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Time Aware Long Short-Term Memory and Kronecker Gated Intelligent Transportation for Smart Car Parking

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ABSTRACT

Technology desires to improve quality of life and impart citizen's health as well as happiness. The concept of Internet of Things (IoT) refers to smart world where prevailing objects are said to be embedded and hence interact with each other (i.e., between objects and human beings) to achieve an objective. In the period of IoT as well as smart city, there is requirement for Intelligent Transport System-based (ITS) ingenious smart parking or car parking space prediction (CPSP) for more feasible cities. With the increase in population and mushroom growth in vehicles are bringing about several distinct economic as well as environmental issues. One of pivotal ones is optimal parking space identification. To address on this problem, in this work, Time-aware Long Short-Term Memory and Kronecker product Gated Recurrent Unit (TLSTM-KGRU) for smart parking in internet of transportation things is proposed. The TLSTM-KGRU method is split into two sections. In the first section, smart parking occupancy is derived using Time-aware Long Short-Term Memory (Time-aware LSTM) for Kuala Lumpur Convention Centre car parking sensor dataset. Following which the resultant smart car occupancy results are subjected to Linear Interpolations and Kronecker product Gated Recurrent Unit for predicting smart parking. When compared against other predictive methods such as SGRU-LSTM and CPSP using DELM, our experimental outcomes denote that TLSTM-KGRU method has improved performance for smart parking occupancy forecast as it not only enhances sensitivity and specificity but also reduces prediction time with minimum delay.

1. Introduction

Through growing economic evolution as well as urbanization, car ownerships are emerging swiftly that aggravates the disparity among parking supply and demand. The majority cities are encountering proceedings associated with the inadequacy of parking places and hence car parking has demanding issue as far as urban areas globally are concerned. As a result, drivers shell out long time penetrating for parking space that not surges time and consumption of fuel but also results in traffic congestion. Hence, it is a crucial practical distress for the Intelligent Transportation System (ITS).

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A novel hybrid method which stacks Gated Recurrent Unit (GRU) and LSTM was presented in Zeng *et al.,* [1]. Designed method integrated the LSTM's accuracy whereas the GRU's prediction effectiveness as well as occupancy, weather conditions prevailing as certain measures for predicting availability of parking in an accurate and timely manner.

Despite prediction accuracy achieved, however, due to the absence of considering additional influencing factors like, traffic condition (i.e., velocity, acceleration and orientation) a significant amount of delay was said to occur while prediction. To address on this issue, multivariate factors (i.e., velocity, acceleration and orientation) were considered as influencing characteristics to further improving the sensitivity with minimum end-to-end delay. Also, by employing partial derivative vanishing gradient is also addressed therefore improving the sensitivity so as to additionally corroborate the accountability of the model.

A Car Parking Space Prediction (CPSP) using Deep Extreme Learning Machine (DELM) (CPSP using DELM) was proposed in Siddiqui *et al.,* [2] with the purpose of not only decreasing the turbulence but also focus on the accuracy aspects. Here, sensors were positioned in distinct parking areas to acquire information pertaining to both unoccupied and occupied space employing neural network model, therefore ensuring high precision rate in a significant manner.

Though the method was proved to be better in terms of precision, the prediction time factor was not analysed. To focus on this issue, Kronecker product Gated Recurrent Unit is designed that with the aid of Kronecker product obtains the interpolated function results in case of change in car occupancy between week-days and week-ends (i.e., considering date into account). With this the specificity rate along with the error rate is reduced to a greater extent.

Increased numbers of cars result in larger parking lots that in turn increase the endeavour to arrange smart parking management systems. By designing efficient management of smart parking ensures in smooth and robust optimization hence improving the effectiveness and other several quality elements.

Empirical path loss model was designed in Olasupo *et al.,* [3] for smart car parking. By using this path loss model resulted in the improvement of intelligent transportation. However, identifying and comprehending all targets under differing driving conditions is said to be critical. To address on this issue, a convention convolutional neural network method was employed in classifying different traffic signs was proposed in [4]. Also, different weather conditions were also involved for providing advanced driving assistance mechanism. However, accuracy factor is also said to be influenced by certain other features like, data type, size of sample and prediction time. In order to design a method by taking into the above said considerations, a correlation between prediction accuracy using deep learning and the features that control was designed in Varghese *et al.,* [5]. An elaborate literature review was also discussed.

Contemporary communication model like, IoT , cellular networks produce an enormous as well as heterogeneous traffic data. In such heterogeneous networks, conventional network management methods for data analysis as well as monitoring are said to be challenging. In addition, the network traffic sample is said to show high complicated behaviour owing to several features like, high mobility in devices and heterogonous network. A survey of deep learning techniques for smart car parking was investigated in Abbasi *et al.,* [6]. Also, a review of neural network methods for smart parking was designed in Shaik *et al.,* [7].

A track record involving both spatial and temporal smart parking occupancy is both laborious and cumbersome to optimize parking resources and to design efficient parking strategies. Those types of data are frequently acquired by means of sophisticated and costly habitation monitoring mechanisms.

In Assemi *et al.,* [8], a metaheuristic optimization method combining photograph of bay-level parking occupancy through transactions from traditional parking payment management model. Finally, resultant data were integrated therefore reducing both the error rate with improved best occupancy estimation. Through increase in the population and frequency of vehicles has resulted in distinct economic and environmental issues. Amongst them one of the major issue remains in identifying a parking space. In [9], Automated Valet Parking employing hybrid robotic valets was proposed.

A method, called, TLSTM-KGRU for smart parking in IoT is proposed. Major objective is to enhance sensitivity, specificity in delay effective and lesser error rate. Numerous works have developed using machine learning and optimization techniques for smart car parking. In contrast, TLSTM-KGRU method merges smart car parking occupancy and accurate smart parking. First delay minimized smart parking occupancy is modelled by means of Time-aware Long Short Term Memory model. Followed by Linear Interpolations and Kronecker product Gated Recurrent Unit-based Smart Parking predictions applied to the smart car parking occupancy results for classification between three distinct types of parking spot availability with minimum error rate and end-to-end delay.

1.1 Contributing Remarks

To overcome the issues from the above state-of-the-art works, TLSTM-KGRU technique is developed through new contributions as listed as follows:

i. To ensure error minimized and delay minimized routing for smart car parking, TLSTM-KGRU method is introduced by exploiting two different processes namely, smart parking occupancy and actual smart parking.
ii. To acquire smart parking occupancy with end-to-end delay and sensitivity cases, Time-aware Long Short-Term Memory is applied based on differential equation in nonlinear formulate and by using partial derivative function for each sample towards efficient determination of smart parking occupancy with minimum end-to-end delay.
iii. Linear Interpolations and Kronecker product Gated Recurrent Unit-based is then applied for optimized smart parking prediction and assigning parking lot based on date and time factors accordingly to the request made by the vehicle sample, therefore reducing the error rate with improved specificity.
iv. Immense experiments are structured to measure performance of TLSTM-KGRU method and conventional methods. Outcomes attained shows that, TLSTM-KGRU method achieved gives enhanced performance in sensitivity, specificity, end-to-end delay and error rate.

1.2 Structure of Manuscript

Remainder of manuscript is structured as below: Section 2 introduces related works concerning smart parking by using optimization and machine learning techniques [21]. Section 3 describes the dataset description and proposes TLSTM-KGRU method for performing accurate and delay minimized smart car parking. The experimental results and performance study of algorithm are given in Section 5. Section 6 summarize the manuscript.

2. Literature Review

Vehicle parking around regions of public interest is customary worldwide issue as well as it aggravates with small number of accessible unfilled parking spaces for several vehicles. Moreover, accessibility of parking spaces differs in both spatial and temporal aspects. The influences of web of things as well as artificial intelligence in smart parking were presented in Provoost *et al.,* [10]. Moreover, neural network and random forest were employed for predicting accurate park occupancy.

Nevertheless, providing short term parking occupancy prediction would ensure the driver in making apt and accurate decisions. Hence short-term prediction methods with low data volume were proposed in Paidi *et al.,* [11]. Intelligent control system based on edge computing was designed in Ming *et al.,* [12]. A convolutional neural network for autonomous vehicle using fuzzy control algorithm was designed, therefore ensuring accuracy.

Mobility is one of the considerable issues as far as modern and contemporary cities are concerned. Moreover, delays as well as other issues concerning transport loss percentage is also said to be in the increasing line. As a result, parking location prediction is hence considered as a major issue in our daily life. A deep Q network was applied in Park *et al.,* [13] as a traffic signal optimization method for ensuring precise parking. A survey of Italian case employing machine learning technique for predicting electric car parking was investigated in Dhanaraj *et al.,* [14].

As a distributed learning method, the objective of federated learning remains in training an already shared learning method over dispersed information as maintain training data. Application of federated learning was broadened for smart parking Huang *et al.,* [15] wherein the parking lot promoter cooperated in training LSTM for evaluating the parking space with no interchanging actual data. Yet another method using kalman filters was applied in Bock *et al.,* [16] for analysing parking space availability. Here by integrating the frequencies probability of misreading was reduced therefore minimizing the error rate in a significant manner.

Motor vehicles are transposing plan people reside, however positioning an enormous burden as far as urbanization is concerned. Most of the major metropolitan cities are facing with the issue of car parking. Improper car parking management has profound effects on the entire city traffic pattern. With the purpose of enhancing the management effectiveness of the car parking, an intelligent parking management system employing Advanced RISC machine and ZigBee was constructed in Xiang *et al.,* [17]. With this type of design resulted in the improvement of car parking and subsequently the entire traffic pattern also.

The information recommendation arrangement for smart car parking nowadays in both large and medium sized parking spaces is not effective in this day and age. It gravitates to be laborious and cumbersome in identifying a vacant parking space in metropolitan cities Ng *et al.,* [22]. One of the issues remains in the evaluation of enormous amount of estimation employing traditional Dijkstra algorithm.

Enhanced Dijkstra optimization algorithm was designed in Liu *et al.,* [18] with the purpose of identifying the best parking path for identifying adjacent vacant parking space on the basis of the blueprint pattern. With this type of design resulted in the optimal parking route and subsequently resulted in the enhancement of overall efficiency. A novel and intelligent convolutional neural network for intelligent smart parking was designed in Alsheikhy *et al.,* [19]. However, the error rate was not focused. To concentrate on this issue, a recommender system was modelled in Saleem *et al.,* [20].

The methods and techniques recommended above either considered vacant parking space reservation or their proposed method were executed without taking into consideration the error rate involved in designing or are specifically concentrated on accuracy of prevailing smart parking system. However, the sensitivity and specificity of the method was not taken for analysis. In this paper, to enhance sensitivity and specificity of smart parking as well as allocate the requested vehicle with minimum delay and error a method called, TLSTM-KGRU is proposed.

3. Methodology

Owing to enhance in number of vehicles and unavailability of adequate quantity of parking slots in wide-reaching metropolitan areas, the end-to-end delay, error rate in addition to the cost to search for parking slots are in increasing numbers. This in turn is said to even escalate the overall traffic density. Moreover, with the communication being modelled IoT-based, i.e., Internet of Transportation things in our work, by employing TLSTM-KGRU method available parking slot can be viewed by the vehicle users and coerce their plan of actions smart parking in internet of transportation things.

3.1 Dataset Description

The dataset used in our work is the KLCC (i.e., Kuala Lumpur Convention Centre) car park sensor datasets. This dataset consists of the data pertaining to car park occupancy based on date and time. The dataset contains four features listed as given below.

Table 1
KLCC Parking Occupancy 2016 dataset

S. No	Features ‘$\boldsymbol{F}$’	Description
1	KLCC label ‘$KLCC$’	Kuala Lumpur Convention Centre label
2	Parking spot availability ‘PS_{avail}’	The availability of parking spot is made based on three types, numeric values, OPEN in case of data being read or FULL denoting no parking availability
3	Date ‘D’	Data when the parking spot availability was queried
4	Time ‘T’	Time on which the parking spot availability was queried

With the above features and corresponding record values subjected to the samples used for simulation, a smart parking in internet of transportation things is designed in the following sections.

3.2 Car Parking System Model

We utilize the car park system network (CPSN) architecture with the features ‘F’ and samples ‘S’ obtained from the raw dataset ‘DS’, stored via input matrix ‘IM’ as given below.

$$IM = \begin{bmatrix} S_1F_1 & S_1F_2 & .. & S_1F_n \\ S_2F_1 & S_2F_2 & .. & S_2F_n \\ .. & .. & .. & .. \\ S_mF_1 & S_mF_2 & .. & S_mF_n \end{bmatrix} \tag{1}$$

The CPSN is constructed in such a manner so as to obtain the car park sensor data that constitute as the infrastructure for the corresponding sensors. Let us further assume that each car park is a vehicle in a CPSN. The CPSN arrangement is shown in Figure 1 where each car park slots‘PS’ is classified and designated with total parking plots ‘N_j’ accordingly.

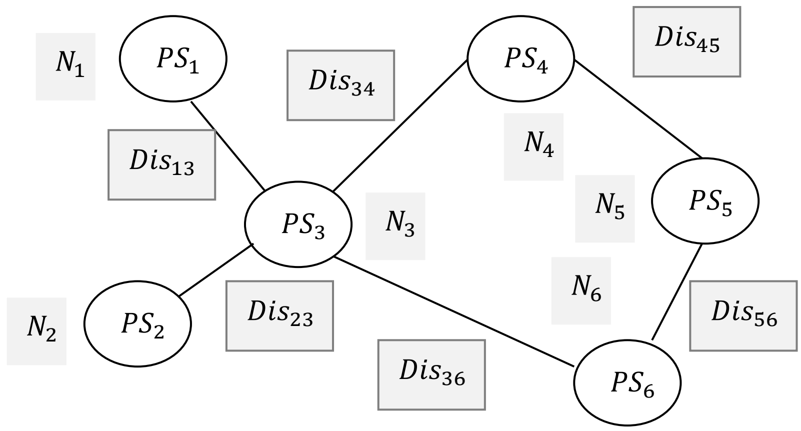

Fig. 1. Structure of car park system network

From the above figure 'PS_1', 'PS_2', 'PS_3', 'PS_4', 'PS_5' and 'PS_6' refers to the car parking slots with total car parking spaces represented by 'N_1', 'N_2', 'N_3', 'N_4', 'N_5' and 'N_6' respectively. Moreover, 'Dis_{36}', represent distance between car parking slot 'PS_3' and 'PS_6' respectively. With the above structure of car park system network, in this work a method called, TLSTM-KGRU for smart parking in internet of transportation things is proposed. The description of TLSTM-KGRU method is elaborated in the following sections.

3.3 Time-Aware LSTM for Smart Parking Occupancy

Constrained on the street parking accessibility and its related traffic congestion have become one of the crucial subjects of intelligent transportation systems. Also, during peak hours, meandering for smart car parking is a frequent situation in areas with impenetrable travel demand. In addition, well-grounded sources for smart parking occupancy are still in short of as far as urban areas are concerned. Due to this result, the effectiveness of users search for penetrating is heavily split the difference owing to the absence of information.

In this section, Time-aware LSTM model is designed on the basis of time series with the purpose of classifying, processing and making predictions accordingly on the basis of unspecified time delays between significant events (i.e., car parking).

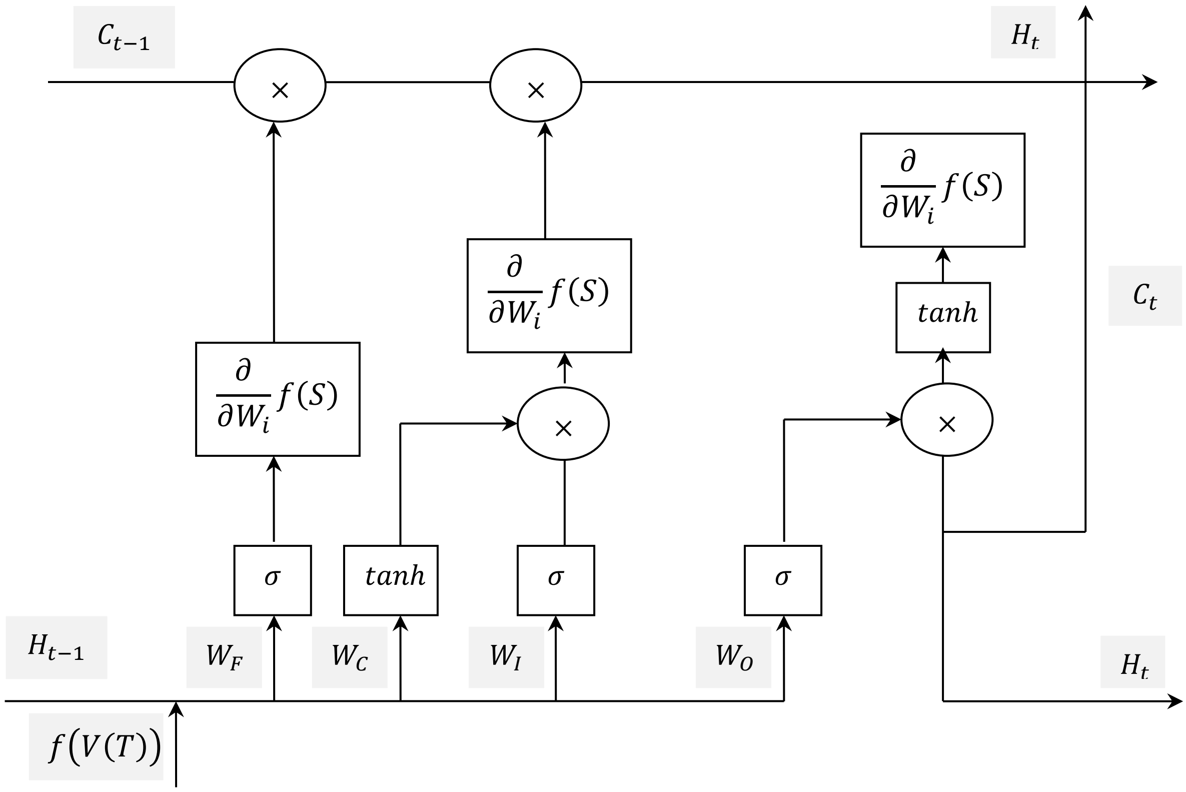

Fig. 2. Structure of Time-aware Long Short-Term Memory

As illustrated in the above figure, to represent the vehicle parking space prediction, initially, a set of differential equations are constructed in a nonlinear formulate as given below.

$$V' = f\big(V(T)\big) + IM(T) \tag{2}$$

$$V(T) = \big[V_x(T), V_y(T), Vel(T), Acc(T), \theta(T), \varphi(T)\big]^T \tag{3}$$

From Eq. (2) and Eq. (3), 'T' represents the time instance variable, '$V(T)$' denotes the state variable consisting of the focal position of the vehicle '$V_x(T), V_y(T)$', velocity '$Vel(T)$', acceleration '$Acc(T)$', orientation '$\theta(T)$' and angular moment '$\varphi(T)$' of the vehicle respectively. In a similar manner nonlinear formulate '$f\big(V(T)\big)$' is mathematically stated as given below.

$$f\big(V(T)\big) = \begin{bmatrix} Vel(T)\cos\big(\theta(T)\big) \\ Vel(T)\sin\big(\theta(T)\big) \\ Acc(T) \\ 0 \\ Vel(T)\frac{\tan(\varphi(T))}{Dis} \\ 0 \end{bmatrix} \tag{4}$$

From the above nonlinear function 'f' as given in Eq. (4) formulates for each vehicle 'V' at time instance 'T' is modeled based on the distance 'Dis' between the vehicles and the corresponding periodic phenomenon '$\cos\big(\theta(T)\big)$' and '$\sin\big(\theta(T)\big)$' is arrived at according to the velocity '$Vel(T)$'

respectively. With the above time-aware factor, an LSTM is designed and according to the result, this information is sent to the requested vehicle by gateway devices located on the road side.

In LSTM, three gates are present, ingress gate that administers input flow activations to memory (i.e., current input '$f(V(T))_t$', previous output 'H_{t-1}' and previous cell status 'C_{t-1}'), egress gate that administers output flow (i.e., current output 'H_t' and current cell status 'C_t') and finally the forget gate that filters by retaining essential parking information and eliminates inessential parking information. In addition to the above three gates, a cell state is present that contains information pertaining to cell update.

$$F_t = \sigma\left(W_F\left[H_{t-1}, f\big(V(T)\big)_t\right] + B_F\right) \tag{5}$$

$$I_t = \sigma\left(W_I\left[H_{t-1}, f\big(V(T)\big)_t\right] + B_I\right) \tag{6}$$

$$C_t' = \tanh\left(W_C\left[H_{t-1}, f\big(V(T)\big)_t\right] + B_C\right) \tag{7}$$

$$C_t = F_t * C_{t-1} + f\big(V(T)\big)_t * C_t' \tag{8}$$

$$O_t = \sigma\left(W_O\left[H_{t-1}, f\big(V(T)\big)_t\right] + B_O\right) \tag{9}$$

$$H_t = O_t * \tanh(C_t) \tag{10}$$

From Eq. (5) to Eq. (9), 'F_t', 'I_t', 'C_t'' refers to the forget gate activation vector, input gate activation vector and cell input activation vector for particular time slot 'T'. In a similar manner, 'C_t', 'O_t' and 'H_t' denotes the cell state, output state and hidden state respectively. Finally, 'W_F, W_I, W_C, W_O' and 'B_F, B_I, B_C, B_O' represents the weight matrices as well as bias vector that require to be learned through training by addressing vanishing gradient using partial derivative. Here to address vanishing gradient, during iteration's the weight is updated by the error function with respect to the current weight and corresponding samples by means of partial derivative function. This partial derivative function is mathematically stated as given below.

$$\frac{\partial}{\partial W_i} f(S) = \lim_{h \to 0} \frac{f(S_1, S_2, \ldots, S_m + h) - f(S_1, S_2, \ldots, S_m)}{h} \tag{11}$$

In this manner, the gradient issue is addressed via partial derivative function as given in Eq. (11), where the gradient value will not be negligible because of fine tuning of the weight for each set of samples 'S'. Finally, the smart parking or parking slot is represented as follows.

$$H_{t_{ij}} = H_{t_{ij}}(\alpha, \beta) = \alpha * \frac{Dis_{ij}}{Dis_{UB}} + \beta * \frac{N_j}{N_{UB}} \tag{12}$$

$$H_{t_{ij}} = \begin{cases} 0, Parking\ slot\ is\ FULL \\ 1, Parking\ slot\ is\ OPEN \end{cases} \tag{13}$$

From Eq. (12) and Eq. (13) results, either the requested parking slot for each sample is declared as full or declared as open and allocated with the requested space. The pseudo code representation of Time-aware LSTM is given below.

Algorithm 1: Time-aware Long Short-Term Memory-based smart parking occupancy
Input: Dataset 'DS', Features '$F = \{F_1, F_2, \ldots, F_n\}$', Samples '$S = \{S_1, S_2, \ldots, S_m\}$'
Output: delay minimized smart parking occupancy
1: **Initialize** '$m = 40000$', '$n = 4$', 'PS'
2: **Begin**
3: **For** each dataset 'DS' with Features 'F', Samples 'S' and parking slot 'PS'
4: Formulate input matrix 'IM' as given in Eq. (1)
5: Construct differential equations in nonlinear formulate as given in Eq. (2) and Eq. (3)
6: Formulate forget gate as given in Eq. (5)
7: Formulate input gate as given in Eq. (6)
8: Formulate cell state as given in Eq. (7) and Eq. (8)
9: Formulate output gate as given in Eq. (9) and Eq. (10)
10: Construct partial derivative function for each sample as given in Eq. (11)
11: Finalize parking slot as given in Eq. (12) and Eq. (13)
12: **If** '$H_{t_{ij}} = 0$'
13: **Then** parking slot is full
14: Proceed with other samples
15: **End if**
16: **If** '$H_{t_{ij}} = 1$'
17: **Then** parking slot is open
18: Parking slot '$PS - 1$'
19: **End if**
20: **End for**
21: **End**

As given in the above algorithm with the objective of improving the sensitivity rate at the cost of minimum end-to-end delay, multivariate factors like, velocity of the vehicle, acceleration of the vehicle and orientation of vehicle were taken into consideration while detecting vehicles for smart parking. Following which the differential equations were applied separately in a nonlinear format so that the end-to-end delay involved in detecting presence or absence of vehicles during smart parking. Next, vanishing gradient involved in fine tuning weights while designing prediction for smart parking slot was made by means of partial derivative that in turn improved the overall sensitivity rate.

3.4 Linear Interpolations and Kronecker Product Gated Recurrent Unit-Based Smart Parking Prediction

Over the past few years, researchers have identified that exogenous variables and gating mechanism may make the most of the pertinence of other data sources, i.e., any information related to seasonal changes, in certain date and time, for making precise predictions more accurately with minimum error rate. Date and time may influence non-recurrent parking demand. In this work, we obtain the date reports from the raw dataset via KLCC Parking Occupancy 2016 and utilize linear interpolations to predict car parking slot in an accurate manner. In the input space, for making an accurate decision, exogenous information is a vector of binary values of the following features: i.e., date and time.

We use linear interpolations to envision the associations between date and parking arrival rate on each car parking area. To evaluate the impact of date factor on parking demand, linear interpolations employing Kronecker product Gated Recurrent Unit are utilized to envision the discrepancies between distributions of parking occupancies on week-days and week-ends, therefore in tune reducing the error rate in a significant manner. Figure 3 shows the structure of Linear Interpolations and Kronecker product Gated Recurrent Unit model.

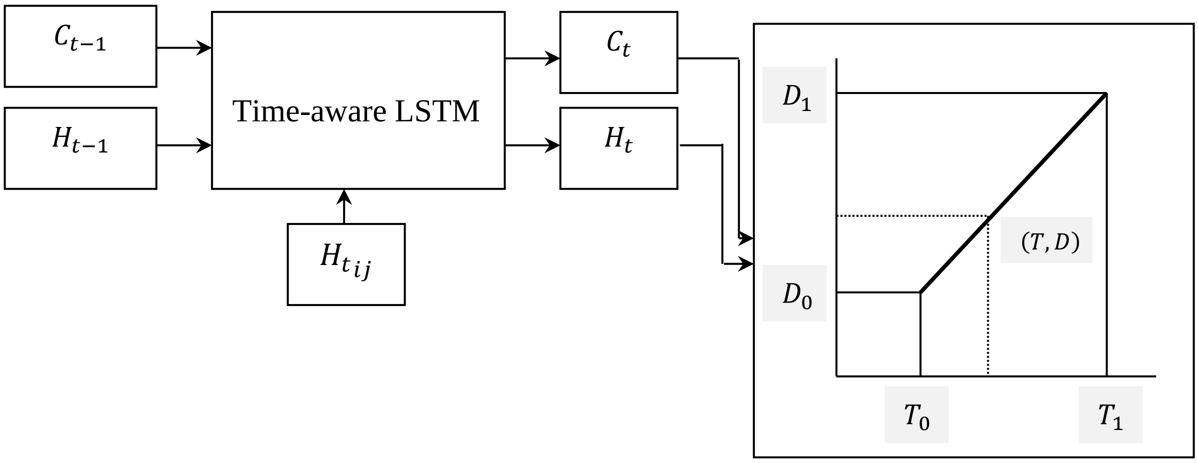

Fig. 3. Structure of Linear Interpolations and Kronecker product Gated Recurrent Unit model

As shown in the above figure to make smart parking in case of seasonal changes with respect to date and time, in our work, we consider configuring the recurrent matrix '$H_{t_{ij}}$' as a Kronecker product of 'Z' matrices '$K_0, K_1, \ldots, K_{Z-1}$'.

$$K = H_{t_{ij}}[K_0 \otimes K_1 \otimes K_2 \otimes \ldots . \otimes K_{Z-1} = \otimes_{z=0}^{Z-1} K_z] \quad (14)$$

From Eq. (14), each '$K_z \in PS^{U_z * V_z}$', and '$\pi_{z=0}^{Z-1} U_z = \pi_{z=0}^{Z-1} V_z = N$' and '$K_z's$' are referred to as Kronecker factors implying linear interpolations between the smart parking occupancy and accurate smart parking respectively. Following which the linear interpolation function between date and time is formulated as given below. With the two features, date and time given by the coordinates '(D_0, D_1)' and '(T_0, T_1)' then the linear interpolant refers to the straight line between these two features. The linear interpolation function from slope equation is formulated as given below.

$$\frac{D-D_0}{T-T_0} = \frac{D_1-D_0}{T_1-T_0} \quad (15)$$

From Eq. (15) by solving the equation for 'D' which is the unknown value at 'T' is mathematically represented as given below.

$$D = D_0 + (T - T_0)\frac{D_1-D_0}{T_1-T_0} \quad (16)$$

$$= \frac{D_0(T_1-T_0)}{T_1-T_0} + \frac{D_1(T_1-T_0)-D_0(T_1-T_0)}{T_1-T_0} \quad (17)$$

$$\frac{D_0(T_1-T)+D_1(T-T_0)}{T_1-T_0} \quad (18)$$

From Eq. (16) to Eq. (18), the results for linear interpolation reflecting seasonal changes in the interval (i.e., certain date and time), accurate and smart parking slot is ensured by sending this information to the requested vehicle by the gateway devices located on the road side. The pseudo code representation of Linear Interpolations and Kronecker product Gated Recurrent Unit is given below.

Algorithm 2: Linear Interpolations and Kronecker product Gated Recurrent Unit
Input: Dataset 'DS', Features '$F = \{F_1, F_2, \ldots, F_n\}$', Samples '$S = \{S_1, S_2, \ldots, S_m\}$'
Output: accurate smart parking
1: **Initialize**'$m = 40000$', '$n = 4$', 'PS', parking slot results '$H_{t_{ij}}$'
2: **Begin**
3: **For** each dataset 'DS' with Features 'F', Samples 'S', available parking slot 'PS' and parking slot results '$H_{t_{ij}}$'
4: Formulate Kronecker product for recurrent matrix '$H_{t_{ij}}$' as given in Eq. (15)
5: Formulate linear interpolation reflecting seasonal changes in the interval (i.e., certain date and time) as given in Eq. (16) to Eq. (18)
6: Send the information to requested vehicle
7: **End for**
8: **End**

As given in the above algorithm of improving specificity rate with lesser time consumed for smart car parking Linear Interpolation function and Kronecker product is applied to the requested sample vehicle exploiting the parking slot results. First, with the requested sample vehicle and parking slot results as input, two unique features, i.e., date and time are taken into consideration for obtaining interpolant results with which reflection between parking occupancy between week-day and week-end can be arrived at. With these objective linear interpolations between date and time are made. Next, Kronecker product is applied via Gated Recurrent Unit and the corresponding information is provided to the requested vehicle, therefore minimizing the overall error rate in a significant manner.

4. Simulation Setup

Experimental conditions of TLSTM-KGRU for smart parking in internet of transportation things are arranged with an Inter® Core (TM) i5-7200U with CPU capacity of 2.50GHz possessing 8GB Random Access Memory through Graphics Processing Unit of NVIDIA GeForce 94MX.

This work employs four distinct performance indices end-to-end delay, sensitivity, error rate as well as specificity to estimate intelligent traffic control scheme towards optimal smart parking and comparative performance. An elaborative and fair comparison is made in Python using KLCC car park sensor datasets with the existing Stacked Gated Recurrent Unit and Long Short-Term Memory (SGRU-LSTM) [1] and Car Parking Space Prediction (CPSP) using Deep Extreme Learning Machine (DELM) (CPSP using DELM) [2] methods.

5. Discussion

5.1 Case 1: End-to-End Delay Analysis

The influence of end-to-end delay is measured based on performance of TLSTM-KGRU technique for smart car parking with increasing sample vehicle size. Proportionate amount of delay is happened while identifying parking slots. This is owing to the reason that while identifying parking slots by the server, different numbers of requests for empty car parking slots are made by each vehicle and only the slots identified with empty parking occupancy has recognized for further processing. Because of this small amount of delay is said to occur between request and response. It is formulated as below

$$E2E\ Delay = \sum_{i=1}^{m} V_i * Time\ \left(H_{t_{ij}}\right) \tag{19}$$

From Eq. (19), end-to-end delay '$E2E\ Delay$' refers to time utilized in detecting the presence or absence of vehicles '$Time\ \left(H_{t_{ij}}\right)$' during smart parking occupancy. Table 2 demonstrate values of end-to-end delay obtained for each of TLSTM-KGRU, GRU-LSTM [1] and CPSP using DELM [2].

Table 2
Comparisons of end-to-end delay

Vehicles	End-to-end delay (ms)		
	TLSTM-KGRU	GRU-LSTM	CPSP using DELM
4500	157.5	216	247.5
9000	165.35	225	255.15
13500	185.25	235.35	285.55
18000	235.55	315.55	385.35
22500	285.15	385.55	435.55
27000	315.35	425.55	500.35
31500	355.55	455.85	585.15
36000	425.15	515.35	635.35
40500	485.35	585.25	685.25
45000	525.55	634.55	735.55

Figure 4 given below depicts graphical plot of end-to-end delay study for 45000 different vehicles or samples involved in car parking occupancy based on date and time. To validate the results and make elaborate comparison with existing methods, GRU-LSTM [1] and CPSP using DELM [2] KLCC car parking occupancy dataset was considered and simulations were performed for 10 dissimilar runs. From Figure 4, blue line denotes proposed TLSTM-KGRU method, red line indicates GRU-LSTM [1] whereas green line points out the CPSP using DELM [2] method. An increase in delay were observed using all the three methods because with the increase in the requests made for parking slots availability heavy congestion is said to occur globally. While performing simulations with 4500 vehicles, delay of 157.5ms, 216ms and 247.5ms were observed using TLSTM-KGRU [1,2] respectively. From the simulation results it is inferred that end-to-end delay incurred using TLSTM-KGRU method was smaller than [1,2]. Reason behind reduction of end-to-end delay by TLSTM-KGRU method was owing to application of Time-aware Long Short-Term Memory algorithm. Through this algorithm different factor like, vehicle velocity, vehicle acceleration and vehicle orientation were considered while detecting vehicles for smart parking. Accordingly, differential equations were applied to different factors separately in a nonlinear format that in turn reduced end-to-end delay by TLSTM-KGRU technique by 23% and 35% than the [1,2].

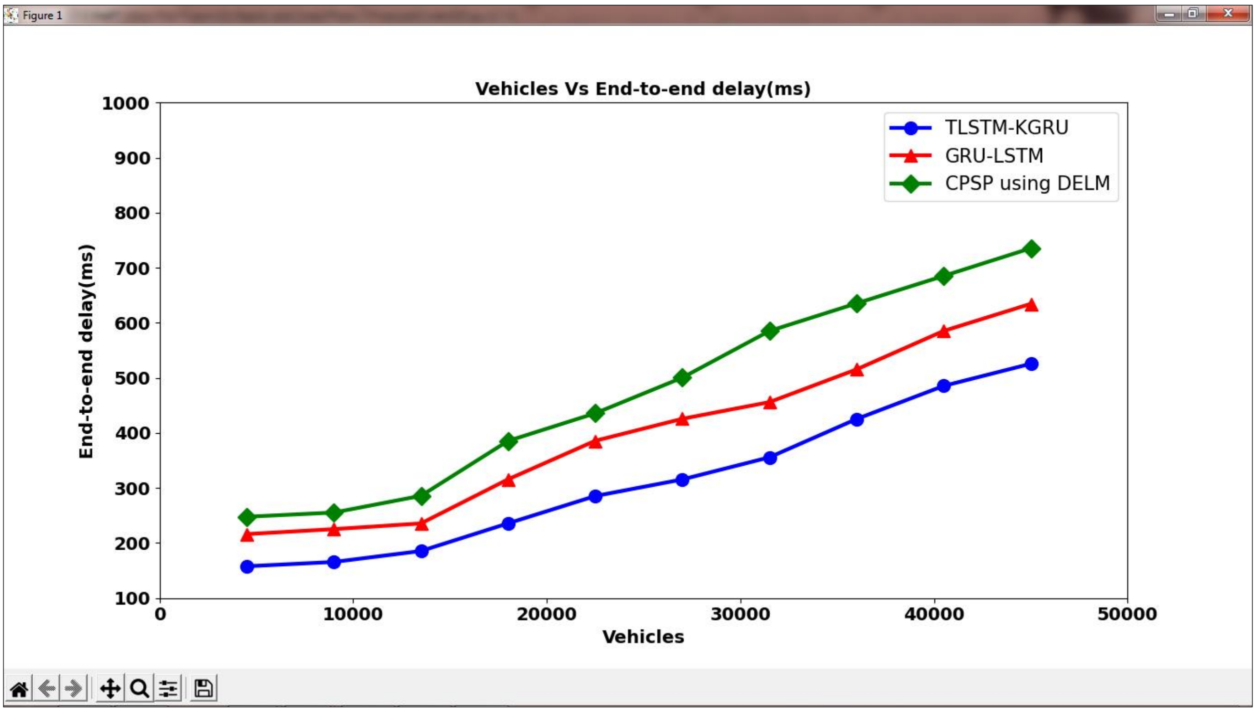

Fig. 4. Performance analysis of end-to-end delay

5.2 Case 2: Sensitivity Analysis

In this section the analysis of sensitivity as well as specificity are made. Sensitivity or true positive rate defined to probability conditioned on individual sample vehicle being correctly parked according to the availability whereas specificity or true negative rate defined to probability conditioned on the individual sample vehicle being incorrectly parked. The smart car parking test that reliably detects the presence of either FULL/OPEN condition, resulting in high true positives and low false negatives is referred to as the high sensitivity. On the other hand, the smart that reliably excludes individual sample vehicles that do not have the condition of either car parking test FULL or OPEN resulting in a high true negatives and low false positives is referred to as high specificity.

$$Sen = \frac{TP}{TP+FN} \tag{20}$$

$$Spe = \frac{TN}{TN+FP} \tag{21}$$

From Eq. (20) and Eq. (21) sensitivity 'Sen' and specificity 'Spe' rates are arrived at depend on true positive rate 'TP' (i.e., car occupancy with FULL correctly identified as FULL) false negative rate 'FN' (i.e., car occupancy with OPEN incorrectly identified as FULL), true negative rate 'TN' (i.e., car occupancy with OPEN incorrectly identified as OPEN) and false positive rate 'FP' (i.e., car occupancy with OPEN incorrectly identified as FULL) respectively. Table 3 given below lists the results of sensitivity and specificity using the proposed TLSTM-KGRU and existing methods [1,2].

Table 3
Comparisons of sensitivity and specificity

Vehicles	Sensitivity			Specificity		
	TLSTM-GRU	GRU-STM	CPSP using DELM	TLSTM-GRU	GRU-LSTM	CPSP using DELM
4500	0.98	0.95	0.92	0.98	0.97	0.96
9000	0.96	0.92	0.85	0.95	0.93	0.9
13500	0.95	0.91	0.83	0.93	0.9	0.87
18000	0.94	0.9	0.8	0.91	0.85	0.83
22500	0.93	0.89	0.78	0.89	0.81	0.78
27000	0.92	0.88	0.76	0.86	0.77	0.75
31500	0.9	0.84	0.73	0.83	0.73	0.7
36000	0.88	0.83	0.7	0.81	0.71	0.65
40500	0.88	0.8	0.68	0.78	0.65	0.63
45000	0.86	0.78	0.65	0.75	0.63	0.6

As given in the above table results, with sensitivity and specificity considered as the pivotal performance parameter to determine the car parking occupancy based on date and time, results are validated for 45000 sample vehicles. To be more specific, higher sensitivity and specificity infers how well a method identifies true positive and true negative cases. On the basis of this comparison with TLSTM-KGRU, GRU-LSTM [1] and CPSP using DELM [2] in Table 3, outcome of sensitivity and specificity is shown. To more precise when number of sample vehicle is 4500, dissimilarities or the true negative and false negative between different methods are limited. With increase in the number of sample vehicle nodes, dissimilarities between these methods becomes more distinguished that infer which TLSTM-KGRU method perform enhanced than [1,2], both in terms of sensitivity and specificity. The reason behind the improvement is due to the weight update performed in the proposed method via partial derivative function. By applying this partial derivative function, vanishing gradient that occurs during parking occupancy rate between week-day and week-end based on fine tuning of weight. By applying this partial derivative function for each sample car parking occupancy was initially obtained in a delay reduced manner. As outcome, the sensitivity rate with TLSTM-KGRU method was observed to be enhanced by 6% and 20% than the [2]. In a similar manner, the specificity rate using TLSTM-KGRU method was observed to be better 10% compared to [1] and 14% compared to [2].

5.3 Case 3: Error Rate Analysis

In this section the analysis of error rate or rate of error involved in smart parking is provided. A small portion of error is said to occur while detecting or identifying smart parking. The error rate is measured as given below.

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

From Eq. (22), error rate 'ER' is measured based on the number of incorrect predictions made or vehicles incorrectly predicted 'V_{IP}' with respect to the total number of predictions or vehicles involved in simulation process 'V_i'. It is measured in terms of percentage (%). Table 4 given below lists the results of error using the proposed TLSTM-KGRU and existing methods [1,2].

Table 4
Comparisons of error rate

Vehicles	Error rate (%)		
	TLSTM-KGRU	GRU-LSTM	CPSP using DELM
4500	1.44	1.77	2.22
9000	1.75	2	2.85
13500	2	2.35	3
18000	2.35	2.85	3.55
22500	2.55	3	3.85
27000	2.85	3.55	4
31500	3	3.85	4.35
36000	3.35	4	4.85
40500	3.55	4.35	5
45000	4	4.85	5.35

Figure 5 given below shows the error rate involved in analysing the car parking occupancy rate between week-day and week-end. An overall of 10 iterations were performed for an average of 45000 sample vehicles acquired to different date and time. Lower the error rate more efficient the method is said to be. In other words, lowering the number of incorrect predictions made or vehicles incorrectly predicted lower the error rate and vice versa. Simulations performed with 4500 sample vehicles observed error rate of 1.44% using TLSTM-KGRU, 1.77% using [1] and 2.22% using [2]. With this simulation results the TLSTM-KGRU method showed lower error rate upon comparison to [1,2]. As a result, the overall error rate observed for obtaining parking occupancy between week-day and week-end were found to be comparatively lower when applied with TLSTM-KGRU method upon comparison to [1,2]. The reason behind the error minimization using TLSTM-KGRU method was owing to the application of Linear Interpolations and Kronecker product Gated Recurrent Unit-based Smart Parking prediction algorithm. By applying this algorithm, first linear interpolation results were obtained between date and time. Following which the recurrent matrix as a Kronecker product were applied subject to the two features date and time therefore making accurate and smart parking slot by sending information to requested vehicle located on the road side. This in turn reduced the error rate using TLSTM-KGRU method by 17% compared to [1] and 32% compared to [2].

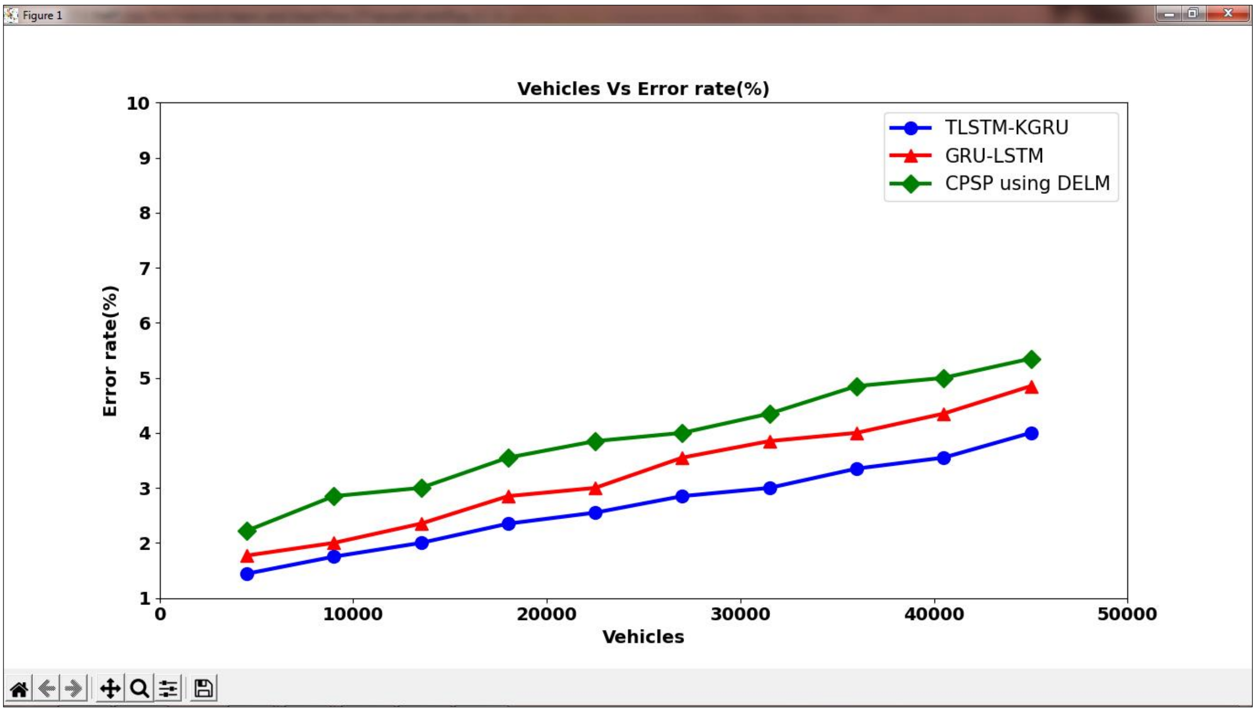

Fig. 5. Performance analysis of error rate

6. Conclusion

Deep learning techniques make over eminent outcomes in predicting parking space occupancy. In this work, novel TLSTM-KGRU is introduced for predicting parking space occupancy. First, for identifying smart parking occupancy in this work Time-aware Long Short-Term Memory which models multivariate factors like, vehicle velocity, vehicle acceleration and large data sets approximately consistent was used. Next, to make smart parking prediction, linear interpolations employing Kronecker product Gated Recurrent Unit in case of seasonal changes with respect to date and time via recurrent matrix was designed for accurate smart parking. For the purpose of exemplifying the efficiency of the method, models were constructed in distinct performance metrics and compared with SGRU-LSTM and CPSP using DELM methods. This outcome exhibits which the architecture and application designed yielded successful results in terms of sensitivity, specificity with minimum $E2E\ Delay$, error rate.

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