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Cox Regressive Outlier Robust Incremental Extreme Learning Machine based IoT aware Smart Car Parking and Route Optimization for Intelligent Transportation



Abstract: -An Intelligent Transport System (ITS) is a wide-ranging framework that influences advanced technologies to improve efficiency of transportation networks. An ITS integrated with an IoT enhances the capabilities of transportation networks. Owing to quick development of vehicles, traffic congestion during road network is major problems. Therefore, intelligent traffic control system is required to create smart transportation through optimization of vehicle route, and so on. In this paper, Cox Regressive Fuzzified Outlier Robust Incremental Extreme Learning Machine (CRFORIELM) is developed for smart ITS. The IoT technology in ITS is used to collect traffic data, vehicle information, Parking slot occupancy data. After data collection process, proposed CRFORIELM technique includes two major processing steps namely parking slot availability detection and traffic aware route optimization. The extreme learning machine includes three types of layers such as input, three hidden layers as well as output layer. Initial hidden layer predicts the parking slot availability using Cox regression is performed. With the parking lot availability predictions, integrate this information into a route optimization algorithm. This algorithm considers the real-time traffic conditions as well as parking availability for detecting optimal route by applying fuzzy triangular membership function in the second hidden layer. Finally, nearest route path is effectively determined to minimize travel time in intelligent transport system. Experimental analysis indicates that the CRFORIELM technique achieved 2%, 5%, 10% improvement in accuracy, sensitivity, specificity and reduced error rates, route detection time by 39%, and 36%, compared to existing methods.

Keywords: Intelligent Transport System (ITS), Smart parking, traffic aware route optimization, Outlier Robust Incremental extreme learning machine, Cox regression, fuzzy triangular membership function

I. INTRODUCTION

In the context of modern urbanization, population expansion, and the vital challenge of traffic congestion, the deployment of ITS to optimize functionality of fostering efficiency, safety, and sustainability. The increasing complexities of urban environments, there is demand for sophisticated solutions to mitigate challenges associated with limited parking space, traffic congestion, etc. Internet of Things (IoT) integration of various sensors utilized to monitor and provide accurate information on parking availability to minimize the travel time and traffic congestion. ML and DL methods act as essential part in making predictions and further enhancing the capabilities of intelligent transportation system. There are persistent challenges in effectively monitoring and managing smart parking and traffic-aware route optimization in Intelligent Transportation Systems (ITS). Traditional methods often fall short in providing real-time insights and predictive capabilities. Additionally, it faces difficulties in accurately predicting parking availability and determining optimal routes, contributing to increased traffic levels, delays, and environmental impacts. This paper addresses these challenges by introducing a comprehensive solution rooted in IoT and advanced machine learning. Moreover, timely traffic and parking availability prediction also pose challenges in conventional methods.

1.1 Problem Definition

There are persistent challenges in effectively monitoring and managing smart parking and traffic-aware route optimization in Intelligent Transportation Systems (ITS). Traditional methods often fall short in providing real-time insights and predictive capabilities. Additionally, it faces difficulties in accurately predicting parking availability and determining optimal routes, contributing to increased traffic levels, delays, and environmental impacts. This paper addresses these challenges by introducing a comprehensive solution rooted in IoT and advanced machine learning. Moreover, timely traffic and parking availability prediction also pose challenges in conventional methods.

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1.2 Research Contribution

This work intends to overcome problems of accurate as well as timely monitoring of parking and traffic condition. The main objective is listed below.

- To improve the accuracy of parking availability prediction, Cox regression employed in CRFORIELM technique
- To minimize error rate of parking availability prediction, outlier robust function employed
- To minimize route detection time, fuzzy triangular membership function is employed for analyzing traffic level and taxicab distance to detect shortest route.
- To improve the sensitivity and specificity, CRFORIELM technique uses outlier robust incremental extreme learning machine (IELM) to accurately perform smart parking and traffic prediction.

To evaluate performance of our CRFORIELM technique, comprehensive experimentation is conducted and compared using various evaluation metrics.

II. LITERATURE STUDY

Faster R-CNN was designed in [1], to enhance sensitivity as well as accuracy at feature extraction for IoT-based ITS. However, it faced challenges in accurately identifying smart parking availability. A novel hybrid method that combines GRU and LSTM was introduced [2] to enhance the accuracy of parking availability prediction. However, it has a significant amount of delay occurs during the prediction process. For smart parking in urban areas within a dynamic environment for minimizing overall waiting time, A novel DQN based method was designed [3]. However, it was observed that the accuracy of predicting the optimal route with the required traffic conditions was not adequate. A ML based approaches was developed [4] to forecast tenancy of parking lots for arriving vehicles. But it failed to minimize congestion issue in Seattle city. A new Convolutional Neural Network (CNN) was introduced in [5] for vehicle parking and management. However, the error rate in the prediction of vehicle parking was not minimized. The Intelligent Parking System (IPS) was developed in [6], consisting of an IoT framework for predicting parking spaces at nearby locations. A machine learning method was developed in [7] for truck parking occupancy prediction. But it failed to further improve the accuracy and robustness of predictions. For predicting parking space tenancy, a novel DL-based ensemble method was designed [8]. ML and NN-based (MLNN) method was designed in [9] for predicting parking segment availability. The designed algorithm was ineffective in reducing traffic in urban areas. A deep LSTM network was designed [10] to predict availability of parking spaces. But it failed to consider weather condition and social events.

A LSTM with multiagent system was developed in [11] for prediction of available smart parking. For forecasting obtainability of parking spaces, Ensemble-based models, integrated with IoT, were developed in [12]. Preprocessed Region-based CNN was developed in [13] for detecting parking positions, achieves higher accuracy. However, it has higher maintenance costs. For addressing effects of weather conditions on intelligent parking recognition, Ensemble method depend on DL was developed in [14]. Custom CNN model was used in [15] to categorize traffic signs with higher accuracy. An approach for traffic sign recognition was developed in [16] specifically designed for complex urban road environments. The method demonstrates higher accuracy and minimal latency. In [17], A user-dedicated smart parking method was designed. However, dynamic occupancy ratio analytics remained unaddressed. A recurrent neural network method was developed in [18] for parking prediction; however, it did not address how parking obtainability is pretentious through traffic flow in close by parking areas. A smart parking system using surveillance cameras was developed in [19], but it failed to effectively perform smart parking in urban transportation. DL with LSTM was developed in [20] to predict parking space availability. But it failed to reduce traffic density. Web-based framework was introduced in [21] for smart parking system. A distributed parking slot allocation approach was developed in [22] for preventing traffic jams and optimizing resource utilization. In [23], multi-agent-depend on-street parking imitation was developed. However; the simulation did not specify the decision rule settings for street parking. An assignment algorithm for parking lots was designed in reference [24] to detect specific parking spaces, aiming to minimize traffic levels. The examination of the on-street parking availability for taxi fleets of various sizes was introduced in [25-27].

III. PROPOSED METHODOLOGY

This paper introduces a novel CRFORIELM technique for creating smart transportation systems through smart parking, aiming to reduce congestions and accidents by implementing vehicle route optimization. The

technique considers the challenges posed by real-time traffic situations as well as real-time free parking situations in urban areas. This CRFORIELM technique aims to address both parking availability prediction related with IoT devices, finally determined for traffic aware route optimization.

3.1 Architecture of Proposed Methodology

The architecture of the proposed CRFORIELM technique includes a structural framework that facilitates a complete workflow of various processes. Specifically designed to integrate parking availability detection, this helps to efficiently manage parking spaces and reduce the traffic congestion on routes through the utilization of machine learning techniques. The Figure 1 shows outlines the specific processes of the proposed CRFORIELM technique.

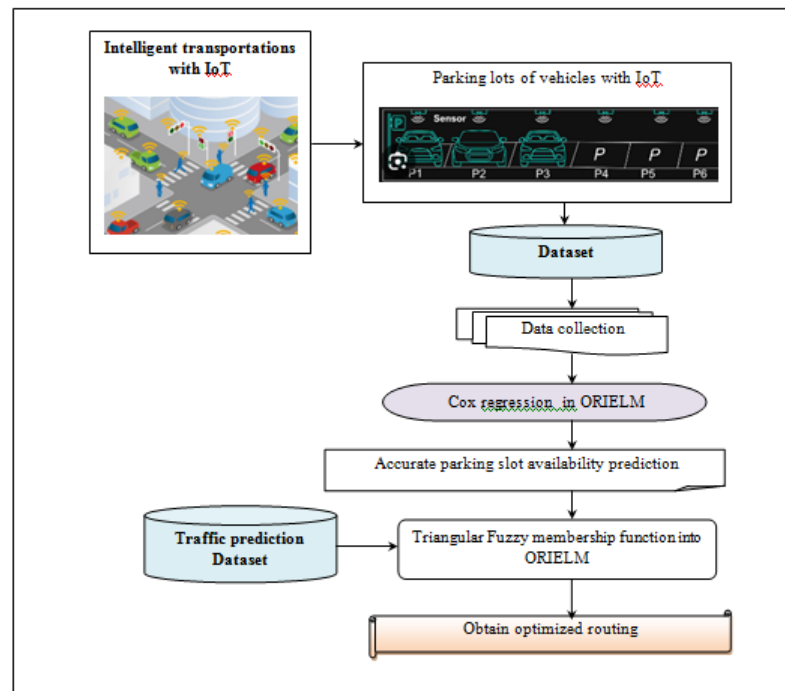


Figure 1 Architecture diagram of proposed CRFORIELM technique

Figure 1 depicts diagram of CRFORIELM technique within an IoT-aware Intelligent Transportation System. The CRFORIELM technique comprises IoT devices for the data collection process. It utilizes an outlier-robust incremental extreme learning approach to facilitate accurate prediction of parking slot availability in a specific area, leveraging spatiotemporal features such as location and date/time information. The detailed discussion of the CRFORIELM technique is presented in the subsection below.

3.2 Outlier robust IELM

Incremental ELM is ML method and it type of single or multiple layers of feed forward neural networks. The incremental ELM is a useful technique for fast and efficient learning from large-scale data, resulting in increases training speed compared to other traditional deep learning algorithms. An incremental approach in this Extreme Learning Machine involves updating the output weights or incorporating new hidden nodes when the new data arrives. This method facilitates the adaptation of the model to dynamic changes in the data distribution over time. The outlier robust is proposed to minimize the error in the accurate prediction.

Figure 2 depicts a structure of Outlier robust incremental extreme learning machine comprises of different layers. Proposed structure did not use any back-propagation i.e. iterative learning process. The architecture includes training samples x_i denotes a training samples i.e. parking lot information's and y_i indicates a desired output. Every layer contains number of neurons to transfer input from one layer to another. As shown in figure 2, L be the number of hidden neurons.

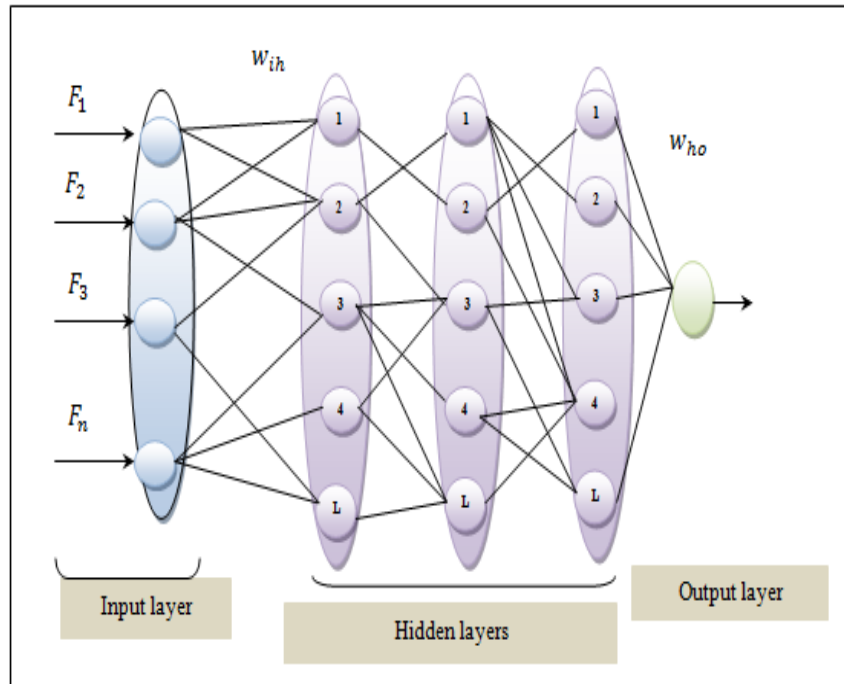


Figure 2 structure of Outlier robust Incremental Extreme Learning Machine

Let us consider the ‘m’ set of requesting vehicles ‘

$$V_m = \{V_1, V_2, V_3, \dots V_m\} \quad (1)$$

Each vehicle has a set of target destinations ‘,

$$D = D_1, D_2 \dots D_g \quad (2)$$

The parking slot of the vehicles are denoted by

$$P = P_1, P_2, P_3, \dots P_n \quad (3)$$

The parking space information are collected from the IoT device during different times (, ,... ‘) of the day is stored in the form of input matrix.

$$I = \begin{bmatrix} V_1 F_1 & V_1 F_2 & \dots & V_1 F_n \\ V_2 F_1 & V_2 F_2 & \dots & V_2 F_n \\ \dots & \dots & \dots & \dots \\ V_m F_1 & V_m F_2 & \dots & V_m F_n \end{bmatrix} \quad (4)$$

Where, input matrix ‘I’ is modeled taken ‘m vehicles ‘V’ as well as ‘n’ features ‘F’ is carried out in input layer. For each input, random weights matrix and bias are generated in the input layer.

$$w_{ih} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \dots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mn} \end{bmatrix} \quad (5)$$

Where, w_{ih} denotes a weight matrix between input and hidden layer.

$$Q_{ih} = \begin{bmatrix} Q_{11} & Q_{12} & \dots & Q_{1n} \\ Q_{21} & Q_{22} & \dots & Q_{2n} \\ \vdots & \vdots & \dots & \vdots \\ Q_{m1} & Q_{m2} & \dots & Q_{mn} \end{bmatrix} \quad (6)$$

Where, Q_{ih} denotes a bias between input and hidden layer. Therefore, the activity of neurons is expressed as follows,

$$A = \sum_{i=1}^n [I * w_{ih}] + Q_{ih} \quad (7)$$

Where, the activity of neurons at the input layer, ‘ F_i ’ denotes parking lot information, w_{ih} denotes weight among input as well as hidden layer, bias function ‘ Q_{ih} ’. Then input is transmitted to initial hidden layer where

Cox regression is applied to analyze the features and detect the availability of parking spot in the space over time. In other words, Cox Regression is kind of ML technique used to method the relationship between time (time to an event) and predictor variables (i.e. availability of parking spot). The mathematical formula for Cox regression is estimated as give below,

$$R(t, z) = h_0(t) * exp(\delta_1 X_1 + \delta_2 X_2 + \dots + \delta_k X_k) \quad (8)$$

Where, $R(t, z)$ indicates a regression function to measure the likelihood of a parking availability rate being occupied in the time unit, $h_0(t)$ initial hazard function, $\delta_1, \delta_2, \dots, \delta_k$ denotes a regression coefficient, X indicates a covariates. The hazard refers to immediate rate at that an incident happens given which individual has outlived to specific time period.

The covariates are used to study the relationship between the independent variables i.e. parking availability rate being occupied in the time unit based on the total capability of parking lot and tenancy of parking lot.

$$X = AVR_{par}(t) \quad (9)$$

$$AVR_{par}(t) = \frac{C_{pl} - Occ(t)}{C_{pl}} \quad (10)$$

Where, $AVR_{par}(t)$ parking availability rate at time 't', C_{pl} indicates a total capacity of parking lot, $Occ(t)$ indicates an occupancy of parking lot at time 't'. The regression function verifies the average parking availability with the threshold function 'TH' as given below

$$Z(t) = \begin{cases} AVR_{par}(t) > TH, & 1 \\ AVR_{par}(t) < TH, & 0 \end{cases} \quad (11)$$

$$H(t) = \begin{cases} 0, P \text{ is FULL} \\ 1, P \text{ is OPEN} \end{cases} \quad (12)$$

From the above equations (11) and (12) results, the requested parking lot 'P' is declared as full or open based on parking availability rate at time 't'. It is greater than the threshold function 'TH', the parking lot is detected as an open. Otherwise, the parking lot is detected as a full. In this way, accurate parking availability is correctly predicted at a particular time.

3.2.1.1 Traffic aware optimized vehicle routing

With the parking slot availability predictions, this information is used for route optimization algorithm. This considers the parking availability to detect optimal route from current point to designation. Many vehicles on the same road at the same time cause the traffic congestion. This increases the delay and travel time. In order to avoid the problem, a traffic prediction is performed in second hidden layer of the incremental extreme learning machine.

Parking slot availability predictions results are transferred from first hidden layer to next hidden layer. Then number of hidden nodes increased in 2nd hidden layer and given traffic data interms of 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 ' $ID = \{ID_1, ID_2, \dots, ID_{id}\}$ ', IoT or Sensors ' $S = \{S_1, S_2, \dots, S_i\}$ '

Triangular fuzzy membership employed to predict road traffic. This function considers the traffic data taken from the dataset as well as output is linguistic terms (i.e., low, medium or normal, high or peak hour traffic) representing the predicted traffic intensity.

First, the percentage of traffic volumes at the specific road are determined based on the proportion of number of vehicles at a particular junction within a time 't' and average vehicles capacity of road on same time 't'.

$$TV = \frac{NV(J,t)}{ACR(J,t)} \quad (13)$$

Where, TV denotes a Proportion of traffic volume, ' $NV(J, t)$ ' denotes an actual number of vehicles observed at the specific junction with time, ' $ACR(J, t)$ ' indicates a average number of vehicles the road can accommodate at the specific junction on that particular time.

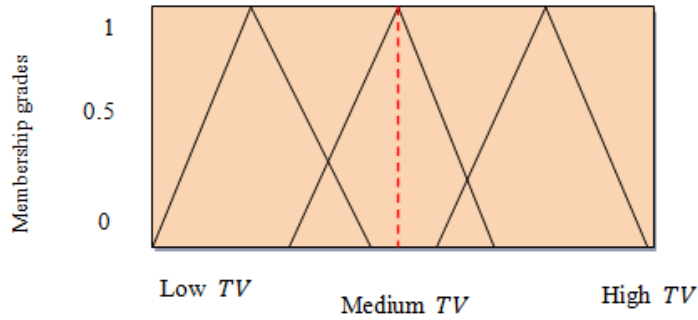


Figure 3 Fuzzy triangular membership function

Figure 3 demonstrates the triangular fuzzy membership function based on traffic volume prediction. The fuzzy membership function analyzes the traffic volume based on rule. The rules are formulated as follows,

$$R = \text{if } (cond) \text{ then } (conclusion) \quad (14)$$

The condition part verifies the estimated traffic volume with threshold (ϑ) and the conclusion part offers the outputs.

$$\mu_{\vartheta} = \begin{cases} \text{if } (TV > \vartheta) ; & \text{high or peak hour traffic} \\ \text{if } (TV < \vartheta) ; & \text{low traffic} \\ \text{if } (TV = \vartheta) ; & \text{medium or normal traffic} \end{cases} \quad (15)$$

Where, μ_{ϑ} indicates a membership grade, TV denotes a Proportion of traffic volume, ϑ indicates the threshold. Based on the above estimation, a triangular fuzzy membership function

// Algorithm 1: Cox Regressive Fuzzified Outlier Robust Incremental Extreme Learning Machine

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 ‘ $S = \{S_1, S_2, \dots, S_l\}$ ’, parking slot $P = P_1, P_2, P_3, \dots, P_n$, vehicle target destinations ‘ D ’, $D = D_1, D_2 \dots D_g$

Output: Increase accuracy

Begin

1. **Collect** the number of parking data or input vector ‘ X ’ using (4)–**input layer**
2. for each input information apply Cox regression —**hidden layer 1**
3. **Measure the parking availability rate at time t ’** $AVR_{par}(t)$
4. **if** ($AVR_{par}(t) > TH$) **then**
5. **return** $H(t) = 1$
6. **Then** parking slot is open
7. **else**
8. **return** $H(t) = 0$
9. **Then** parking slot is full
10. **end if**
- 11: **For each** vehicle ‘ V ’ route ‘ R ’ between starting point to destination –(**hidden layer**
- 2)
 - 12: Measure the traffic volume using (13)
 - 13: Apply the triangular fuzzy membership function
 - 14: **if** ($TV > \vartheta$) **then**
 - 15: Traffic volume is classified as ‘peak hour traffic ‘
 - 16: **else if** ($TV < \vartheta$) **then**
 - 17: Traffic volume is classified as ‘low traffic’
 - 18: **else if** ($TV = \vartheta$) **then**
 - 19: Traffic volume is classified as ‘normal traffic’
 - 20: **end if**
 - 21: **If** the route with peak hour traffic **then** (**hidden layer 3**)

22: Find shortest route to parking using (16)
 23: **end if**
 24: **For each output**
 25: **Apply** outlier robust function using (19) (20) to minimize the error
 26: **end for**
 27: Obtain the accurate smart parking and route optimization results -- **output layer**
End

provides an outcomes either low or peak hour traffic or normal traffic. In this way, accurate prediction is said to be performed.

To implement traffic-aware routing, an alternative shortest route to the destination is determined in third hidden layer with the presence of peak-hour traffic. In order to find another route nearby the parking place coordinate (p_2, q_2) , taxicab distance is estimated from the starting point coordinate (p_1, q_1) . In the two-dimensional real coordinate space, the distance is measured as follows,

$$TD = |p_1 - p_2| + |q_1 - q_2| \quad (16)$$

Where, TD denotes a taxicab distance between the location of starting points (p_1, q_1) and the destination (i.e. parking place) i.e. (p_2, q_2) . Therefore, the minimal distance is selected for optimal route for reaching the destination point with normal traffic conditions. As a result, the optimal routing is determined by selecting the route with the shortest distance and normal traffic conditions.

Finally, output of hidden layer is linear combination of different functions as given below,

$$Y = \sum A (w_{ho} K + Q_{ho}) \quad (17)$$

Where, K' represents the hidden layer output, A indicates an activation function of hidden neuron, ' w_{ho} ' denotes the weight among hidden as well as output layer neuron, Q_{ho} bias among hidden and output layer.

$$A = (1 + \exp(\mu_g))^{-1} \quad (18)$$

The outlier robust function aims to minimize the following function,

$$OR = \arg \min |\varepsilon^2| + \frac{1}{\alpha} |w_o|^2 \quad (19)$$

Where, OR denotes an outlier robust function, $\arg \min$ denotes a argument of minimum function, ε indicates a error function, α indicates a the regularization parameter, w_o indicates a weight of the output. The regularization parameter is a hyperparameter used in machine learning models to control the balance between fitting the training data well and preventing overfitting

$$\varepsilon = (y_{ex} - y_{act}) \quad (20)$$

Where, ε denotes an error rate, y_{ex} denotes an expected outcome, y_{act} indicates an actual outcome. As a result, smart parking approach minimizes travel distance, reduces traffic level. By adopting this strategy, accurate smart parking and optimized routing is achieved in intelligent transportation systems, resulting in minimized travel time and reduced delays. The pseudo code for the proposed a CRFORIELM is described as given below,

IV. RESULT

In this section, the CRFORIELM technique, along with two existing methods, Faster R-CNN [1] SGRU-LSTM [2], DQN-based algorithm [3], are implemented using Python programming language. The evaluation is performed using the integration of two dataset such as using KLCC Parking Occupancy 2016 dataset and traffic prediction dataset. The KLCC Parking Occupancy 2016 dataset is collected from (<https://www.kaggle.com/datasets/myapit/klccparking>). This dataset includes 4 features and 47605 instances for parking availability prediction.

Another traffic prediction dataset is taken from the <https://www.kaggle.com/datasets/fedesoriano/traffic-prediction-dataset> for forecasting hourly traffic information on four dissimilar junctions. This dataset include 48120 observations of number of vehicles every hour in four dissimilar intersection. Dataset includes four attributes namely DateTime, Junction, Vehicles and ID.

4.1 Result and Analysis

This part presents comparative study of CRFORIELM method, along with three existing methods, Faster R-CNN [1] SGRU-LSTM [2], DQN-based algorithm [3]. The performance analysis employs metrics such as

accuracy, error rate, route detection time, sensitivity and specificity. The performance of each technique in terms of these metrics is illustrated through a table and graphical representations.

Accuracy: It is referred as number of correctly predicted parking availabilities for individual vehicles. It is measured as below:

$$Accuracy = \sum_{i=1}^n \left[\frac{V_{CP}}{V_i} \right] * 100 \tag{21}$$

Where, denotes a number of correct parking availability predictions of vehicles, indicates total number of vehicles, denotes total number of vehicles. Therefore, accuracy is measured in percentage (%).

Error rate: the error rate involved in smart parking is detected. It is measured as given below.

$$ER = \sum_{i=1}^m \frac{V_{IP}}{V_i} \tag{22}$$

Where error rate ‘ER’ is measured based on the number of incorrect parking availability predictions ‘V_{IP}’ with total number of vehicles ‘V_i’. It is measured in percentage (%).

Route detection time: it defines as amount of time taken for optimal route recognition for normal traffic is dissimilar as of heavy traffic. It is mathematically expressed as given below.

$$RDT = \sum_{i=1}^m V_i * Time (OR) \tag{23}$$

Where, ‘RDT’ denotes a route detection time and the time consumed in attaining optimal routes ‘Time (OR)’, It is calculated in milliseconds (ms).

Sensitivity: It defines to potentiality of ITS-basis of intelligent transportation to car parking availably and optimal routes are correctly identified for the vehicles. The sensitivity rate is mathematically formulated as given below.

$$Sen = \frac{TP}{TP+FN} \tag{24}$$

Where, ‘Sen’ denotes a sensitivity ‘is calculated depend on number of true positives ‘TP’ as well as number of false negatives ‘FN’ respectively. Here TP rate mention to car parking availably and optimal routes are correctly identified for the vehicles whereas false negative rate refers to the car parking availably and optimal routes are incorrectly identified for the vehicles.

Specificity: it is calculated depend on number of true negative as well as number of false positives. It is expressed as below.

$$Spe = \frac{TN}{TN+FP} \tag{25}$$

Where, specificity ‘Spe’, is calculated based on true negative ‘TN’ and false positive ‘FP’. Here, TN refers to car parking availably and optimal routes for the vehicles properly recognized as best whereas FP rate indicate to car parking availably and optimal routes are incorrectly identified for the vehicles. shown in Table 1.

Table 1 Comparisons of accuracy

Number of Vehicles	Accuracy (%)			
	CRFORIELM	Faster R-CNN	GRU-LSTM	DQN-based algorithm
4500	99.22	97.66	98.22	98.86
9000	99	97.22	98	98.33
13500	98.51	96.66	97.65	97.92
18000	98.5	95.55	97.15	97.77
22500	98	95.11	97	97.33
27000	97.77	95	96.44	97.037
31500	97.14	94.76	96.14	96.34
36000	96.94	94.30	96	96.25
40500	96.81	94.18	95.64	96.18
45000	96.71	94	95.14	95.77

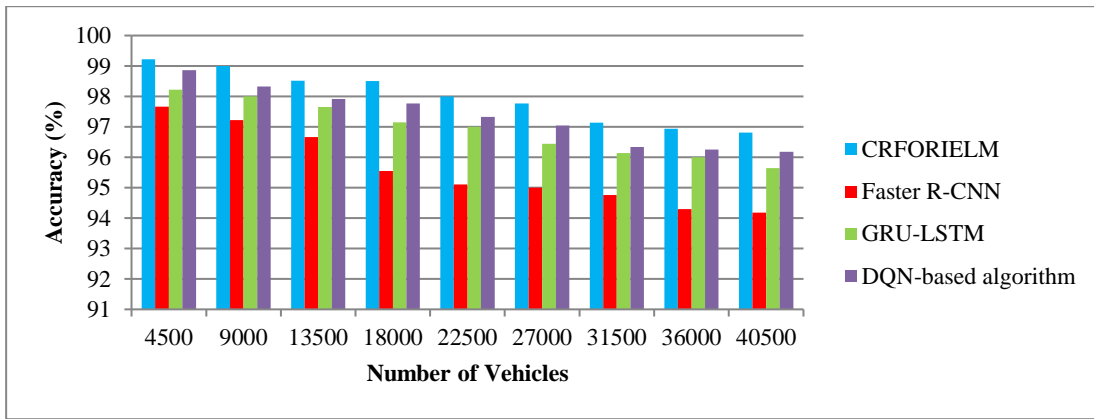


Figure 4 graphical representation of accuracy

Figure 4 depicts a graphical illustration of accuracy versus the number of vehicles, ranging from 4500 to 40500. The results graphically illustrate that the proposed CRFORIELM technique attains higher accuracy compared to existing methods [1], [2], and [3]. For each method, ten different results were observed with varying numbers of vehicles. The observed outcomes demonstrate that the CRFORIELM technique outperforms other deep learning methods. The overall accuracy performance using the CRFORIELM method is enhanced by 3%, 1%, and 1% than the [1], [2], [3]. This enhancement achieved through the application of robust outlier incremental extreme learning machines for analyzing smart car parking using Cox regression based on the capacity of parking slot and occupancy level of parking slot. Based on this analysis, parking slot OPEN and FULL are correctly predicted with higher accuracy.

Table 2 Comparisons of error rate

Number of Vehicles	Error rate (%)			
	CRFORIELM	Faster R-CNN	GRU-LSTM	DQN-based algorithm
4500	0.77	2.33	1.77	1.13
9000	1	2.77	2	1.66
13500	1.48	3.33	2.35	2.07
18000	1.5	4.44	2.85	2.22
22500	2	4.88	3	2.66
27000	2.22	5	3.55	2.96
31500	2.85	5.23	3.85	3.65
36000	3.05	5.69	4	3.75
40500	3.18	5.81	4.35	3.81
45000	3.284	6	4.85	4.22

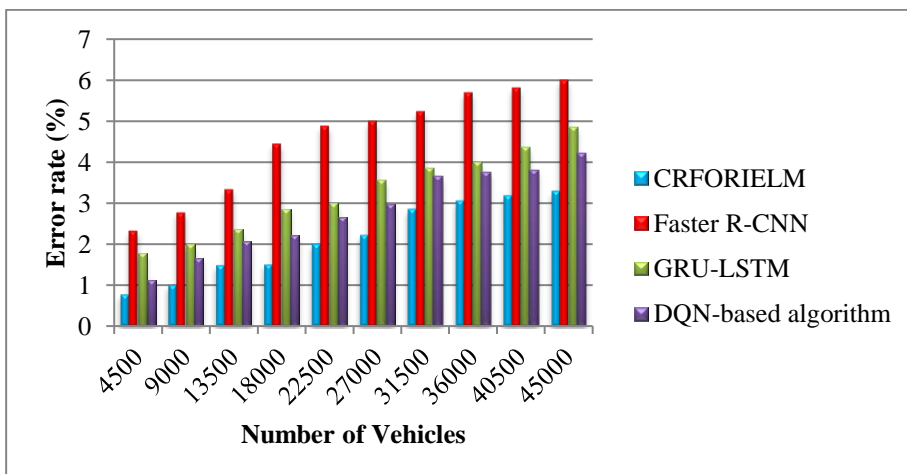


Figure 5 graphical representation of error rate

Figure 5 depicts a graphical depiction of the error rate in smart parking versus the number of vehicles, ranging from 4500 to 40500. The results graphically illustrate that the proposed CRFORIELM technique achieves a lower error rate compared to existing methods [1], [2], and [3]. For each method, ten different results were observed with varying numbers of vehicles. The observed results demonstrate that the CRFORIELM technique outperforms other methods. The overall error rate performance using the CRFORIELM technique is reduced by 55%, 37%, and 26% when compared to [1], [2], [3] respectively. This improvement is achieved by incorporating an outlier robust function into the incremental extreme learning machines. This function reduces deviation among predictable as well as actual outcomes through regularization parameter for analyzing smart car parking shown in Table 2.

Table 3 Comparisons of route detection time

Number of Vehicles	Route detection time (ms)			
	CRFORIELM	Faster R-CNN	GRU-LSTM	DQN-based algorithm
4500	148.5	247.5	202.5	175.5
9000	155.22	285.35	235.2	193.2
13500	175.32	315.55	285.65	212.3
18000	186.23	385.35	310.25	256.3
22500	205.22	435.15	398.45	296.58
27000	236.52	485.25	425.22	318.52
31500	255.22	545.55	496.36	385.62
36000	305.2	625.35	545.65	412.25
40500	425.25	685.55	612.02	536.52
45000	521.2	735.35	685.65	612.37

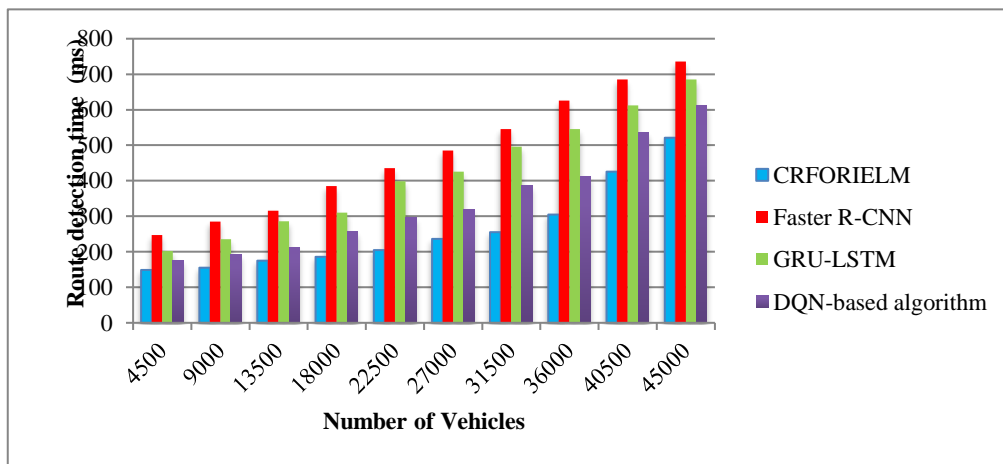


Figure 6 graphical representation of Route detection time

Figure 6 above depicts the Route detection time using four different methods. The figure illustrates a direct proportion between number of vehicles included in experiments as well as route detection time. In other words, the overall time consumption enhances through an enhances in number of vehicles. However, a CRFORIELM technique minimizes route detection time when compared to conventional techniques. Overall result specifies which the route detection time of CRFORIELM techniques is significantly reduced by 46%, 38%, and 23% than the conventional techniques. This reduction is attained to fact that CRFORIELM techniques perform traffic prediction by applying a triangular fuzzy membership function to an outlier-robust incremental extreme learning machine and classify it into low, normal, or high traffic. Finally, if the traffic is predicted as high, the algorithm determines the shortest optimal route with minimal distance near the parking place using the taxicab distance measure shown in Table 3. This minimizes the time taken for detecting the route between the starting point of the vehicle and the destination.

V. CONCLUSION

The ITS leverages advanced technologies to address challenges associated with urbanization, population growth, and increasing traffic congestion. This paper proposes an IoT based CRFORIELM technique for smart vehicle parking and the detection of traffic-aware route optimization with higher accuracy and minimal time consumption. The CRFORIELM technique collects parking information at different locations and time intervals. First, parking availability prediction is performed to reduce traffic levels, minimizing the prediction error rate. Following this, a fuzzy triangulation membership function is applied in the outlier-robust incremental extreme learning machine to predict traffic levels and optimize the routes with higher accuracy. Quantitative performance results indicate that the presented CRFORIELM technique has achieved 2% improvement in accuracy of smart parking availability prediction. There is also a notable reduction in error rates and optimal route detection times by 39% and 36%, respectively. Additionally, sensitivity and specificity have improved by 5% and 10%, respectively, when compared to existing methods. This work can be further enhanced by incorporating a cryptographic technique to increase the reliability of data transmission in the IoT-aware Intelligent Transportation System. Incorporating these cryptographic measures into the IoT-aware ITS for smart parking enhances the overall security of data transmission, mitigates the risk of unauthorized access, and ensures the reliability and trustworthiness of the information exchanged within the system.

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