRFSODCNL technique minimizes the packet loss rate. This is achieved by considering the available bandwidth, path length, and node buffer capacity. The maximum bandwidth availability and the minimum distance of the route path from source to destination are selected by applying a multi-criteria fish swam optimization. Besides, energy-aware neighbor node selection also improves the data delivery between the vehicles and minimizes the packet drop rate. This is proved by using mathematical calculations. Let us consider 30 data packets being sent from the source node. There are 4 data packets are dropped at the destination end and the packet loss rate is 13%. This shows that the QRFSODCNL technique minimizes the packet loss. The packet loss rate of the proposed QRFSODCNL technique is compared to existing methods. The average of ten results confirms that the packet loss rate of QRFSODCNL technique is reduced by 67%, 58%, 62%, 49% , 41% and 20% as compared to CIoVS [1], QRA [2], EEMSFV [3], IDCIoV[4], Heterogeneous architecture [24], and PRCBGWO respectively.

5.3. End to end delay

End to end delay is referred to the time difference between the data packet arrival and data packet transmission. The end to end delay is computed using the following mathematical formula,

$$EED = (T_{Dp}(A) - T_{Dp}(S)) (20)$$

Where EED denotes an end to end delay, $T_{Dp}(A)$ represents the data packet arrival time, $T_{Dp}(S)$ denotes a data packet sending time. EED is measured in milliseconds (ms). The simulation results of end to end delay of different methods with the number of data packets. By applying the 30 data packets, the proposed QRFSODCNL technique obtains $16ms$ of end to end delay.

Table 4. End to end delay

No. of data packets	End to end delay (ms)						
	CIoVS	**QRA**	**EEMSFV**	**IDCIoV**	**Heterogeneous Architecture**	**PRCBGWO**	**QRFSODCNL**
30	26	22	24	20	19	18	16
60	35	30	32	27	26	25	23
90	36	32	33	30	29	28	25
120	40	37	38	35	34	32	29
150	43	40	41	38	34	35	33
180	46	42	43	40	39	37	35
210	50	45	47	42	41	40	38
240	52	48	49	46	45	44	42
270	55	52	53	50	49	47	45
300	57	54	55	52	51	50	48

The other methods CIoVS [1], QRA [2], EEMSFV [3], IDCIoV[4], PRCBGWO, Heterogeneous architecture [24] obtains, $26ms, 22ms, 24ms, 20ms\ and\ 18ms$, 19ms of delay. The mathematical results show that the end to end delay is found to be minimized using the QRFSODCNL technique than the other methods. The end to end delay of the different methods is shown in Figure 4.

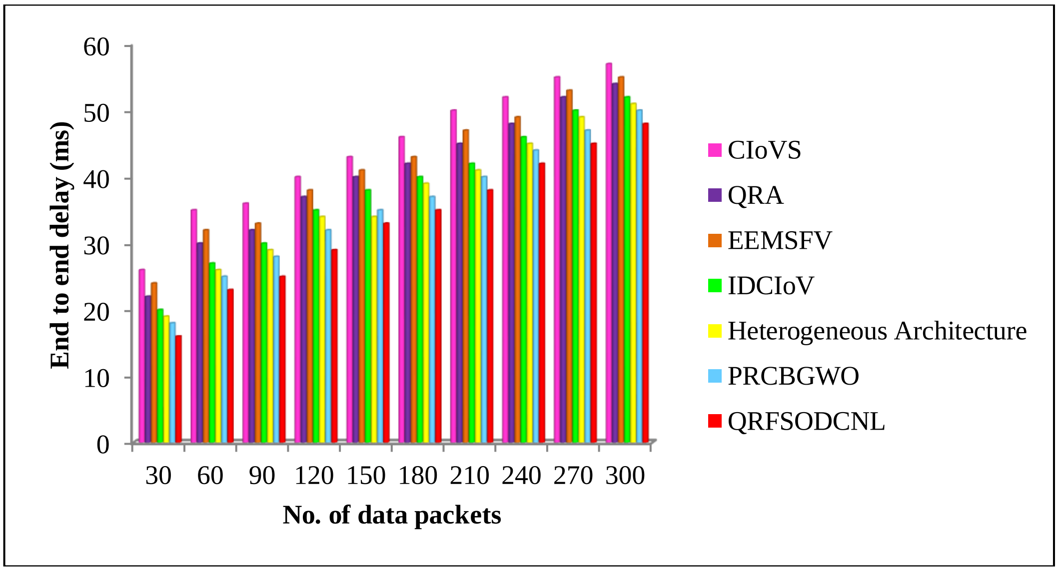

Figure 4. End to end delay

Figure 4 depicts the number of data packets for different methods. As depicted in the above graphical results, the proposed QRFSODCNL technique provides a minimum end to end delay as compared to existing methods. This is because of applying the quantile regression by analyzing the vehicle node characteristics. The energy-efficient neighbouring node is selected for data transmission. The optimization technique discovers the route path with less distance and hops counts between the source and destination. The source node transmits the data packet to the destination via the minimal number of hop counts and greater bandwidth availability resulting in minimizing the delay. The comparison of ten various results shows that the end to end delay of QRFSODCNL technique is comparatively minimized by 26%, 18%, 21%, 13% and 10%, 7% as compared to CIoVS [1], QRA [2], EEMSFV [3], IDCIoV[4], Heterogeneous architecture [24],PRCBGWO.

5.4. Throughput

Throughput is defined as an amount of data received at the destination within a given period of time. The throughput is calculated as follows,

$$\text{Throughput} = \frac{\text{AmountofDPR (bits)}}{\text{T (sec)}} \quad (21)$$

WhereDPRrepresents a data packet received, T denotes a time in seconds (sec). The throughput is measured in the unit of bits per second (bps).

Table 5. Throughput

Size of data packets (KB)	Throughput(bps)						
	CIoVS	**QRA**	**EEMSFV**	**IDCIoV**	**Heterogeneous Architecture**	**PRCBGWO**	**QRFSO DCNL**
30	105	128	120	135	136	142	170
60	130	180	165	220	230	250	280
90	195	280	240	310	320	342	370
120	310	405	360	430	440	463	510
150	410	480	450	510	520	543	580
180	500	580	550	620	630	675	710
210	580	650	620	700	720	741	812
240	620	720	700	760	890	812	920
270	730	810	780	890	900	974	1010
300	840	980	890	1056	1070	1120	1150

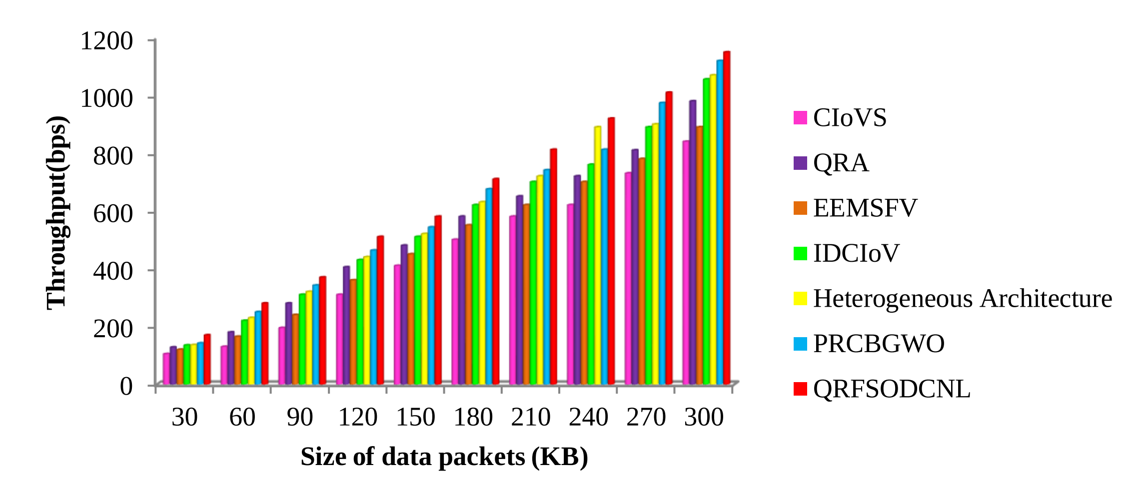

Figure 5. Throughput

Table 5 and figure 5 denotes simulation results of throughput using different methods with various sizes of the data packet. The graphical results of the throughput are found to be increased using the QRFSODCNL technique. The multi-criteria optimization technique discovers the best available route path among source vehicle and destination vehicle via neighbouring nodes. While routing the data packets from the source node, an efficient neighbouring node is selected based on the quantile regression function with various vehicle node characteristics. The selected neighbouring node efficiently transfers the data packets from one to another. This, in turn, improves the data packet transmission. The reported results proves that the throughput is significantly improved by 58%, 28%, 39%, 18% and 14%, 9% when compared to CIoVS [1], QRA [2], EEMSFV [3], IDCIoV [4], Heterogeneous architecture [24], PRCBGWO respectively.

6. CONCLUSION

An efficient deep learning technique QRFSODCNL is introduced to achieve reliable data transmission in IoV and minimal delay as well as packet loss. The number of vehicle nodes is given to the input layer of deep neural learning. The deep convolution neural learning includes one input layer, three hidden layers, and one output layer. At first, the number of vehicles is given as input to the input layer. Then, the inputs are transferred into the first hidden layer. After that, the inputs are learned in hidden layers using the regression analysis with multi-criteria optimization. The node characteristics are analyzed and identify the location of the neighbouring node. Followed by, multiple paths are identified in the second hidden layer from source to destination. Finally, the multi-criteria fish swarm optimization is applied in the third hidden layer to determine the best path for delivering the data packets with minimum delay. The simulation is performed with metrics namely packet delivery ratio, packet loss rate, end-to-end delay, and throughput. The result analysis clearly shows that the QRFSODCNL technique improves reliable data transmission with higher packet delivery ratio and throughput as well as minimizes the packet loss, end to end delay when compared to the state-of-the-art methods. In the future, if any link failure occurred during the data transmission, an alternate route path is considered for data transmission to avoid the packet loss rate.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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