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IoT Based Smart Parking System Using Deep Long Short Memory Network

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Received: 12 September 2020; Accepted: 13 October 2020; Published: 15 October 2020

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Abstract: Traffic congestion is one of the most notable urban transport problems, as it causes high energy consumption and air pollution. Unavailability of free parking spaces is one of the major reasons for traffic jams. Congestion and parking are interrelated because searching for a free parking spot creates additional delays and increase local circulation. In the center of large cities, 10% of the traffic circulation is due to cruising, as drivers nearly spend 20 min searching for free parking space. Therefore, it is necessary to develop a parking space availability prediction system that can inform the drivers in advance about the location-wise, day-wise, and hour-wise occupancy of parking lots. In this paper, we proposed a framework based on a deep long short term memory network to predict the availability of parking space with the integration of Internet of Things (IoT), cloud technology, and sensor networks. We use the Birmingham parking sensors dataset to evaluate the performance of deep long short term memory networks. Three types of experiments are performed to predict the availability of free parking space which is based on location, days of a week, and working hours of a day. The experimental results show that the proposed model outperforms the state-of-the-art prediction models.

Keywords: internet of things; deep long short term memory (LSTM); car parking; smart city; smart parking; deep learning

1. Introduction

The world population is frequently migrating from rural to urban areas, increasing the population density of large cities than ever before. According to the United Nations Population Division, two-thirds of the world's population is expected to live in cities by 2050. On a practical level, the global urban infrastructure required to advance technology to meet the smart city's demands. In this regard, the advancement in sensors technology and sensors networks technology presents anew governance model to build, deploy, and promote sustainable development systems to address escalating urbanization challenges [1–4]. Sustainable Urban Mobility and reducing traffic congestion are some of the most critical challenges of urban development especially in case of limited availability of parking space [5,6].

With the growth of technology, the concept of the Internet of Things (IoT) and deep learning can be used in the planning of Smart cities which can gradually tackle urban mobility problems and can also help to provide a sustainable infrastructure economically, ecologically, and socially to the citizens [1]. At present, many intelligent systems mostly in the form of mobile applications help drivers by reporting traffic jams, road conditions, accidents, and alternative routes. However, due to a large number of vehicles active on roads, parking is still a tedious task. As indicated by [7], drivers waste liters of gas simply trying to find parking. Normally, 30% of traffic congestion is caused while searching for an available parking space. As conferred in [5], on average drivers waste 3.5 to 14 min to find a free parking spot. Besides, it also causes driver frustration, traffic congestion, fuel consumption, and air pollution, and all these factors act as challenges for sustainable development. In this specific circumstance, knowing ahead of time about the available parking spots can mitigate this issue. The use of deep learning techniques with the integration of IoT can ameliorate this problem by predicting the parking occupancy and availability with great precision.

Different techniques have been proposed by various researchers for different types of data collected in the literature to solve this problem. In existing works mostly researchers used machine learning techniques and time-series models to calculate the occupancy of parking places and time duration from the data collected from sensors. Due to the continuous increase in sensor data, the traditional decision support systems cannot provide the performance like the deep neural networks, because deep neural networks can estimate any non-linear and linear functions with copious samples. Relatively, the traditional decision support systems require the selection of the right features or kernel. Subsequently, deep learning techniques can be utilized for the prediction of occupancy, especially for feed-forward networks. Nevertheless, any simple deep feed-forward networks cannot integrate temporal domain information, which is essential for parking prediction especially in case of duration problems [2,8].

A recurrent neural network (RNN) [9] is a type of neural network that utilizes the sequential nature of its input. RNN is generally applied to many time-dependent tasks such as text prediction, point of sale tagging, and electricity consumption. All of these problems have time-dependent input. That is, the estimation of an event relies upon the events which show up previously. Parking occupancy and duration of occupancy both are time-series problems [5,8]. The occurrence of every parking event is highly dependent on the time of the day, the end time of the last event [10] and crowed sensing [11,12]. Hence, RNN can be used for the prediction of the occupancy of parking space and time duration.

In this paper, we propose a framework that aims to predict the availability of parking for the given city parking. Our proposed system uses a deep long short term memory (DLSTM) network [13], a deep learning model, and also integrates the data gathered from different sources of information through the internet of things. To train our model, the main dataset we used is the Birmingham Parking dataset. To validate our model, different performance evaluation techniques were used to estimate the availability of parking space at a given time at parking slot. The proposed smart parking systems will save the searching time to locate a free parking space. It helps to save energy consumption by reducing the searching time of free parking space availability. It also reduces traffic congestion by efficiently providing the information about the availability of parking space. The day-wise, parking lot, and hour-wise prediction of parking space availability will facilitate the drivers to schedule their drive while considering the availability of parking slots at a particular parking location on a certain day and specific time.

Rest of the article is organized as follows: Section 2 describes the existing work on sensor networks, internet of things and its applications in smart cities and smart parking management systems using machine learning techniques. Section 3 contains the detailed description of the smart parking system architecture, proposed DLSTM model, and data collection and performance evaluation techniques. Section 4 represents the experimental results with respect to location, day, and time. Finally, Sections 5 and 6 present the discussion, concluding remarks, and future directions respectively.

2. Literature Review

Recent developments in sensor devices, communication technology, ubiquitous computing, artificial intelligence, and wireless sensor network (WSN) gained momentum to the adoption of IoT based applications [14,15]. Internet of things combined with cloud computing and big data analytics is speeding up the advancement of solutions to monitor the mobility of traffic in smart cities [16,17]. Numerous solutions have been developed aimed at finding the availability of parking spaces to increase the quality of life in overpopulated cities [18,19]. In essence, the smart car parking systems deliver information to drivers about the availability of free parking lots while considering the distance and number of free spaces.

Deep learning methods have brought innovative advancements in monitoring the mobility of vehicles in smart cities. Paidi et al. [20] presented a comprehensive survey on the applicability of sensors, technologies, and techniques for predicting the availability of parking space in open parking lots. The authors suggested that the combination of deep learning and computer vision-based techniques are suitable for locating the availability of free parking spaces. Cai et al. [21] proposed a deep learning technique with a novel vehicle filter for real-time measurement of parking lots. The authors demonstrated that the proposed system achieved significant accuracy as compared to the industry benchmark system with low cost and scalability. Vu and Huang [22] introduced a combination of deep contrastive network and spatial transform to infer the availability of free parking space. The proposed technique was robust to the effects of spatial variations, parking displacements, variations in car sizes, occlusion, and distortion. Zhang et al. [23] developed a deep learning-based self-parking system. The proposed system first marks the parking points in the image then classify those points as free or occupied slots. The authors also developed a parking slot detection image database. The database contains 12,165 images of indoor and outdoor parking slots. Bock et al. [24] investigated the applicability of taxi fleets to detect the availability of on-street parking. The authors detected the free parking spots by analyzing the taxi transit frequencies, and parking spaces availability information obtained from vehicles equipped with global positioning system (GPS) sensors. Tekouabou et al. [25] proposed the combination of IoT and ensemble techniques to predict the availability of free parking spots in the smart city. Then evaluated the performance of the proposed system on the Birmingham parking dataset, and achieved 94% prediction accuracy with the bagging ensemble technique.

In this work, our objective is to develop an IoT based decision support system to predict the real-time availability of car parking spaces. We developed an RNN approach to predict the real-time availability of parking slots at a given time. We used the long short term memory (LSTM) model, as it proves to be the best RNN architecture to solve time series data problems. The proposed model predicts the availability of free parking slots at each parking location individually to give a better insight into the drivers to choose their route and destination. Most recent works related to the prediction model used in this research are presented in [26,27]. In [27], Jingyuet. al. developed LSTM and gated recurrent unit (GRU) models to predict the availability of free parking slots. The authors demonstrated that the GRU model performed better than the LSTM model. Similarly, Yang et al. [26] adopted the combination of graph convolutional neural network and RNN based model to predict the real-time occupancy of parking slots. Graph neural network was developed to extract the spatial information of traffic flow and RNN was developed to extract the temporal information of traffic flow. It is demonstrated that the proposed model performed better than state-of-the-art parking availability prediction models.

Moreover, a comprehensive review of existing techniques is presented in Table 1 to demonstrate the advantages and disadvantages of state-of-the-art techniques.

Table 1. Comprehensive of existing techniques used for smart parking occupancy prediction.

Reference	Method	Pros	Cons
[21]	Mask Region-based Convolutional Neural Network (Mask-RCNN)	This method achieved significant accuracy as compared to the benchmark system with low cost and scalability	It is found that a straight forward application of Mask-RCNN resulted in a noisy measurement of lot utilization
[22]	Contrastive Feature Extraction Network (CFEN)	CFEN overcomes the perspective distortion problem	In this model due to cluttered and distributed featuresthe learned network is over-fitted
[23]	Deep Convolutional Neural Networks (DeepPS)	DeepPS is very fast and can process one frame within 23ms because it is written in C++	DeepPS is not work perfectly when the imaging conditions are poor
[24]	SFpark project	This system works as significant alternate to the expensive deployment of static parking sensors	This system suffered from the problem of mismatches in parking availability from crowd sensing with varying fleets sizes
[25]	Ensemble based model	This model improved the results as well as reducing system complexity	In this model the algorithm works like nearest neighbor that is a lazy technique, used non parametric method to solve regression problem
[27]	Wavelet Neural Network model	This model gives very high accuracy	In this model it is also found that it is easy to fall into the local excellent and slow training due to gradient descent method used for parameters optimization

3. Methodology

In this paper, the sensors based smart car parking availability prediction architecture is proposed. To develop the car parking prediction system, we have adopted the architecture of the smart car parking system presented in [21]. It gathers the car parking data through a variety of parking sensor networks deployed at various car parking locations. Aggregated sensors networks dataset from different locations on a cloud, then applied deep learning techniques to analyze this data to locate the availability of free parking spaces on various car parking locations. Intending to predict the availability of free parking space through sensors network, we explore the various transportation management services in a smart city e.g., parking management service, parking location service, parking supervision service, vehicle tracking service, and vehicle registration service. After gathering the data from these services, we developed the deep learning-based decision support system to monitor the real-time car parking locations as illustrated in Figure 1.

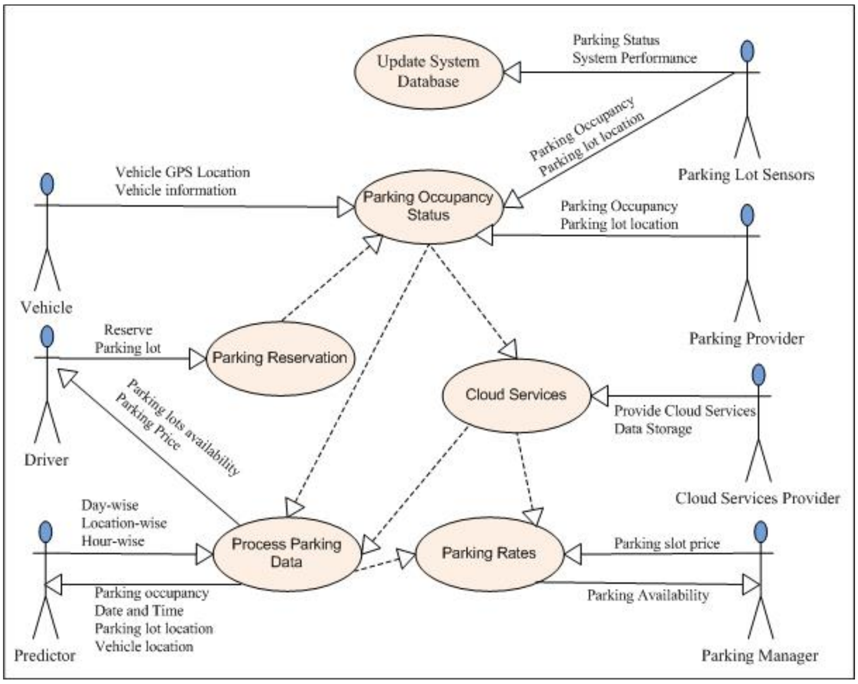


Figure 1. Internet of Things (IoT) based smart parking system use case diagram.

The architecture of the proposed IoT based smart parking system is illustrated in Figure 2. It has four layers: sensors layer, communication layer, processing layer, and services layer. The sensors layer collects information about vehicle movement from different parking locations through various types of sensors. Then this information is passed to cloud service via sensor networks on the communication layer. The long range wide area network (LoRaWAN) protocol was used to transmit data from sensors to gateway. LoRaWAN is energy efficient and long range protocol that can easily transmit data from the entire parking lot.

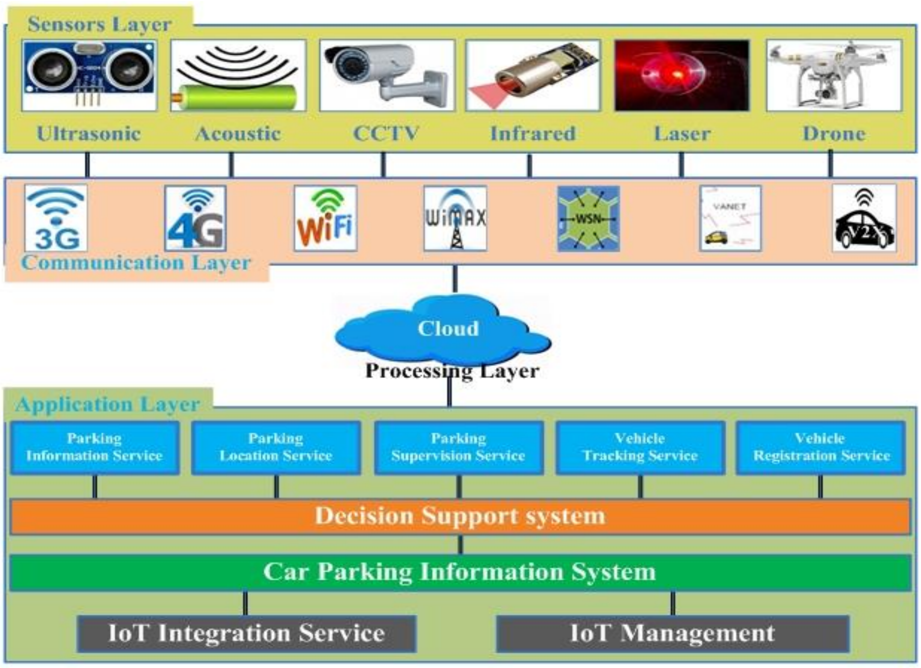


Figure 2. Sensors Network-based decision support system for car parking availability prediction.

After that, the gateway transmits the information from parking lots through Message Queuing Telemetry Transport (MQTT) protocol to cloud and database server. The processing layer stores and analyzes a huge amount of data that comes from the communication layer. It provides various services to lower layers with the help of different technologies such as cloud computing, databases, and big data processing. The processing layer is connected to a set of vehicle management and parking management services. These services are managed with the help of a decision support system, which takes decisions about the management of different parking and vehicle management services. The decision support system a deep learning approach that is connected to the car parking information system which provides information about the availability of free parking space at different locations. The car parking information system is connected to various end user devices, such as dashboards, and mobile devices through HTTP protocol. A similar IoT based architecture is presented in [28].

3.1. Car Parking Information System

The car parking information system (CPIS) informs the drivers about the availability of parking slots on different parking locations. The availability of parking slots is a highly time-dependent problem. The sequential nature of the information regarding parking slots occupancy and duration of occupancy required to be analyzed using time series analysis techniques. In this regard, we applied RNN to exploit the sequential nature of car parking data. The CPIS highly depends on the performance of the decision support system to provide accurate information about the availability of parking slots to the drives as presented in Figure 3. Figure 3 demonstrates that data is being collected through different sensors from various parking lots then this data is transmitted through the communication layer to the processing layer where data is stored for processing purposes. From the processing layer the stored data of various parking lots is fetched by the decision support system in response to a query invoked by a car driver who wants to know the availability of a free parking slots at different parking locations either at a specific parking lot or at a specific day or on a particular time period. The fetched data is processed by a deep learning-based decision support system to predict the availability of free parking slot well before time. The output of the decision support system is passed to the CPIS to inform the driver about the availability of parking slots on a parking location on the given day in a specific hour.

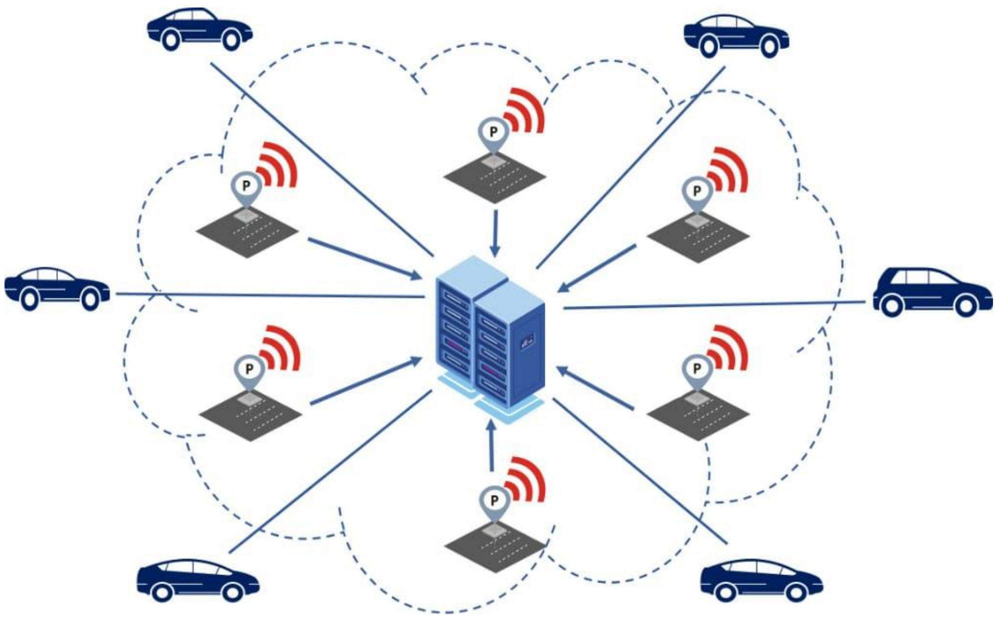


Figure 3. Smart car parking information system.

3.2. Decision Support System

The proposed decision support system for parking space availability prediction takes the sensors data as input and predicts the availability of parking slots on various parking locations at a given time. After obtaining the sensors' data we applied a deep recurrent neural network to predict the availability of parking slots. The RNN is naturally suitable to predict the time-dependent events. Car parking availability prediction is a time-dependent problem and can be considered as a dynamic prediction problem. In this research, we applied the DLSTM to predict the availability of parking space. LSTM is a special type of RNN that can efficiently predict the long term dependencies. The architecture of the LSTM cell is presented in Figure 4.

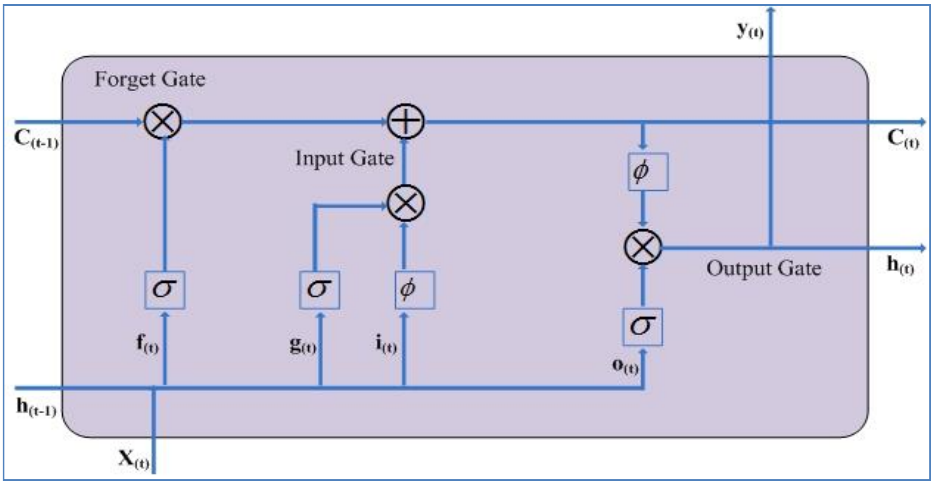


Figure 4. Long short term memory (LSTM) architecture.

Figure 4 illustrates that long term state $C_{(t)}$ is introduced along with short term state $h_{(t)}$. Three gates (input gate, output gate, and forget gate) are introduced to control the flow of input to the cell. The forget gate combines the current input $X_{(t)}$ and previous short term state $h_{(t-1)}$. The computation of $f_{(t)}$ and $y_{(t)}$ is defined as expressed as:

$$f_{(t)} = \sigma(W_{xf^T} x_{(t)} + W_{hf^T} h_{(t-1)} + b_f) \quad (1)$$

$$y_{(t)} = \phi(W_{x^T} x_{(t)} + W_y y_{(t-1)} + b) \quad (2)$$

The symbol σ represents the sigmoid function and ϕ represents the activation function. The input gate determines the value of outgoing long term state $C_{(t)}$, and output gate $O_{(t)}$ determines the configuration of the outgoing short term state $h_{(t)}$. Whereas, $f_{(t)}$ denotes the forget gate and $g_{(t)}$ is a layer that behaves similarly as in recurrent network. In Figure 4 it can be noticed that long term, short term states, and cell output are computed through element-wise multiplication denoted by $\otimes$. Specifically, the current long term state $C_{(t)}$ is determined by adding the values governed by forget gate and input gate denoted by $\oplus$. The current long term state $C_{(t)}$ and output $y_{(t)}$ was determined as:

$$c_{(t)} = f_{(t)} \otimes C_{(t)} + i_{(t-1)} + i_{(t)} \otimes g_{(t)} \quad (3)$$

$$y_{(t)} = h_{(t)} = o_{(t)} \otimes \phi C_{(t)} \quad (4)$$

In DLSTM multiple LSTM layers are stacked vertically; the output of each LSTM cell is passed to form the input sequence of the next layer and to the connections in the same layer. As the input passes through one layer to other layers, each progressive layer represents the input in a new dimensional space. Thus, adding more layers enables the network to learn the new relations between input and output on different dimensions. Hence, in this research, a deep LSTM is developed for car parking availability prediction. The architecture of deep LSTM is presented in Figure 5. Figure 5 illustrates that the outputs of an LSTM cell are passed to both the next layer LSTM cell in the same position and the next LSTM cell in the same layer.

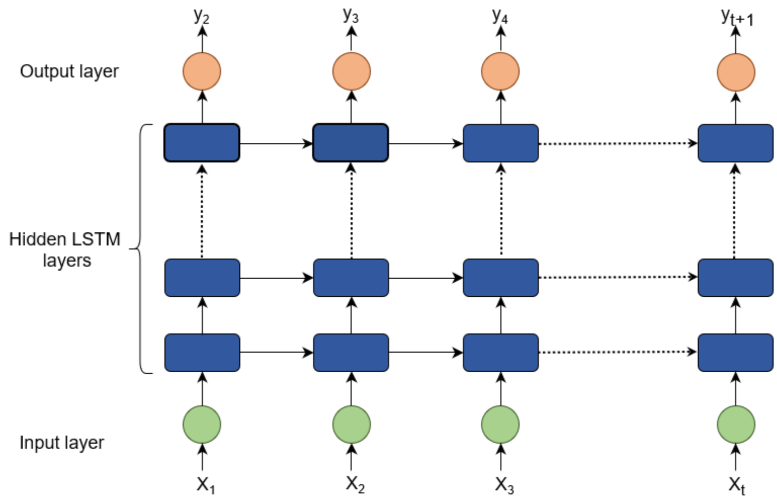


Figure 5. Deep LSTM architecture.

In the Figure 5, each rectangular box is used to show the LSTM cell. The input passes to the network architecture and each layer produced information according to the given input. Thus, adding more numbers of the layer increases the chances of finding a connection between input and output to due proper learning at different levels. So, in this research paper, a deep LSTM is constructed. It is the specific type of neural network that uses previous output as input while also having hidden states. The output at each layer passes through both adjacent LSTM cell and to the next above layer as shown in Figure 5.

3.3. Performance Evaluation Techniuqes

To evaluate the performance of deep LSTM network we used the root mean square error (RMSE), mean absolute error (MAE), mean squared error (MSE), median absolute error (MdAE), and mean squared log error (MSLE). The mathematical formulation of these performance evaluation techniques is defined as:

$$\text{RMSE} = \sqrt{1/n} \sum_{i=1}^{n} (y_i - \hat{y_i})^2 \tag{5}$$

$$\text{MAE} = 1/n \sum_{i=1}^{n} |y_i - \hat{y_i}| \tag{6}$$

$$\text{MSE} = 1/n \sum_{i=1}^{n} (y_i - \hat{y_i})^2 \tag{7}$$

$$\text{MdAE} = \text{median}\left(\sum_{i=1}^{n} |y_i - \hat{y_i}| \right) \tag{8}$$

$$\text{MSLE} = 1/n \sum_{i=1}^{n} \left(\log((y_i) + 1) - \log((\hat{y_i}) + 1) \right)^2 \tag{9}$$

The symbol yi is the actual avail parking space that is computed by taking the difference in occupancy and capacity values. Whereas,$\hat{y}i$ is the predicted available parking space, predicted by deep LSTM network. The difference between actual available parking space and predicted parking space is computed by $yi - \hat{y}i$. The experimental results achieved using a deep LSTM network.

3.4. Dataset

The dataset which we have used for the training and testing of deep LSTM network was collected from 30 parking locations in Birmingham city. The total area of 30 parking locations can accommodate 39,956 vehicles. The detailed description of the car occupancy sensors dataset is presented in Table 2.

Table 2. Features in Birmingham car park dataset.

Features	Descriptions
SystemCodeNumber	A variable that Identifies car park id
Capacity	Variable that contain the capabilities of park
Occupancy	The variable that contains occupancy of park
LastUpdated	Variable that have Date and Time of the measure

3.5. Data Processing

The dataset used for testing purpose contains four attributes: "SystemCodeNumber", "Capacity", "Occupancy", and "LastUpdated". The attribute "Capacity" provides the information about the total capacity of a parking location, "Occupancy" provides the information about the number of occupied parking space at a given time, and "LastUpdate" contains the date and time information of the occupied parking spaces at a certain parking location. In order to apply the regression model to predict the availability of free parking lots at given time on a specific day at a particular parking location we derived a new attribute called "free parking space". The value of "free parking space" attribute was computed by taking the difference of "Capacity" and "Occupancy" attributes. This free parking space attribute was used as a target variable in the deep learning based regression model.

3.6. Ethics

There are many advantages of monitoring the occupancy of parking lots, movement of vehicles and humans. On the other hand, it would create safety and ethical concerns if the information of vehicle movement and parking lots is insecure. The smart car paring system contains even more ethical constraints as it provides detailed information about the movement of vehicles in a building or parking lot. The movements of vehicles are always being known to the application. However, this type of application would be a big concern when used to monitor the parking lots of critical nature, workplaces, and residences. Along with the technological developments for smart parking management system, we will incorporate these safety and ethical issues and try to take appropriate measurements to address these issues.

4. Results

The performance of the proposed deep LSTM network-based decision support system was evaluated on the available sensors dataset [29]. Three different experiments have been performed which are parking location wise, day wise and hour wise. In the parking location wise experiments, the system predicts the availability of free parking space at different parking lots in a given time. In the day wise experiments, the system predicts the parking lots occupancy on seven days from Friday to Thursday. Finally, it predicts the hourly parking lots occupancy from 08:00 a.m. to 05:00 p.m. We have used 70% data for deep LSTM network training and the remaining 30% for testing purposes. Then 20% out of the training set is used for validation and the remaining used for the training purpose. The experiments are performed on the whole dataset as well as on each parking lot individually. The results achieved using all samples demonstrate the overall availability of parking space in the whole city. Whereas, the experiments performed using samples of individual parking locations demonstrate the availability of parking space at a specific parking lot at a given time. In other words, the overall results provide a general overview of parking space availability, and the parking location-wise results provide information about the availability of parking space at a specific parking lot. For the experimental purpose, we implemented the algorithms using the most famous deep learning framework Keras. We applied a deep LSTM network to predict the availability of car parking slots at a specific location, at a given time and on a specific day.

4.1. Parking Location Wise Parking Space Occupancy

Table 1 demonstrates the experimental results on the overall dataset and 30 parking lots individually. It illustrates the performance of proposed deep LSTM with performance evaluation measures: RMSE, MAE, MSE, MdAE, and MSLE. The overall performance of deep LSTM is 0.068, 0.0411, 0.0046, 0.028, and 0.002 with RMSE, MAE, MSE, MdAE, and MSLE, respectively. From these results we can analyze that prediction accuracy of the proposed decision support system is 93.2%, 95.9%, 99.6%, 97.2%, and 99.8% respectively with five measures. The values presented in Table 3 demonstrate the reliability of the proposed decision support system. In general, from all performance measurement parameters, the minimum prediction accuracy is 93.2% (RMSE) and the maximum prediction accuracy is 99.8% (MSLE).

Table 3. Results of deep LSTM for parking availability prediction against each parking location separately.

Parks ID	RMSE	MAE	MSE	MdAE	MSLE
Broad Street	0.117	0.059	0.014	0.022	0.007
Others-CCCPS98	0.078	0.042	0.006	0.027	0.003
BHMBCCMKT01	0.089	0.047	0.008	0.032	0.005
BHMEURBRD01	0.119	0.059	0.014	0.026	0.007
Others-CCCPS135a	0.106	0.062	0.011	0.035	0.005
BHMMBMMBX01	0.113	0.065	0.013	0.043	0.006
Others-CCCPS105a	0.105	0.056	0.011	0.037	0.006
Others-CCCPS202	0.123	0.062	0.015	0.029	0.007
Shopping	0.113	0.067	0.013	0.040	0.006
BHMNCPNST01	0.077	0.042	0.006	0.026	0.003
BHMNCPHST01	0.118	0.066	0.014	0.039	0.007
Others-CCCPS8	0.098	0.051	0.010	0.032	0.005
BHMBCCTHL01	0.138	0.069	0.019	0.031	0.007
Others-CCCPS119a	0.060	0.029	0.004	0.016	0.002
BHMBCCSNH01	0.106	0.064	0.011	0.039	0.005
BHMNCPLDH01	0.099	0.062	0.010	0.038	0.005
BHMNCPPLS01	0.084	0.046	0.007	0.030	0.004
BHMBCCPST01	0.110	0.054	0.012	0.028	0.006
BHMEURBRD02	0.120	0.061	0.014	0.023	0.006
NIA Car Parks	0.048	0.025	0.002	0.014	0.002
NIA South	0.059	0.029	0.004	0.015	0.002
Bull Ring	0.148	0.080	0.022	0.053	0.012
BHMBRCBRG03	0.100	0.053	0.010	0.034	0.006
BHMBRCBRG01	0.177	0.098	0.031	0.059	0.016
BHMNCPRAN01	0.095	0.054	0.009	0.022	0.004
BHMBRCBRG02	0.148	0.079	0.022	0.051	0.012
BHMNCPNHS01	0.133	0.071	0.018	0.028	0.009
NIA North	0.122	0.063	0.015	0.033	0.007
BHMBRTARC01	0.133	0.108	0.018	0.100	0.012
Overall	0.068	0.0411	0.0046	0.0283	0.002
Mean	0.109	0.059	0.012	0.035	0.006
Max	0.177	0.108	0.031	0.1	0.016
Min	0.048	0.025	0.002	0.014	0.002
Std	0.028	0.018	0.006	0.016	0.003

By analyzing the performance of the proposed decision support system on individual parking slots we can notice that the average, maximum, minimum, and standard deviation with RMSE is 0.109, 0.177, 0.048, and 0.028, respectively. Similarly, the average, maximum, minimum, and standard deviation with MSLE are 0.006, 0.016, 0.002, and 0.003, respectively. In the computation of average, maximum, minimum, and standard deviation the overall results are not considered.

While comparing the five loss functions RMSE, MAE, MSE, MdAE, and MSLE, the experimental results demonstrate that MSLE gives the lowest mean value as compare to other four-loss functions.

Next to MSLE, MSE gives the minimum mean value as compare to the other three-loss functions. On the other hand, RSME gives the highest mean value. We can say that among the five loss functions, MSLE and MSE are the best performance evaluation techniques.

When we applied our models on the whole dataset, we obtained the loss curve presented in Figure 6. The deep LSTM network achieved a minimum error rate with 100 epochs. In Figure 6 error rate is represented on the y-axis and epochs are presented on the x-axis. Similarly, Figure 7 gives a clear idea about the predication variation on each parking location using five loss functions. In the representation of each loss function, the y-axis represents the error rate and the x-axis represents the parking locations. The RMSE, MAE, MSE, MdAE, and MSLE for each park lots are shown as (a) to (e), respectively.

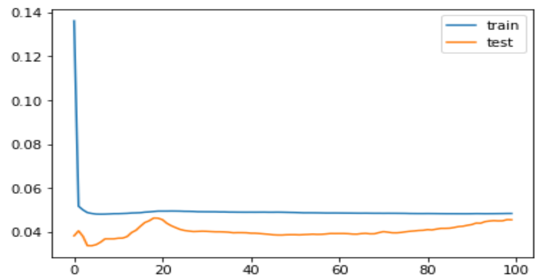
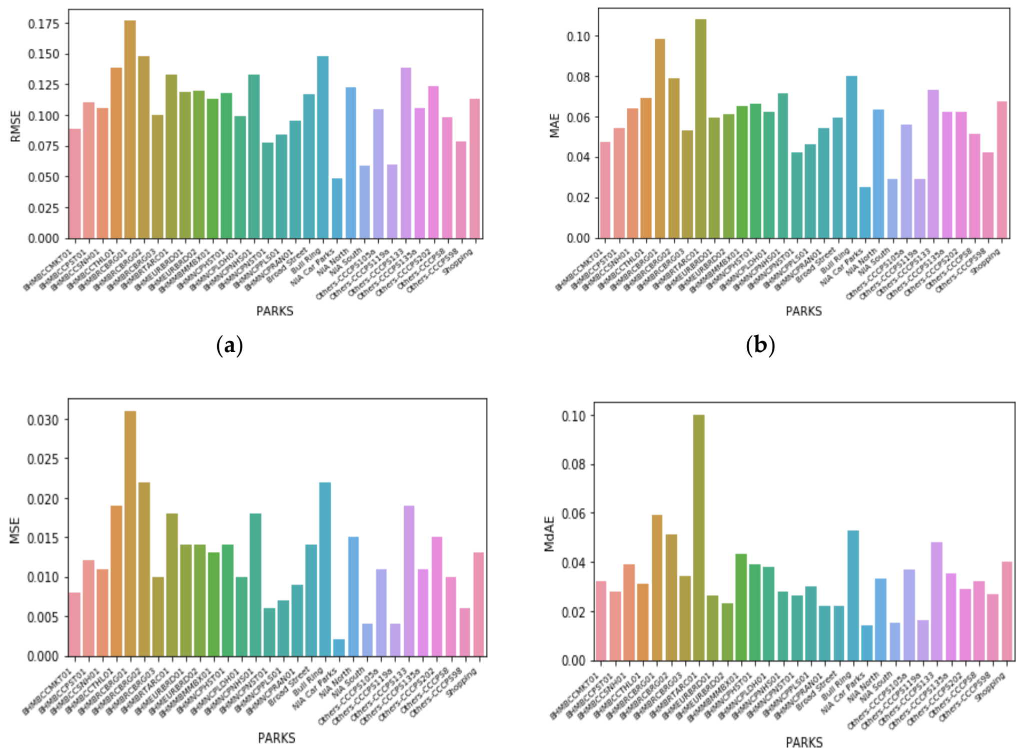


Figure 6. Loss curve on training and test Data.



(**a**) (**b**) (**c**) (**d**)

Figure 7. Parking availability prediction error rate against each parking location using loss functions: (**a**) root mean square error (RMSE), (**b**) mean absolute error (MAE), (**c**) mean squared error (MSE), (**d**) MdSE.

4.2. Day-Wise Parking Space Occupancy

The day-wise prediction was made to facilitate the drivers to check the availability of parking on specific day. First, we divide our dataset intoday-wise and then perform prediction day-wise through proposed model. The results produced by Deep LSTM on day-wise dataset are presented in Table 4. Table 4 demonstrates the experimental results on the day-wise parking space availability. It illustrates the performance of proposed deep LSTM with performance evaluation measures: RMSE, MAE, MSE, MdAE, and MSLE. The day wise MSE of deep LSTM is 0.0168, 0.0139, 0.0135, 0.0125, 0.0157, 0.0151, and 0.0173 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively. These values demonstrate the reliability of the proposed decision support system with respect to day-wise parking space availability. It will help the drives to schedule their drive on a specific day of a week. By analyzing the performance of the proposed decision support system on day-wise parking space availability we can notice that prediction variation is very low on the seven days of week as shown in Figure 8. It clearly shows that result for Saturday and Sunday is not very accurate due to unpredictable situation on these days but on the other days result are more accurate as compare to Saturday and Sunday. In Figure 8, x-axis represents days and y-axis represents error rate.

Table 4. Day-Wise Results of LSTM recurrent neural network (RNN).

Days	RMSE	MAE	MSE	MdAE	MSLE
Monday	0.0188	0.0168	0.00035	0.0165	0.00019
Tuesday	0.0157	0.0139	0.00025	0.0142	0.00010
Wednesday	0.0154	0.0135	0.00024	0.0132	0.00011
Thursday	0.0145	0.0125	0.00021	0.0107	0.00011
Friday	0.0175	0.0157	0.00031	0.0158	0.00016
Saturday	0.0178	0.0151	0.00032	0.0135	0.00019
Sunday	0.0183	0.0173	0.00034	0.0173	0.00020

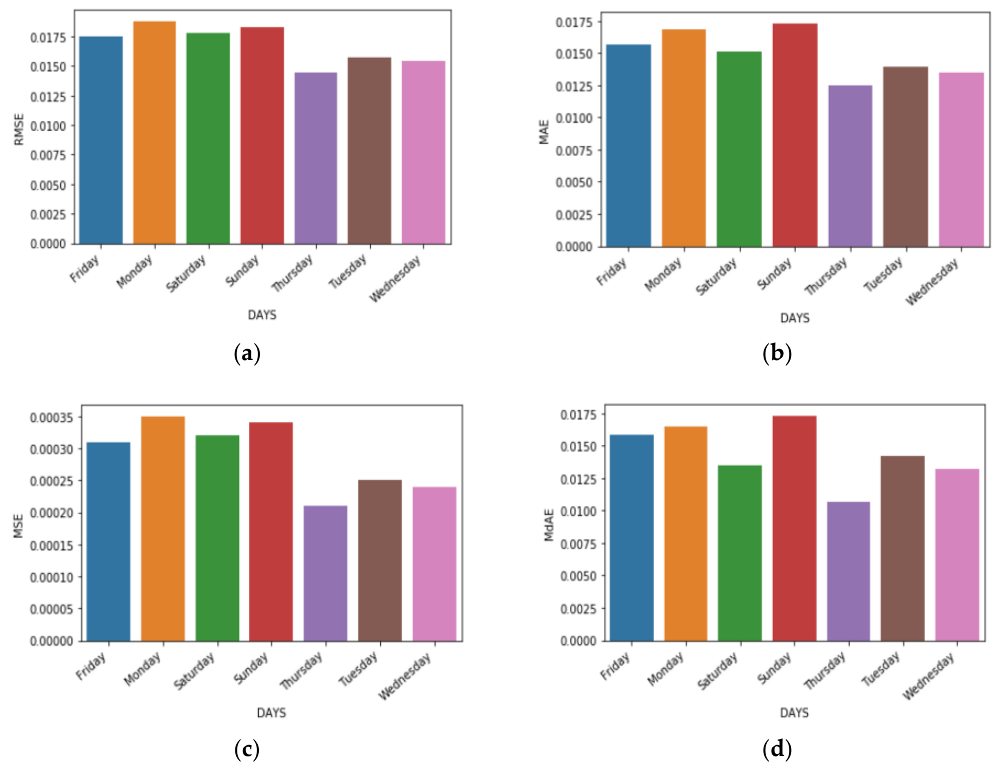


Figure 8. Parking availability prediction error rate with respect to day-wise using loss functions: (**a**) RMSE, (**b**) MAE, (**c**) MSE, (**d**) MdSE.

4.3. Hour-Wise Parking Space Occupancy

In hour-wise prediction, the dataset is divided into the hours of days whose data is available in Birmingham car park dataset. The data is available from 8:00 a.m. to 4:30 p.m., so dataset is divided into 9 different hours as presented in Table 5. In Table 5 demonstrates the results of each hour as shown with respect to performance evaluation techniques. Table 5 demonstrates the experimental results on the hour-wise parking space availability. It illustrates the performance of proposed deep LSTM with performance evaluation measures: RMSE, MAE, MSE, MdAE, and MSLE. The hour-wise MSE of deep LSTM is 0.0698, 0.1071, 0.0999, 0.0937, 0.0861, 0.0848, 0.0881, 0.0875, and 0.0902 for 08:00 a.m. to 05:00 p.m.

Table 5. Hour-Wise Results of deep LSTM.

Hours	RMSE	MAE	MSE	MdAE	MSLE
8:00 a.m.–9:00 a.m.	0.1085	0.0698	0.0117	0.0389	0.00912
9:00 a.m.–10:00 a.m.	0.1441	0.1071	0.0207	0.0796	0.0109
10:00 a.m.–11:00 a.m.	0.1476	0.0999	0.0217	0.0669	0.0107
11:00 a.m.–12:00 p.m.	0.1474	0.0937	0.0217	0.0549	0.0103
12:00 p.m.–1:00p.m.	0.1318	0.0861	0.0173	0.0536	0.0078
1:00p.m.–2:00 p.m.	0.1290	0.0848	0.0166	0.0528	0.0073
2:00 p.m.–3:00 p.m.	0.1256	0.0881	0.0157	0.0630	0.0068
3:00 p.m.–4:00 p.m.	0.1247	0.0875	0.0155	0.0589	0.0070
4:00 p.m.–5:00 p.m.	0.1209	0.0902	0.0146	0.0673	0.0068

These values demonstrate the reliability of the proposed decision support system with respect to hourly parking space availability. It will help the drivers to schedule their drive on a specific hour of a day. By analyzing the performance of the proposed decision support system on hour-wise parking space availability we can notice that there is a little bit of variation in prediction of parking availability accuracy for no hours of a day as shown in Figure 8. It represents that the performance of proposed decision support system is significant for all hourly slots except three hourly slots from 09:00 a.m.–10:00 a.m., 10:00 a.m.–11:00 a.m., and 11:00 a.m.–12:00 p.m., whereas, x-axis represents hours and y-axis represents error rate.

In Figure 9, the results of hour-wise predictions are shown. From Figure 9 we can notice that the proposed model is more inaccurate on 9:00 a.m.–10:00 a.m., 10:00 a.m.–11:00 a.m., and 11:00 a.m.–12:00 p.m. but on other hour results are well and good. In Figure 9 x-axis represents hours and y-axis represents error rate.

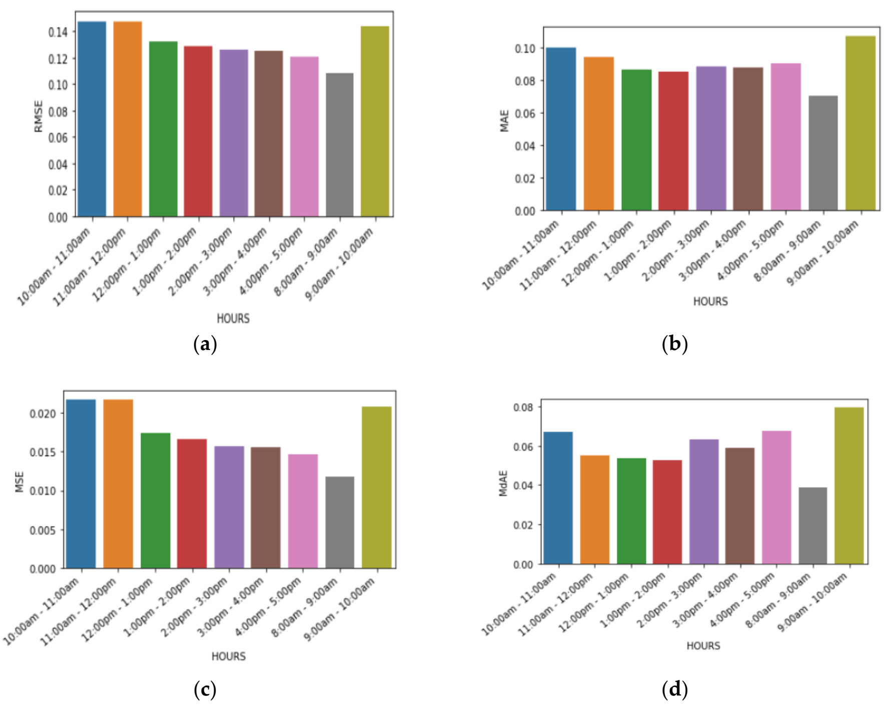


Figure 9. Parking availability prediction error rate with respect to hour-wise using loss functions: (**a**) RMSE, (**b**) MAE, (**c**) MSE, (**d**) MdSE.

5. Discussion

The proposed decision support system was tested on Birmingham parking sensors dataset recorded from April 2016 to December 2016 during 8:00 a.m. to 4:30 p.m. During the system verification, the performance of the decision support system was extensively analyzed in three different ways: location-wise, day-wise, and hour-wise. While comparing the performance of the proposed technique with existing techniques to predict the availability of parking space. We observed that existing techniques focues on the avaialability of parking space at specific location [30] or on a certain day [31]. On the other hand, the proposed technique provides a more clear insight about the availability of parking space while considering the parking location, days of the week, and hours. This information helps the drivers to sechedule their drives in a particular location of the city with respect to day and time. It helps to reduce the traffic congestion and feul consumption by providing the location-wise, day-wise, and hourly parking occupancy information. Moreover, the integration of proposed IoT based smart parking decision support system with modern traffic management systems [32] and automated vehicular traffic congestion measurement techniques [33] will efficiently reduce the traffic congestion and fuel consumption. Moreover, the implementation of advanced neural network based ensemble learning technique may also help to increase the performance of decision support system [33].

The performance of the proposed approach is also analyzed by varying the number of parking lots. In this regard six experiments are performed while considering the parking lots as: 5, 10, 15, 20, 25, and 30 as presented in Figure 10. It is observed that the proposed approach performed significantly by gradually increasing the number of parking lots. A minor variation in prediction error is noticed that highlights the generalization and scalability of the proposed approach. From Figure 10 it can be noticed that the MAE with different number of parking lots varies from 0.0335 to 0.0540. It also demonstrates that the MAE with 5, 10, 15, 20, 25, and 30 parking lots is 0.0420, 0.0380, 0.0335, 0.0450, 0.0450, and 0.410, respectively.

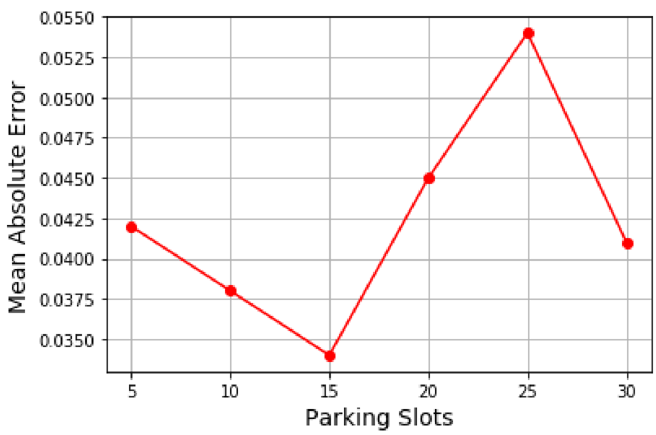


Figure 10. Performance evaluation of proposed approach by varying the parking lots count.

The results presented in [31] are not directly comparable to the proposed technique, because this technique predicts only the day-wise parking space occupancy. When we look at the day-wise mean value of MAE for seven days, we can observe a better performance as compared to the work presented in [31]. The best day-wise MAE is 0.0125 on Thursday and the worst MAE is 0.0173 on Sunday. It can be observed that proposed techniques outperform the existing techniques on all day-wise predictions. Similarly, the proposed technique performed significantly as compared to the results presented in [30], where parking locations wise parking space availability is predicted. The mean absolute error for all parking locations is 0.059 which is slightly better than the best MSE value reported, which 0.067 through the polynomials is as illustrated in Table 6. Additionally, the proposed technique is simple and fast as compared to the techniques applied in [30].

Table 6. Performance (MAE) comparison with other techniques.

Reference	Technique	MAE
[24]	Polynomials	0.067
	Fourier Series	0.079
	k-means clustering	0.102
	Polynomials fitted to the k-mean centroid	0.101
	Shift and phase modifications to the KP polynomials	0.073
	Time series	0.067
	Recurrent Neural Network	0.079
[25]	Polynomials	Monday = 5.368 Tuesday = 12.173 Wednesday = 8.2633 Thursday = 5.6741 Friday = 3.9284 Saturday = 3.6687 Sunday = 15.259
	k-means clustering	Monday = 1.3067 Tuesday =1.3178 Wednesday = 1.3828 Thursday = 1.3806 Friday = 1.4357 Saturday = 1.1299 Sunday = 1.1916
Proposed	Deep LSTM	Monday = 0.0168 Tuesday = 0.0139 Wednesday =0.0135 Thursday =0.0125 Friday =0.0157 Saturday =0.0151 Sunday =0.0173

6. Conclusions

The development of IoT based smart parking information systems is one of the most demanded research problems for the growth of sustainable smart cities. It can help the drives to find a free car parking space near to their destination (market, office, or home). It will also save time and energy consumption by efficiently and accurately predicting the available car parking space. In this research, we have developed an IoT based smart car parking framework. This paper mainly focuses on predicting the availability of car parking spaces using the sensors data. In this regard, we have developed a simple and fast decision support system that supports the car parking information system about the availability of car parking locations on a day of week in a given time slot. In the decision support system, we employed a deep LSTM network to predict the availability of car parking space. The proposed deep LSTM network predicts both the overall availability of parking space and location wise availability of parking space. It also predicts the day-wise and hour-wise parking space occupancy. The location wise, day-wise, and hour-wise car parking availability prediction gives a better insight to the drivers to choose their route and destination. With the help of the proposed system, drivers will be able to locate the parking space from any location at any time. We believe that with the combination of cloud technology and sensors network the collection and analysis of sensors data will become easier as compared to using traditional techniques. In the future, this work will be extended to implement all the services (parking location, parking information, parking supervision, vehicle tracking, vehicle registration, and identification) described in the adopted smart parking framework. Future work will also focus on the development of various techniques to predict the real-time availability of parking lots using image and video data captured through various sensors.

There are few limitations of this study. The first limitation of this study is that the decision support system predicts the availability of parking lots only considering the parking occupancy information.

Further it does not consider the weather condition and social events. Future research will be devoted to considering the weather conditions and social events information along with parking lots occupancy information. Second, the proposed approach has been developed only considering the parking lots information. Further research will investigate the roadside parking space availability and traffic congestion information to reduce the impact of estimation uncertainties.

Author Contributions: G.A. and T.A. have proposed the research conceptualization and methodology. The technical and theoretical framework is prepared by, M.I. and U.D. The technical review and improvement have been performed by M.S. (Muhammad Sohail), A.G. and M.S. (Maciej Sulowicz). The overall technical support, guidance, and project administration is done by M.S. (Maciej Sulowicz), R.M., C.M. and Z.B.F. The editing and finally proofread is done by M.S. (Maciej Sulowicz) and C.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the AGH University of Science and Technology, grant No. 16.16.120.773 and by project NAWA (Narodowa Agencja Wymiany Akademickiej) to pay the APC of the journal.

Acknowledgments: The authors acknowledge the Ministry of Education and the Deanship of Scientific Research, Najran University. Kingdom of Saudi Arabia, under code number NU/ESCI/19/001.

Conflicts of Interest: The authors declared there is no conflict of interest.

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