International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Route Optimization Using Radial Interpolated Quantum Finite Automata for Intelligent Transportation

V. Subapriya[1], S. Rajaprakash[2]

Submitted: 24/04/2023 **Revised:** 25/06/2023 **Accepted:** 04/07/2023

Abstract*:* Internet of Things (IoT) is novel pattern which is giving immeasurable services. Several applications integrate physical objects by internet as well as transmit data gathered over network without human interference. Artificial Intelligence (AI) is the potentiality of a machine to carry out analytical consequences like, assessing, inferring, learning and problem-solving that humans are competent of carrying out at ease. Nevertheless, there still remains scope to IoT in transportation (i.e., Internet of Transportation things) where AI benefits from Intelligent Transportation Systems (ITS). This is owing to the reason that with the immense growth in population has resulted in increase in demand for vehicles. This has inspired several researchers to come up with numerous features by designing pertinent applications to make transportation smart by optimization vehicle route, ensuring smooth and smart parking, therefore paving ways and mechanisms in reducing congestions and accidents. In this work to circumvent traffic jams as well as solve congestion problems, Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization technique is applied to identify optimal route. Sensors positioned on each of the junctions are used to collect data at different time. A Radial Basis Interpolated Neural Network (RBI-NN) algorithm is first applied to identify the arrival time of vehicles for data allocation. Next, Quantum Finite Automata (QFA) is applied for group routing so which traffic congestion is reduced. Grouping here are formed based on the number of vehicles and junction. The Quantum Finite Automata algorithm assigned routes to vehicles to evade congestion and therefore ensuring optimized vehicle routing. Simulation outcomes represent that RBINN-QFA method give high routing accuracy as well as minimum route detection time with improved sensitivity and specificity. The finding put forwards an abstract development for performing machine learning techniques in gathering ITS-oriented data as well as smart city optimal routing.

Keywords: *Artificial Intelligence, Internet of Transportation things, Intelligent Transportation Systems, Radial Basis, Interpolated Neural Network, Quantum Finite Automata*

1. Introduction

With the evolution of urban patterns resulted in the rise of vehicle ownership, creating surging traffic congestion and accidents. Owing to this, an acceptable urban evolution, specifically, construction of smart city features acute issues. ITS can give untimely enlightenment as well as genuine planning of traffic to address this issue. IoVs (Internet of Vehicles) have played a notable part in ITS. The IOV assist evaluating road network volume via signal control, acquiring network traffic in real time manner, efficiently distributing traffic data, taking the edge of congestion control and so on.

With purpose of extracting IoT-based ITS's electronic information characteristics, Faster Region-based Convolutional Neural Network (Faster R-CNN) was designed in [1] . As a result, the Faster R-CNN highlighted strong and well founded performance for accumulating and examining ITS data. Altogether, Faster R-CNN explored ITS-intended electronic information fathering and automatic detection in urban management of traffic.

[1]Vinayaka Missions Research Foundation, Salem, Tamil Nadu State-636308, subapriyarajesh@gmail.com

[2]Department of Computer Science and Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Missions Research Foundation, Paiyanoor, Chengalpattu District. TamilNadu State-613104, srajaprakash_04@yahoo.com

Tree-based Machine and Ensemble Learning was proposed in [2]. By means of these ensemble learning techniques, high detection accuracy was said to be provided with low computational costs by only selecting pertinent features. Moreover, precise results were said to be evolved for IOV-based vehicular network traffic.

Technologies have been problem solvers for several business industries in the recent past, to name a few being, banking sector, insurance company, healthcare, etc. Some of these solutions have shifted the method with which businesses are being operated by cutting the cost, enhancing efficiency and so on. Amongst them, one of the latest technologies received widespread interest is transport industry which is dumped with several issues like, delay, routing and so on.

For predicting traffic flow in urban nature, deep irregular convolutional residual LSTM network referred to as DST-ICRL was proposed in [3] .However with autonomous vehicles in concern as part of ITS, accuracy still remains a major factor to be addressed. To focus on this issue, a traffic safety solution employing deep learning with a fusion of autonomous as well as manual vehicles in fifth generation enabled ITS was presented [4].

Accurate traffic forecasting or routing plays a significant aspect in intelligent traffic scheme as well as of great importance as far as urban traffic planning and traffic control is concerned. In [5], novel traffic forecasting or routing methods named, temporal graph convolutional network (T-GCN) was designed. Numerous AI techniques were discussed in [6] towards intelligent transportation.

In the IoT, the evolution of the new contemporary epoch aimed at the ITS to improve road safety as well as traffic, major issues remains in making timely decision under rapid topological changes, higher mobility rate. Hence, optimized as well as congestion-free route is necessitated for acquiring data from vehicles. An overview of future ITS was investigated in [7].

A holistic study to ensure route optimization was presented in [8]. Mini edge AI platform was employed in [9] for modeling quantization of traffic in real time. Yet another vehicle path optimization technique employing Genetic Algorithm was designed in [10] therefore minimizing the cost incurred in distribution and improving the customer satisfaction.

We propose a technique, called, Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) for optimal routing. The major objective is to enhance routing accuracy and routing time besides the improvement of sensitivity and specificity rate. Several works have introduced through ITS data routing. Comparative conventional, RBINN-QFA method integrates data collection and optimal route discovery. First traffic and data collection is designed by means of Radial Basis Interpolated Neural Network-based traffic data collection model.

Next, with the obtained data for normal traffic and peak hour traffic interpolation is performed. Following which, Quantum Finite Automata-based Optimized Vehicle Routing is applied to the collected data for retrieving optimal routes with minimum routing time and maximum accuracy.

1.1 Contributing remarks

The contributions of the RBINN-QFA method include the following:

- To ensure accurate and timely routing for Internet of Transportation things, a Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) method is introduced on the basis of two distinct processes namely, data collection and routing.
- To select participatory sensor data, Radial Basis Interpolated Neural Network is applied based on normal traffic, peak hour traffic and finally the interpolated results are arrived at towards computationally efficient traffic data collection with minimal routing time and maximum routing accuracy.
- Quantum Finite Automata-based Optimized Vehicle Routing is then applied for arriving at the optimal route with the objective of ensuring correlative operating productivity and feasible solution for obtaining high relevant optimal route generation with high sensitivity and specificity.
- Immense experiments are organized to determine performance of RBINN-QFA technique and conventional methods. Outcomes attained shows that, RBINN-QFA method gives enhanced performance of routing accuracy, routing time, sensitivity and specificity.

1.2 Structure of the article

Remainder of the manuscript is structures as follows: Section 2 introduces literature review concerning routing for ITS. Section 3 explains the dataset description in detail and proposes Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization method. Section 5 gives experimental results and performance analysis of algorithm .Section 6 concludes the manuscript.

2. Literature Review

For over the past last two decades, significant transportation has been evolving and hence, efficient mechanisms of management of such systems in a cooperative fashion have started increasingly important. To be more specific, traffic signal operation in an adaptive fashion is said to be crucial for circumventing traffic flow stagnation.

Quantum annealing was applied in [11] with the purpose of optimizing traffic signal. Yet another traffic predicting as well as routing optimization method called, online learning data driven model was designed in [12] to reduce time involved in routing. However, failed to focus coverage ratio .To concentrate on this coverage ratio aspect, IoT-Based electric vehicles routing and charging algorithm was presented in [13]. By employing this algorithm, in addition to the computational complexity, the coverage ratio was also said to be improved significantly. Radio signal quality was employed in [14] for sensor localization.

With the swift evolution of logistics establishment, road transport optimization has limitation which controlled in evolution of associated industries. Also in IoT, traditional routing solutions meet several requirements. To enhance the constrained communication distance and poor IoT communication quality, intelligent optimal routing mechanism was presented in [15]. Weighting employing linear additive mechanism was employed to not only improve the scalability factor but also to minimize the packet loss rate. A review of machine learning techniques for optimal routing was investigated in [16].

A review of route optimization mechanisms for the internet of vehicle was presented in [17]. Yet another study to improve the routing by means of two tier model was presented in [18]. A weighted graph model in addition to filtering technique was proposed in [19] with the purpose of reducing link quality and resource utilization. In spite of enhancement observed in both link quality as well as resources, overhead factor was not focused. To concentrate on this aspect, a routing protocol based on the dynamic pattern was presented in [20][21].

Inspired by the above mentioned articles, though some routing mechanism ensures accuracy but did not focus on the routing time factor. On the other hand, in spite of enhancement observed in both precision and recall, two major important routing aspects, like sensitivity and specificity were not focused. To concentrate on all the above said four performance metrics Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization method is designed.

3. Methodology

In this work to circumvent traffic jams as well as resolve congestion problmes, Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization technique is applied to identify best route. Idea is to explore the capabilities of Radial Basis Interpolated Neural Network for Intelligent Transportation Systems, by using probabilistic automata for route optimization. Here, a modified radial basis function neural network is implemented. Users or vehicles with vehicle ID will exchange information or typical signal consideration with each other (i.e., between vehicles via vehicle ID) and traverse to less congested routes, following the messages received by other users, as given in the above system design similar to the way finite automata is derived via mathematical abstraction when searching for optimal route. Figure 1 shows the structure of Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization method.

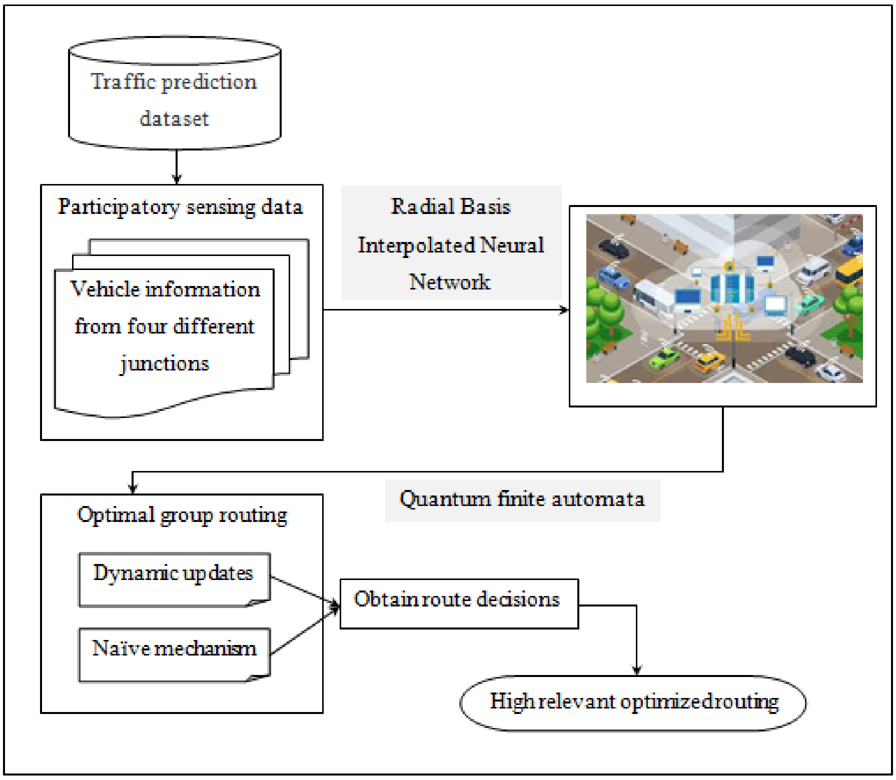

Figure 1 Structure of Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization method

As shown in the above figure, with the traffic prediction dataset provided as input, the objective of the proposed RBINN-QFA method lies in optimizing vehicle routes for intelligent traffic control with minimum time and maximum accuracy. With this objective, first, distinct vehicle information from four junctions is obtained using Radial Basis Interpolated Neural Network-based traffic data collection model. Second, group routing is performed by employing Quantum Finite Automata.

3.1 System model

Format for recording vehicle's driving data from traffic forecast dataset (https://www.kaggle.com/datasets/fedesoriano/traffic-prediction-dataset), system to dispense traffic information between contacted vehicles and typical signal considerations to estimate real-time traffic data of next time zone are primary described. Here, the time bounded signal considerations flow, left, right, U-Turn, diagonal right, pedestrian and straight. Once, this signal considerations have been set for each vehicles with the corresponding ID, the signal starts functioning in an automatic fashion in a round robin manner immeasurably without any manual interference. Also, each vehicle shows the waiting time in seconds across all direction (i.e., left, right, straight, diagonal right and so on) based on the Vehicle ID and measuring the frequency of vehicles involved in simulation. Here, peak hour calculation is also made in such a manner so as to fine tune the vehicle waiting time across all the directions. Also four types of signals are taken into consideration (i.e., one way, two ways, three ways, pedestrian). In case of one way, right turn is performed on the opposite side whereas the left turn is said to be halted. In case of two ways, U-turn is performed from left to right whereas right turn is performed from right to left. In case of three ways, free left turn halting is ensured on diagonal left, diagonal straight halting is performed at diagonal left and diagonal right, whereas right turn halting is performed at diagonal left and diagonal right. Also, finally, in case of pedestrian, road crossing has to be made within the stipulated time and the time is measured on the basis of traffic, where time differs between peak hours and non peak hours. The above said design is made for simulation model with one signal. Also simulations are performed in this work by connecting more signals to verify everything is synchronizing in a smooth fashion to ensure robust and optimized traffic control by the proposed method meeting the shortest route detection time with maximum accuracy.

3.2 Dataset description

In our work to validate route optimization for Internet of Transportation things, traffic prediction dataset (https://www.kaggle.com/datasets/fedesoriano/traffic-prediction-dataset) is employed. Over recent years, we have a surge in increase in traffic congestion globally. Some of the bestowing considerations consist of increasing population in the urban side, aging infrastructure, ineffective and bumbling traffic signal timing and inadequacy of data time collected in real time fashion. The influences are notable. One of the noted traffic data analytics company INRIX has evaluated that cost incurred in traffic congestion was found due to fuel wastage, lost time and the increased transportation goods cost via thronged areas. Also given with both the physical and financial constraints, cities must employ novel techniques to enhance traffic conditions. This traffic prediction dataset consists of 48120 samples of distinct numbers of vehicle each hour in four distinct junctions, namely, DateTime, Junction, Vehicles and ID respectively. The sensors on each of these four distinct junctions were acquiring data or data packets at different time intervals. Also, certain have provided constrained data or data packets calling for extreme care when generating or producing subsequent projections.

3.3 Radial Basis Interpolated Neural Network-based traffic data collection

The IoT is a significant conveyor for gathering information, processing and transmitting the information to intended recipients. Related technologies such as machine learning, deep learning as well as so on are extensively utilized in several domains, specially logistics industry. Ceaseless enhancement of urbanization puts together the organization of a good urban administration system, an issues that has to be addressed to improve urban economic system development. The robust data allocation of the transportation path of vehicle is an essential association as far as the urban logistics distribution system is concerned that associates the production line, warehouses, and consumers. Radial Basis Interpolated Neural Network model for robust data allocation is designed.

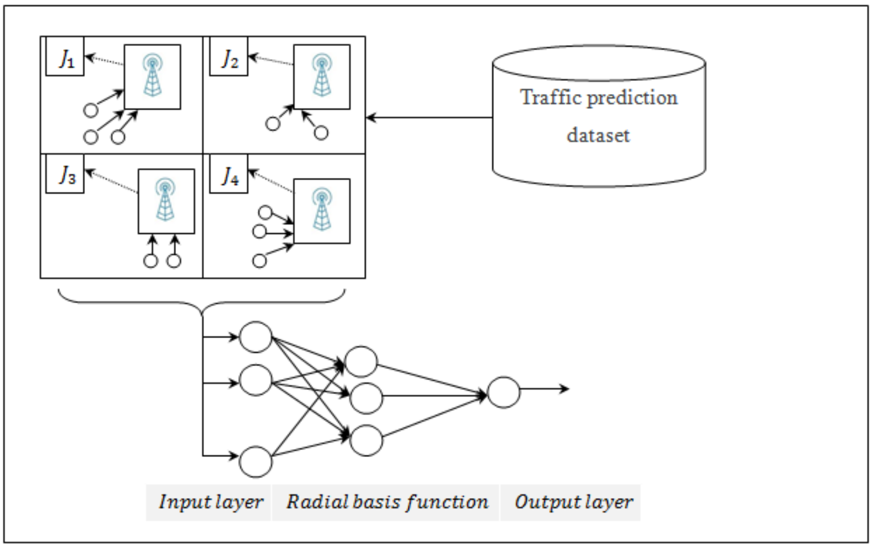

Figure 2 Structre of Radial Basis Interpolated Neural Network-based traffic data collection model

From the above figure the sensor in junction 1 'J_1' collects the data from the corresponding vehicles or samples and in a similar manner the sensor in junction 'J_2' collects the data from the respective vehicles. The process is continued for two other junctions. This data collection process is performed using Radial Basis Interpolated Neural Network (RBI-NN) model via heuristic search. The purpose of using this model is that with the heuristic search, route detection time involved in the Internet of Transportation things would also be reduced. To be more specific, in a particular date (i.e., '$DateTime$'), with four junctions (i.e., '$J = \{J_1, J_2, ..J_j\}, j = 4$') considered for simulation and distinct time (i.e., '$DateTime$') involved different numbers of vehicles (i.e., '$V = \{V_1, V_2, \dots, V_v\}, v = 45000$') with corresponding vehicle ID (i.e., '$ID = \{ID_1, ID_2, \dots, ID_{id}\}, id = 45000$') information are obtained. Sensors '$S = \{S_1, S_2, S_3, S_4\}$' positioned on each of the four junctions are used to collect data (i.e., date time, vehicles, ID with junction specification) at different time.

The Radial Basis Function neural network is neural network by three layers, an input layer, hidden layer and output layer. Given a set of vehicles 'V' taken at corresponding traffic control system for simulation 'J', the objective remains in identifying interpolation function '$J(V)$' that informs us via sensors the corresponding information regarding, the date, time, number of vehicles and vehicle ID so that robust information can be arrived at and used for further processing. In the input layer, an input vector matrix is formulated employing the traffic prediction dataset. Next, in the hidden layer, three processes are performed distinctly, namely normal traffic assessment, peak hour traffic assessment and the interpolation. Finally, in the output layer, the information pertaining to vehicles in the corresponding junction is obtained for further processing. Initially, the arrival time of vehicles at each junction for optimal routing is designed. With the traffic prediction dataset obtained as input and employing samples or vehicles and features involved, the input vector matrix is formulated as given below.

$$IV = \begin{bmatrix} V_1F_1 & V_1F_2 & \dots & V_1F_n \\ V_2F_1 & V_2F_2 & \dots & V_2F_n \\ \dots & \dots & \dots & \dots \\ V_mF_1 & V_mF_2 & \dots & V_mF_n \end{bmatrix} \quad (1)$$

From the above equation (1), the input vector matrix 'IV' is modeled taken into consideration 'm vehicles and 'n' features is performed in the input layer. Also with the global objective being obtaining the route with minimal time and maximum accuracy, the junction of the lowest known heuristic cost is initially obtained in the hidden layer. First, normal traffic is assessed following which peak hour traffic is assessed and finally, interpolated to obtain vehicle arrival time. This is obtained by employing heuristic function '$Z(n)$' formulated as given below to assess order in that heuristic visits vehicles or samples and afterward to evaluate overall cost for collecting data in each junction.

$$Z(n) = P(n) * [X(n) + Y(n)] \quad (2)$$

From the above equation (2), '$X(n)$' represents the time of collecting the data from starting vehicle to current vehicle 'n' and '$Y(n)$' indicates the heuristic estimate of the time of collecting the data from the current vehicle 'n' to the destination vehicle. As shown in figure 2 , if angle 'θ' between neighbor junction of current vehicle or sample and linear line between current vehicle and destination vehicle is smaller, it means that direction of adjacent junction has nearer to destination, which is used as recurrent network as in [1]. Thus, the RBI-NN algorithm in our work updates the actual heuristic function '$Y(n)$' through multiplying angle function as given below for normal traffic.

$$Z(n) = P(n) * [X(n) + Y(n)] \tag{3}$$

$$P(n) = 1 - \frac{(360-\theta)}{(360+\theta)} \tag{4}$$

From the above formulation, the smaller the angle is, the neighbor junction with smaller 'θ' is selected that in turn identifies or collects the data quickly. Also '360' denotes four quadrants employed in our work. Also taking into consideration the peak hour calculation with which the signal fine tunes the waiting time of the vehicles across all the directions, the equation given in (3) is modified by weighting factors '$W(n)$' and '$W(n+1)$' as given below.

$$Z(n) = P(n) * [X(n) * W(n) + Y(n) * W(n+1)] \tag{5}$$

$$W(n) = \begin{cases} 1 - \left(\frac{F_{na} - F_n}{F_{na} + F_n}\right), F_{na} < F_n \\ 1, F_{na} = F_n \\ 1 + \left(\frac{F_{na} - F_n}{F_{na} + F_n}\right), F_{na} > F_n \end{cases} \tag{6}$$

$$W(n+1) = \begin{cases} 1 - \left(\frac{F_{n+1a} - F_{n+1}}{F_{n+1a} + F_{n+1}}\right), F_{n+1a} < F_{n+1} \\ 1, F_{na} = F_n \\ 1 + \left(\frac{F_{n+1a} - F_{n+1}}{F_{n+1a} + F_{n+1}}\right), F_{n+1a} > F_{n+1} \end{cases} \tag{7}$$

From the above equation (6), '$W(n)$' is evaluated by taking into consideration the average frequency duration in which the signal should operate 'F_n' and highest frequency limit of every junction segments from starting vehicle to current vehicle 'F_{na}'. In a similar manner, '$W(n+1)$' is evaluated in (7) by utilizing average frequency duration in which the signal should operate 'F_{n+1}' and average frequency duration of every junction segments from current vehicle to every adjacent vehicle 'F_{n+1a}' respectively. Finally, interpolation results are modeled for intelligent traffic control system. This is formulated employing interpolation condition as follows.

$$f(V) = \exp[V\, Cos\,(3\pi V)], V_i[J], J = 1,2,3,4 \tag{8}$$

From equation (8), vehicles '$V_v[J]$' are said to be equally spaced points or junctions '' in the overall network space. Then, the junctions are formed as given below.

$$J(V) = \sum_{i=1}^{m} W_V \varphi\,(V - V_m) \tag{9}$$

From the above equation (9), 'φ' forms the radial basis function for the corresponding vehicle 'V' in such a manner that '$s(V_i) = f(V_i[J])$', where each vehicle lies in a specific junction 'J' interpolates 'f' at the selected signal. In matrix form, this is represented as given below and stored in the output layer by the corresponding sensors 'S'.

$$Res = J(V) = \begin{bmatrix} \varphi(V_0 - V_0) & \varphi(V_1 - V_0) & \dots & \varphi(V_m - V_0) \\ \varphi(V_0 - V_1) & \varphi(V_1 - V_1) & \dots & \varphi(V_m - V_\cdot) \\ \dots & \dots & \dots & \dots \\ \varphi(V_0 - V_m) & \varphi(V_1 - V_m) & \dots & \varphi(V_m - V_m) \end{bmatrix} \begin{bmatrix} W_0 \\ W_1 \\ \dots \\ W_m \end{bmatrix} = \begin{bmatrix} f(V_0) \\ f(V_1) \\ \dots \\ f(V_m) \end{bmatrix} \tag{10}$$

From the above equation results (10), the sensors in the respective junctions collect vehicle information via a single dimensional interpolation function is obtained from 'm' vehicles and we can identify an '$m-1$' degree polynomial that goes exactly through all junctions. In other words, by selecting our basis function (i.e., robust vehicle data collection) to be consecutive powers of 'V' up to '$m-1$', we can solve our interpolation system for our function.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \dots, F_n\}$', Junctions '$J = \{J_1, J_2, \dots J_j\}$', time (i.e., '$DateTime$'), vehicles or samples '$V = \{V_1, V_2, \dots, V_i\}$', vehicle ID '$ID = \{ID_1, ID_2, \dots, ID_{id}\}$', Sensors '$S = \{S_1, S_2, \dots, S_i\}$'
Output: Computationally efficient traffic data collection 'Res'
Step 1: Initialize '$m = 45000$', '$n = 4$', '$j = 4$', '$m = 45000$', '$id = 45000$' Step 2: Begin Step 3: For each Dataset 'DS' with Features 'F', Junctions 'J' and vehicles or samples 'V' Step 4: Formulate input vector as given in equation (1) **//Input layer** Step 5: Formulate input vector matrix as given in equation (1) **//Hidden layer** **//Normal traffic** Step 6: Formulate heuristic function for normal traffic as given in equation (2) Step 7: Evaluate normal traffic calculation as given in equation (3) Step 8: Evaluate angular function as given in equation (4) **//Peak hour traffic** Step 9: Formulate heuristic function for peak hour traffic as given in equation (5) Step 10: Formulate peak hour traffic calculation as given in equations (6) and (7) **//Interpolated function** Step 11: Evaluate interpolated function for each vehicles in the junction as given in equations (8) and (9) **//Output layer** Step 12: **Return** interpolated results 'Res' as given in equation (10) Step 13: **End for** Step 14: **End**

Algorithm 1 Radial Basis Interpolated Neural Network-based traffic data collection

As depicted in above algorithm improving routing time as well as route detection accuracy, a neural network employing radial basis interpolated function is employed. First, with the traffic prediction dataset obtained as input, an input vector matrix is formulated in input layer. Second, in hidden layer, in addition to the radial basis function for obtaining the interpolated results, normal traffic data and peak hour traffic data are gathered. Lastly interpolated outcomes are provided as output in output layer.

3.4 Quantum Finite Automata-based Optimized Vehicle Routing

The objective of optimized vehicle routing is to design a set of vehicle routes to accomplish transportation demands, in an endeavor to improve the rate of sensitivity and specificity. In this work, mathematical formulates are obtained by means of correlative operating productivity (i.e., update the intelligent traffic control system dynamically) and via feasible solution (i.e., drivers' affinity towards routes with IoT data on the basis of naïve mechanism) respectively. These two evaluations are made by employing Quantum Finite Automata-based Optimized Vehicle Routing (QFAOVR). The QFAOVR is applied for group routing so which traffic congestion reduced. Grouping here are formed based on the number of vehicles and junction. The QFAOVR algorithm assigned routes to vehicles to circumvent congestion and therefore ensuring optimized vehicle routing. Figure 3 shows the structure of Quantum Finite Automata-based Optimized Vehicle Routing model.

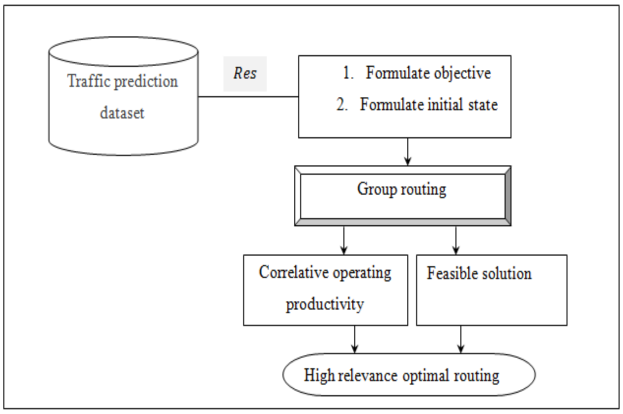

Figure 3 Structure of Quantum Finite Automata-based Optimized Vehicle Routing model

As shown in the above figure, given a specific instance, solving issues enhances to discovering solution from space of every possible solutions, 'Sol', which improves both sensitivity and specificity. Or to put it more formally, for some instance and particular during unique set of parameters, 'V', 'J' as well as 'Res', as well as through quality function, '$f(OR)$' which returns optimal route of any provided solution 'Sol', objective 'Obj' improves by finding an optimal route 'OR' (i.e., with improved sensitivity and specificity), such that

$$f: Sol \rightarrow Obj(Res) \quad (11)$$

$$Obj\ (Res) \rightarrow f(OR) = \min\{f(Res_i) | Res_i \in Sol\} \quad (12)$$

The complexity lies in total number of probable solutions, 'M', that expands in an exponential manner with increasing vehicle size 'i' respectively and therefore compromising the sensitivity and specificity rate. To address on this aspect, Quantum Finite Automata-based Optimized Vehicle Routing is designed. Starting point of QFAOVR is a quantum system through 'M' states, one for every solution in 'Sol', initialized in identical position as given below.

$$|Sol >= \frac{1}{\sqrt{M}} \sum_{(Res_i) \in Sol} |(Res_i) > \quad (13)$$

The above said initial state has evolved by recurrent execution of correlative operation and quantum feasible solution. The correlative operative integrated function or intelligent traffic control update dynamically is then mathematically represented as given below.

$$Int_{DM}(\alpha_j) = \exp(-i\alpha_j[DM]) \quad (14)$$

From the above equation (14), the correlative operation is modeled based on the '$\alpha_j \in Obj$' and diagonal matrix 'DM' such that '$DM|(Res_i) = f(J(V_i)|V_i >$'. The quantum feasible integration solution based on naïve mechanism is then mathematically represented as given below.

$$Int_{FS}(\beta_j) = \exp(-i\beta_j GL) \quad (15)$$

From the above equation (15), 'GL' represent the generalized Laplacian that associates the feasible solution to the issue. Generalized Laplacian is defined given below.

$$< J(V_i)|GL|J(V_j) >= \begin{cases} J(V_{ij}) < 0, if\ J(V_i) \neq J(V_j),\ J(V_i) is\ adjacent\ to\ J(V_j) \\ J(V_{ij}) = 0, if\ J(V_i) \neq J(V_j),\ J(V_i) is\ not\ adjacent\ to\ J(V_j) \\ any\ number, otherwise \end{cases} \quad (16)$$

Group routing employed in our work by means of correlative operation and feasible solution carried out to balance the load on parallel routes while transmitting information and as a result increases the sensitivity and specificity of smart vehicle systems significantly. This is mathematically represented as given below.

$$OR \rightarrow Int_{DM}(\alpha_j) \cup Int_{FS}(\beta_j) \quad (17)$$

As given in the above equation (17), by forming the group based on dynamic update of traffic and naïve mechanism, the QFAOVR algorithm approach assigned the routes with maximal relevance.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \ldots, F_n\}$', Junctions '$J = \{J_1, J_2 \ldots J_j\}$', time (i.e., '$DateTime$'), vehicles or samples '$V = \{V_1, V_2, \ldots, V_i\}$', vehicle ID '$ID = \{ID_1, ID_2, \ldots, ID_{id}\}$', Sensors '$S = \{S_1, S_2, \ldots, S_l\}$'
Output: High relevance optimal route generation
Step 1: **Initialize** '$m = 45000$', '$n = 4$', '$j = 4$', '$m = 45000$', '$id = 45000$' Step 2: **Initialize** traffic data collection 'Res' Step 3: **Begin** Step 4: **For** each Dataset 'DS' with Features 'F', Junctions 'J', vehicles (i.e., samples) 'V' and traffic data collection 'Res' Step 5: Formulate the objective function as given in equations (11) and (12) Step 6: Initialize quantum states as given in equation (13) **//Dynamic update of traffic** Step 7: Evaluate correlative operative integrated function as given in equation (14) **//Feasible solution** Step 8: Evaluate quantum feasible integration solution as given in equations (15) and (16) Step 9: **End for** Step 10: **Return** optimal route results 'OR' Step 11: **End**

Algorithm 2 Quantum Finite Automata-based Optimized Vehicle Routing

As given in the above algorithm, with the traffic data collected obtained as input, automata generate group routing employing traffic patterns updated dynamically and by means of feasible solution. To start with the initial state is designed by employing traffic data collected in the above section. Second, an integrated function employing correlative operation is applied to obtain the feasible solution, therefore improving the overall routing process.

4. Experimental Setup

The experimental conditions of the proposed intelligent traffic control system are arranged through Inter® Core (TM) i5-7200U with CPU capacity of 2.50GHz possessing 8GB Random Access Memory with Graphics Processing Unit of NVIDIA GeForce 94MX. In addition to that software environment is set to Windows 10 64-bit. This work employs four distinct performance indices routing accuracy, route detection time, sensitivity and specificity to evaluate the intelligent traffic control system towards optimal routing as well as comparative performance. Following measurements are employed to compare as well as estimate intelligent traffic control system towards optimal routing for Internet of Transportation things quantitatively.

5. Numerical Outcomes and Performance Assessment

Radial Basis Interpolated Neural Network and Quantum Finite Automata (RBINN-QFA) route optimization method experimental performance values as well as assessment outcomes compared to Faster Region-based Convolutional Neural Network (Faster R-CNN) [1] and Tree-based Machine and Ensemble Learning methods. The data, i.e., traffic prediction data for the internet of transportation are presented in the methodology section. Machine learning techniques based on neural network are compared in routing accuracy, route detection time, sensitivity and specificity.

5.1 Routing accuracy

Route of data or data packets consisting of observations of number of vehicles each hour in four different junctions is an essential part of any ITS-based intelligent traffic control system. Constructing a viable solution that will allow data collection and optimal routing would require implementing a low powered congestion that can route data between devices. The vehicles involved in the simulation are necessitated to compute certain aspects in a dynamic manner, depending on the nature of the traffic. These all are said to be ensured only by following accurate routing. The routing accuracy is mathematically formulated as given below.

$$RA = \sum_{i=1}^{m} \frac{V_{AR}}{V_i} * 100$$

(18)

From equation (18), routing accuracy 'RA' is measured depend on vehicles or samples 'V_i' and vehicles accurately routed 'V_{AR}'. RA is measured in percentage (%). Table 1 demonstrate values of the route accuracy obtained using three methods, RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2] by applying equation (18).

Table 1 Performance results of routing accuracy using RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2]

Vehicles	Routing accuracy (%)		
	RBINN-QFA	Faster R-CNN	Tree-based Machine and Ensemble Learning
4500	96.33	95.66	94.55
9000	95.25	93.15	90.25
13500	93.15	90	86.35
18000	90	87.45	84
22500	88.25	83.25	81
27000	85.35	80	77.25
31500	82.25	78.45	75
36000	83.45	79	76
40500	85	80.35	78
45000	88.15	83	79

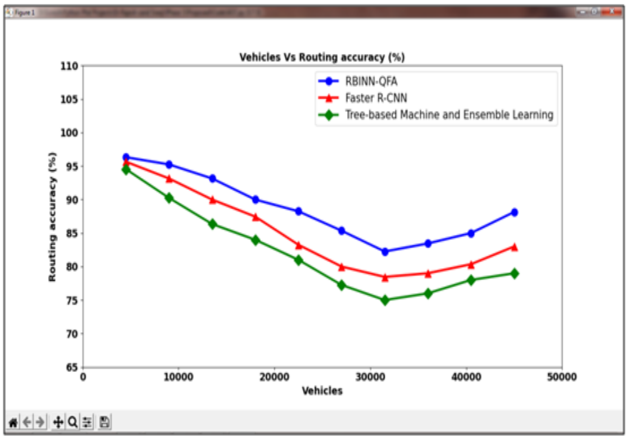

Figure 4 Routing accuracy analyses

Figure 4 depicts graphical representation of routing accuracy using proposed RBINN-QFA technique and conventional methods, faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2]. From figure 4 , x axis indicates distinct numbers of vehicles or samples involved in the simulation of ITS and y axis represents the actual routing accuracy rate obtained using the three methods when substituted in the formula (18). A decreasing trend was observed with vehicle intensity between 4500 and 30000 whereas an upsurge was observed greater than 30000 up to 45000. This is because with higher numbers of vehicles observed there remains a larger chance of obtaining route than with lower numbers of vehicles, therefore improving the routing accuracy. With 4500 vehicles involved in the simulation, optimal routes were identified for 4335 vehicles using RBINN-QFA method, 4305 vehicles using [1] and 4255 vehicles using [2]. As a result the RA using three methods were 96.33%, 95.66% and 94.55% showing a significant improvement using RBINN-QFA method than the [1] and [2]. The cause behind enhancement was because of application of Radial Basis Interpolated Neural Network-based traffic data collection model. With this type of design, traffic data collected at both normal traffic and peak hour traffic were obtained separately using two different functions. Following which the interpolated results were obtained, therefore improving the routing accuracy using RBINN-QFA method by 4% , and 8% than the [1] ,[2].

5.2 Route detection time

Sooner route detection time made higher is the probability of occurrence of congestion and accidents. Route detection times depend specifically on the numbers of vehicles, junctions in solution space and the date/time. This is due to reason which the route detection time for normal traffic is different from the heavy traffic. The route detection time is formulated as.

$$RDT = \sum_{i=1}^{m} V_i * Time\ (OR) \quad (19)$$

From the above equation (19), the route detection time 'RDT' is arrived at depend on samples or vehicles 'V_i' and time utilized in obtaining optimal routes '$Time\ (OR)$'. It is measured in milliseconds (ms). Table 2 demonstrates the values of the route detection time obtained using, RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2] by applying equation (19).

Table 2 Performance results of routing detection time using RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2]

Vehicles	Routing detection time (ms)		
	RBINN-QFA	Faster R-CNN	Tree-based Machine and Ensemble Learning
4500	157.5	247.5	292.5
9000	185.35	285.35	335.35
13500	215.25	315.55	400.35
18000	255.45	385.35	455.25
22500	325.55	435.15	525.55
27000	385.15	485.25	600.15
31500	435.35	545.55	655.35
36000	485.55	625.35	755.35
40500	535.25	685.55	800.15
45000	615.45	735.35	835.35

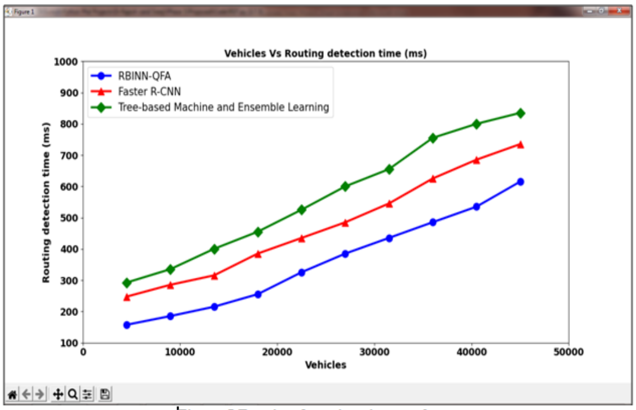

Figure 5 Routing detection time analyses

Figure 5 shows the routing detection time obtained for each normal traffic and peak hour traffic operations performed in intelligent traffic control system. It is visible that initially routing detection time increases through increase in numbers of vehicles however as it reaches table occupancy of 22500 vehicles, it slowly increases. But, the routing detection time for ITS operation is considerably lower than the conventional counterpart [1] and [2]. It is obvious from the attained outcomes that routing detection time achieved for proposed method is lower and stable than its conventional variant. This is evident from the simulation results where 4500 vehicles, routing detection time using RBINN-QFA was observed to be 157.5ms, 247.5ms using [1] and 292.5ms using [2], therefore corroborating the objective. The reason behind the improvement was due to application of Radial Basis Interpolated Neural Network-based traffic data collection algorithm. By using this algorithm, the traffic data collection is simulated as a neural network structure that is locally adjusted in the overall network space owing to the reason that Radial Basis Function is a local approximation network. Moreover, the hypothesis that the mapping from input (i.e., sensor data collected from a respective junction) to output (i.e., data collection) is said to be nonlinear whereas mapping between hidden layer and output layer is linear that in turn speeds up the overall learning process. In this manner, the local minima is avoided therefore reducing the routing detection time using RBINN-QFA method by 26% upon comparison with [1] and 38% upon comparison with [2].

5.3 Performance analysis of sensitivity

Sensitivity refers to the potentiality of ITS-based intelligent transportation towards optimal routing to correctly identify vehicles with optimal routes. It is formulated as below.

$$Sen = \frac{TP}{TP+FN}$$
(20)

From equation (20), sensitivity 'Sen' is measured based on number of true positives 'TP' and number of false negatives 'FN'. Here true positive rate refers to the non-optimal route for a vehicle correctly identified as non-optimality whereas false negative rate refers to the non-optimal route for a vehicle incorrectly identified as optimal.

Table 3 Performance results of sensitivity using RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2]

Vehicles	Sensitivity		
	RBINN-QFA	Faster R-CNN	Tree-based Machine and Ensemble Learning
4500	0.98	0.97	0.95
9000	0.96	0.94	0.92
13500	0.95	0.93	0.9
18000	0.94	0.92	0.89
22500	0.93	0.9	0.88
27000	0.92	0.89	0.86
31500	0.9	0.88	0.85
36000	0.88	0.86	0.84
40500	0.87	0.85	0.82
45000	0.86	0.84	0.82

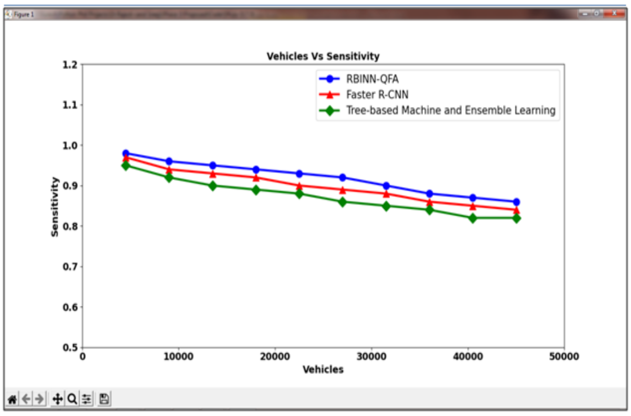

Figure 6 Sensitivity analyses

Figure 6 shows the sensitivity analysis using the proposed RBINN-QFA method and its counterparts [1] and [2]. Figure 6 shows the reduction of sensitivity with an increase in the vehicles or samples for simulation. The sensitivity rate utilized is much higher as compared to existing counterpart. This is evidence from the simulation where the true positive rate were observed to be 4450, 4400 and 4300 whereas the false negative rate were found to be 50, 100 and 200 using the three methods, RBINN-QFA method, [1] and [2] respectively. With this the overall sensitivity rate were found to be 0.98, 0.97 and 0.95 respectively, therefore showing an improving using RBINN-QFA method upon comparison to their counterparts. The sensitivity rate improvement using RBINN-QFA technique was owing to application of Quantum Finite Automata-based Optimized Vehicle Routing model. By applying this model, first, the objective was formulated, following which the initial state, i.e., the network traffic data are collected. Next, group routing was performed to balance the load on parallel routes while transmitting traffic information (i.e., normal and peak hour traffic) in addition to the interpolated results employing Quantum Finite Automata algorithm, therefore improving the overall sensitivity using RBINN-QFA method by 2% and 5% than the [1], [2].

5.4 Specificity

Specificity on other hand refers to the potentiality of ITS-based intelligent transportation towards optimal routing to correctly identify vehicles without optimal routes. The specificity rate is mathematically represented as given below.

$$Spe = \frac{TN}{TN+FP}$$
(21)

From equation (21), specificity 'Spe', is measured depend on true negative 'TN' and the false positive 'FP' respectively. Here, true negative refers to the optimal route for a vehicle correctly identified as optimal whereas false positive rate refers to the optimal route for a vehicle incorrectly identified as non-optimal. Table 4 provides the values of the specificity rate using, RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2] by applying (21).

Table 4 Performance results of specificity using RBINN-QFA, Faster R-CNN [1] and Tree-based Machine and Ensemble Learning [2]

Vehicles	Specificity		
	RBINN-QFA	Faster R-CNN	Tree-based Machine and Ensemble Learning
4500	0.99	0.98	0.97
9000	0.98	0.96	0.95
13500	0.96	0.94	0.92
18000	0.95	0.93	0.91
22500	0.94	0.91	0.9
27000	0.93	0.9	0.88
31500	0.91	0.88	0.86
36000	0.9	0.86	0.85
40500	0.88	0.85	0.83
45000	0.87	0.84	0.83

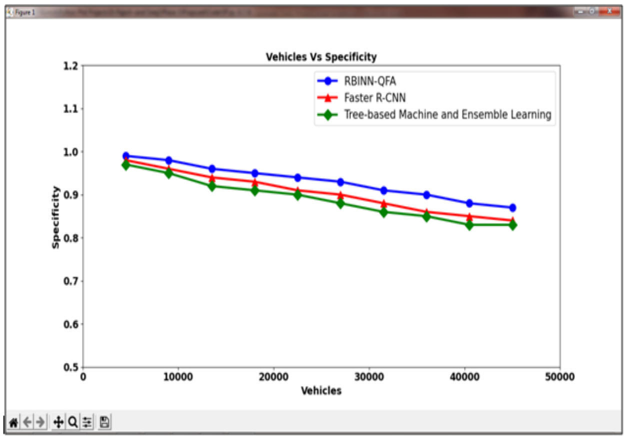

Figure 7 Specificity analysis

Finally, figure 7 shows the graphical representation of specificity analysis for the proposed RBINN-QFA method in contrast with the standard ITS. Attained outcomes for RBINN-QFA method were compared through standard ITS that follows conventional machine and ensemble learning. The variation of specificity rate with and enhance in number of vehicles obviously outperforms its conventional counterpart [1] and [2] with a significant difference. This is owing to flow classification based on quantum operations and optimal routing management using the proposed method. With the simulations performed for an average of 4500 vehicles, the true negative rate by three methods were examined 4465, 4450 and 4400 whereas false positive rate were 35, 50 and 100 using RBINN-QFA method, [1] and [2]. With this the overall specificity rate were observed to be 0.99, 0.98 and 0.97 respectively. The specificity rate improvement over RBINN-QFA method upon comparison to [1] and [2] was due to the application of QFAOVR algorithm. By applying this algorithm, with the aid of the automata group routing were generated using distinct traffic patterns both updated in a dynamic fashion and also via feasible solution. With this an improvement using RBINN-QFA method was said to be inferred by 3% and 5% than the [1] , [2].

6. Conclusion

The conventional format of the incoming traffic from intelligent traffic control system comprises of several undesirable attributes that are not essential for routing, decision making, processing, as well as hence neglected. For this cause, an artificial intelligence representation or AI-enabled network format employed to handle this circumstance. For attaining this goal, we tried to embed AI and automata to flow forwarding architecture of ITS during Radial Basis Interpolated Neural Network and Quantum Finite Automata model. In the initial phase, the proposed RBINN-QFA method obtains the normal traffic data, peak hour traffic data and finally interpolates them to model computationally efficient traffic data to be collected for further processing. In the next phase, optimal routing is focused by employing Quantum Finite Automata-based Optimized Vehicle Routing. In addition, to focus on the sensitivity and specificity aspect, group routing is performed to analyze dynamic updates and obtain feasible solution and reducing the route detection time also in a significant manner. Simulations are performed to validate the proposed RBINN-QFA method and the conventional methods in routing accuracy, route detection time, sensitivity and specificity. Moreover, simulation outcomes exhibit RBINN-QFA method outcome conventional ITS methods of numerous performance matrices, therefore providing optimal route avoiding unnecessary accidents. From the analysis, proposed method seems better results and outperforms its convention counterpart.

References

[1] Yang Cui, Dongfei Lei, “Optimizing Internet of Things-Based Intelligent Transportation System’s Information Acquisition Using Deep Learning”, IEEE Access, Feb 2023 [Faster Region-based Convolutional Neural Network (Faster R-CNN)]

[2] Preeti Rani, Rohit Sharma, “Intelligent transportation system for internet of vehicles based vehicular networks for smart cities”, Computers and Electrical Engineering, Elsevier, Jan 2023 [Tree-based Machine and Ensemble Learning]

[3] Bowen Du, Hao Peng, Senzhang Wang, Md Zakirul Alam Bhuiyan, Lihong Wang, Qiran Gong, Lin Liu, and Jing Li, “Deep Irregular Convolutional Residual LSTM for Urban Traffic Passenger Flows Predict”, IEEE Transactions on Intelligent Transportation Systems, Oct 2020

[4] Keping Yu, Long Lin, Mamoun Alazab, Liang Tan, and Bo Gu, “Deep Learning-Based Traffic Safety Solution for a Mixture of Autonomous and Manual Vehicles in a 5G-Enabled Intelligent Transportation System”, IEEE Transactions on Intelligent Transportation Systems, May 2021

[5] Ling Zhao, Yujiao Song, Chao Zhang, Yu Liu , Pu Wang , Member, IEEE, Tao Lin, Min Deng, and Haifeng Li, “T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction”, IEEE Transactions on Intelligent Transportation Systems, Oct 2020

[6] Lakshmi Shankar Iyer, “AI enabled applications towards intelligent transportation”, Transportation Engineering, Elsevier, Jul 2021

[7] Agachai Sumalee, HungWai Ho, “Smarter and more connected: Future intelligent transportation system”, IATSS Research, Elsevier, Jun 2018

[8] Ritesh Dhanare, Kapil Kumar Nagwanshi, and Sunita Varma, “A Study to Enhance the Route Optimization Algorithm for the Internet of Vehicle”, Wireless Communications and Mobile Computing, Wiley, Apr 2022

[9] AndréBroekman, Petrus Johannes Gräbe, Wynand J.vdM. Steyn, “Real-time traffic quantization using a mini edge artificial intelligence platform”, Transportation Engineering, Elsevier, Mar 2021

[10] Qian Yu, Yuanguo Wang, Xiaogang Jiang , Bailu Zhao, Xiuling Zhang, Xiaobei Wang, and Qingqing Liu, “Optimization of Vehicle Transportation Route Based on IoT”, Mathematical Problems in Engineering, Hindawi, Sep 2021

[11] Daisuke Inoue, Akihisa Okada, Tadayoshi Matsumori, Kazuyuki Aihara, & Hiroaki Yoshida, “Traffic signal optimization on a square lattice with quantum annealing”, Scientific Reports, Oct 2021

[12] Zhengang Guo, Yingfeng Zhang, Jingxiang Lv, Yang Liu, and Ying Liu, “An Online Learning Collaborative Method for Traffic Forecasting and Routing Optimization”, IEEE Transactions on Intelligent Transportation Systems, May 2020

[13] Yongsheng Cao, “Online Routing and Charging Schedule of Electric Vehicles With Uninterrupted Charging Rates”, IEEE Access, Sep 2022

[14] Ennio Gambi, Linda Senigagliesi, Andrea Barbaresi, Matteo Mellini, Adelmo De Santis, “A WKNN-based approach for NB-IoT sensors localization”, Digital Communications and Networks, Elsevier, Apr 2022

[15] Baofeng Ji, Mingkun Zhang, Ling Xing, Xiaoli Li, Chunguo Li, Congzheng Han, Hong Wen, “Research on optimal intelligent routing algorithm for IoV with machine learning and smart contract”, Digital Communications and Networks, Elsevier, Jun 2022

[16] Ajay Kumar Dogra1, Jagdeep Kaur2, “Moving towards smart transportation with machine learning and Internet of Things (IoT): a review”, Journal of Smart Environments and Green Computing, Nov 2022

[17] Ritesh Dhanare, Kapil Kumar Nagwanshi, and Sunita Varma, “A Study to Enhance the Route Optimization Algorithm for the Internet of Vehicle”, Wireless Communications and Mobile Computing, Wiley, Apr 2022

[18] Ritesh Dhanare, Kapil Kumar Nagwanshi, and Sunita Varma, “A Study to Enhance the Route Optimization Algorithm for the Internet of Vehicle”, Wireless Communications and Mobile Computing, Wiley, Apr 2022

[19] Mohammadhossein Ghahramani, MengChu Zhou, Anna Molter, and Francesco Pilla, “IoT-Based Route Recommendation for an Intelligent Waste Management System”, IEEE Internet of Things Journal, Vol. 9, No. 14, Jul 15, 2022

[20] Sankar Sennan, Somula Ramasubbareddy, Sathiyabhama Balasubramaniyam, Anand Nayyar, Chaker Abdelaziz Kerrache, Muhammad Bilal, “MADCR: Mobility Aware Dynamic Clustering-Based Routing Protocol in Internet of Vehicles”, China Communications, July 2021

[21] P. Satyanarayana, T. Sushma, M. Arun, V. S. Raiu Talari, S. Gopalakrishnan and V. G. Krishnan, "Enhancement of Energy Efficiency and Network Lifetime Using Modified Cluster Based Routing in Wireless Sensor Networks," 2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), Coimbatore, India, 2023, pp. 127-132, doi: 10.1109/ICISCoIS56541.2023.10100580.

[22] Raj, R., & Sahoo, D. S. S. . (2021). Detection of Botnet Using Deep Learning Architecture Using Chrome 23 Pattern with IOT. Research Journal of Computer Systems and Engineering, 2(2), 38:44. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/31

[23] Patil, R. A. ., & Patil, P. D. . (2023). Skewed Evolving Data Streams Classification with Actionable Knowledge Extraction using Data Approximation and Adaptive Classification Framework. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 38–52. https://doi.org/10.17762/ijritcc.v11i1.5985