Google Scholar Crossref doi scopus

Impact factor 6.2

Geoscience Journal

ISSN:1000-8527

Indexing:

- Scopus
- Google Scholar
- DOI, Zenodo
- Open Access

GEOSCIENCE JOURNAL
ESTD. 2020
ISSN:1000-8527

www.geoscience.ac

Registered

A STUDY ON ARTIFICIAL INTELLIGENCE ALGORITHMS IN INFORMATION SYSTEMS RESEARCH: CURRENT PERSPECTIVES AND RESEARCH OPPORTUNITIES

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Abstract

The field of artificial intelligence (AI) has advanced significantly over the last ten years. The extent to which management research employs AI algorithms is not well-documented, despite the abundance of AI research. Despite being essential to coordinating, expanding, and fortifying the use of AI, the context, goal, and kind of AI employed in earlier projects are still unknown. By doing a systematic literature review (SLR) on 12 top information systems (IS) journals and employing a specially designed generative pre-trained transformer (GPT) in our analysis, we fill this knowledge gap. To address the lack of a succinct AI taxonomy, we offer a conceptual framework with eight dimensions to group our findings according to applied AI application domains, methodologies, and algorithms. As a result, we highlight underrepresented algorithms with significant promise, uncover and debate trends, and determine research directions. We provide a conceptual review of the literature that could be used as a foundation for future study into the developing field of artificial intelligence.

Keywords: Artificial Intelligence (AI), Information Systems, Conceptual Framework, Machine Learning, Data Analytics, Intelligent Systems

1. Introduction

In major cities, automobile traffic congestion is currently proving to be a serious issue. It has been demonstrated that traffic congestion significantly affects a variety of industry sectors. In 2020, traffic congestion cost the US economy more than 101 billion dollars in lost revenue. Transportation delays and higher fuel use were the primary causes of the losses [1]. Automobile fuel combustion increases the emission of dangerous chemicals that have been shown to have a detrimental effect on health [2]. These chemicals have been connected to early mortality as well as cardiovascular and respiratory disorders.

The World Health Organisation reports that in 2012, air pollution from traffic caused more than 1 million and 600,000 fatalities in China and India, respectively [3]. Thus, it is essential to look for measures that would lessen air pollution caused by traffic. According to studies [4], the hunt for a parking spot accounts for about 40% of traffic congestion in the majority of big cities. In fact, the ineffective search for open parking spots lengthens search durations and lines, which exacerbates traffic congestion. For instance, vehicles in the US look for a parking spot for an average of 17 hours per year [5].

In order to successfully aid drivers in their parking spot search, a number of techniques, including machine learning, have been suggested as a means of predicting parking space availability in the future. For large-scale, long-term parking spot occupancy forecasting (i.e., three hours), our study provides a framework for assessing multiple machine learning methods. Using two methods that combined metrological data and Information about on-street parking from the city of Los Angeles, we employed machine learning models to estimate parking spots over the long run. Additionally, a comparison of the calculation time and efficiency of the various models is provided. Therefore, we provide a resource for the best machine learning algorithms for long-term forecasting, which may be used as a foundation for creating intelligent and environmentally friendly parking remedies.

This article is structured as follows: an outline of the most recent studies on parking spot occupancy prediction is given in the first part. The dataset, machine learning algorithms, and modelling and prediction techniques are covered in Section 2. The results of comparing the various approaches in terms of calculation time and efficiency are shown and discussed in section 3. Section 4 wraps up this effort and offers some thoughts for the future.

2. Related Work

Numerous approaches have been proposed to forecast the availability of parking spaces. Numerous of these approaches are based on or contrasted with traditional machine learning models according to how well they perform. Both Brief (less than half an hour) and extended (more than 30 minutes) parking spot occupancy predictions are possible. In order to implement an City of Seattle's smart on-street parking charging system (Washington, USA), Sandeep Saharan et al. [6] compared the effectiveness of neural network (NN), decision tree (DT), random forest (RF), and linear machine learning (LIN) models.

The Random Forest outperformed the others in terms of accuracy when it came to parking spot forecast one hour in advance. Jelen Goran & al. [7] used two methods to assess how well the Random Forest as well as CatBoost machine learning model system predicted one-hour parking slot availability beforehand. The model solely employed parking spot availability data in the fundamental approach. Conversely, the contextual strategy made use of both parking spot availability data as well as metrological data.

In every method examined, the CatBoost outperformed the random forest in terms of efficiency. In a different research, Yanxu Zheng et al. [8] used a collection of short-term parking features to examine the effectiveness of three models for machine learning: neural networks, regression trees, and support vector type regression. When comparing the efficacy of the appropriate feature sets and framework of the different combinations for the Melbourne (Australia) as well as San Francisco (California, USA) datasets, the regression tree using a set of characteristics that includes the previous assessments, time of day, and day of the week performs the best.

Nevertheless, the prediction models utilised in these earlier studies were only based on a small number of parking lots and were completed in less than an hour. Autonomous machine learning algorithms have not been used to analyze massive, long-term projections of no more than three hours. Furthermore, approaches that employ machine learning techniques as a benchmark have concentrated on a small number of prediction models, disregarding or restricting the benchmarking to less than four models in order to identify the models that exhibit the highest performance within a certain forecast time horizon.

In this study, we evaluate over ten machine learning algorithms to identify the most effective methods that may serve as a guide for long-term occupancy forecast parking spot calculations based on precise forecasting and time required for computation.

3. Motivation

3.1. Mobility and smart transport challenges

Without a question, one of the primary cornerstones of modern centres is the transportation infrastructure. Dependable transport networks are essential to growth, sustainability, and economic growth. The transition of urban areas to smart cities in the past few decades has brought attention to the necessity of resolving several transport issues in order to stay up with the changing environment and growth of smart cities.
Transportation systems are evolving towards enhanced intelligence as a result of the incorporation of new information and communication technologies (Figure 1).

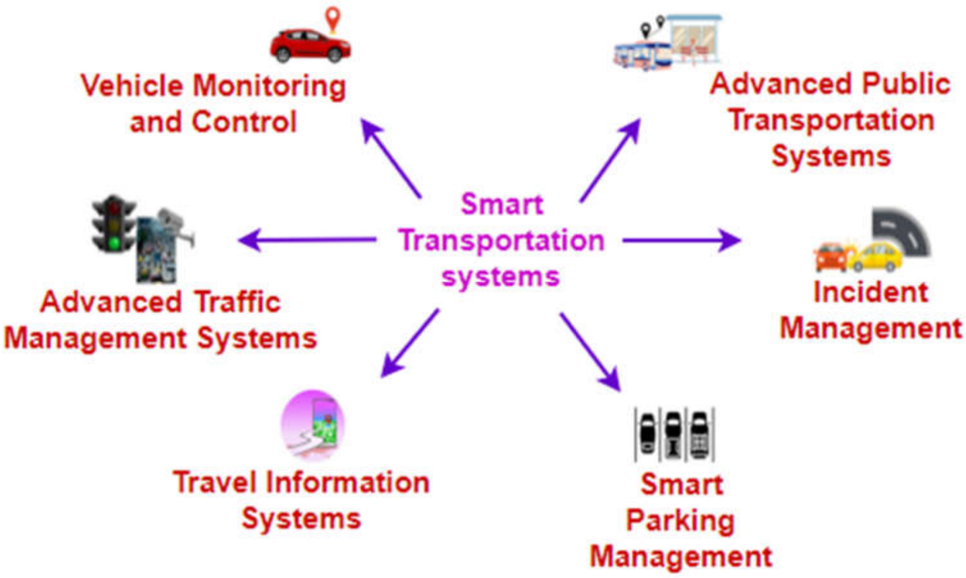

Figure 1. Intelligent transport system

Essential systems like traffic management systems and message-displaying circulation signs make up smart transportation systems. On the other hand, more sophisticated systems that integrate data from several different sources, specifically a place to park guidance and scheduling systems, make up effective transportation systems.
These types of systems primarily rely on cutting-edge technology like: - Wireless Sensor technologies (magnetic sensors RFID sensors, and CCTV cameras) that can communicate therewith their surroundings to gather information regarding road conditions in real time. Sharing of information is made possible via Technologies for short- or long-range connections, such as WiFi, 3G, 4G, and 5G.

In order to transmit the gathered data, wireless sensor networks are outfitted with either passive or active sensors that communicate using lightweight routing protocols.

These technologies have several application areas, including as management of resources, safeguarding the environment, roadway security, and the fluidification of metropolitan traffic. These technologies have a wide range of application areas, such as:

- Transportation safety
- Urban traffic fluidification
- Resource management
- Environmental Preservation

These difficulties are inextricably intertwined, especially when it comes to lessening traffic in cities. The primary cause of this is poor parking lot management, which has a negative impact on traffic flow and the functioning of urban facilities.

3.2. Smart parking

In order to ease congestion in roadways as well as to promote accessibility in cities, smart parking offers options. There are several parts that make up the intelligent parking system [9]. Figure 2 depicts the most often used. The parking system for reservations as well as the transportation guidance and information system are two of these elements that are essential for lowering metropolitan traffic congestion.
The Parking information and guidance systems (PIG) main goal is to notify users about parking space availability and offer assistance in locating those spots. By enabling cars to spend less time searching for a parking spot, such a system will help alleviate traffic congestion in some locations. Through the application of deep learning algorithms and the collecting of multisource data, the information offered regarding parking spot availability has grown increasingly accurate in recent years. A number of related concerns must be addressed for the PGI method to be more applicable. One of these queries is how to prevent many drivers from vying for the same parking spot.

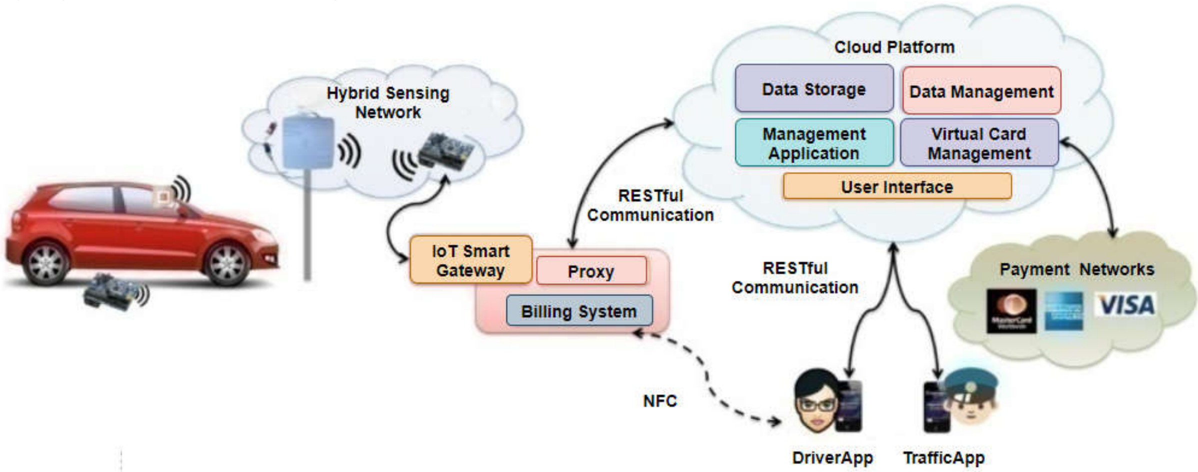

Figure 2. Smart parking system
In conjunction with smart price management, the parking system for reservation ensures a booking management system that includes parking spot reservations, preventing several cars from driving about looking for open spots. By employing strategies to dynamically price parking spots and improve the accuracy of information on current availability, parking spaces may be managed intelligently.

The majority of the previously discussed smart parking components, including ERP and PRS, primarily depend on accurate parking spot availability forecast. It is important to make this forecast as accurate as possible in order to overcome some of the major issues facing transportation systems, which means urban traffic congestion.

4. Materials and methods

To compare the many models taken into consideration in this study, we used two methods. The first method just uses parking data to assess the various algorithms. This initial method's goal is to evaluate and pinpoint the most effective models using just historical parking data. The second method investigates the response of the first method to the incorporation of outside data.

Our goal in this second technique is to assess if the previous strategy's outcome is still true after including outside data. The latter strategy appears to be more important as some authors have proposed using external data, such traffic flow or weather data, to improve the accuracy of availability prediction [7,10].

4.1. Pre-Processing and Data acquisition

Most approaches that have been proposed for forecasting parking space availability have built their prediction models using historical parking space occupancy data gathered from many sources. Nonetheless, research has indicated that the prediction efficacy is increased when external data sources, including weather data, are used to influence parking spot occupancy [7,10,11]. Thus, in order to investigate how our prediction models respond to combining various data types, as external data, we are utilizing historical parking on streets information from Los Angeles, the state of California, in the United States, in addition to weather data.

Parking Data

The Los Angeles Department of Transportation's (LADOT) webpage provided the parking data [12, 13, 14]. All of the city's on-street parking spots are overseen by LADOT. We noticed that Los Angeles on-street parking information was collected at erratic periods. Our first step was to aggregate the parking data by hours because our goal is to provide hourly estimates. Next, utilising data on the sensors' geographic locations, each and every sensor, denoted by an identification device (ID), is connected to a particular street.

Lastly, the following formula [1] is used to determine the number of free parking spots (NPL) for each street level as well as each hour t:

$$\text{NPLstreet(k)(t)} = \sum_{i+1}^{n} Espace_i(t) \qquad (1)$$

wherein n is the overall amount of parking spaces on a street k, k is its index, and Space(i), which has a value between 0 and 1, indicates the state of a parking place i at time t, depending on whether it has been used or free. The value that needs to be forecast for each hour on a certain street is represented by this NPL quantity at any given time.

To lessen the comparatively large number of streets, an aggregation method is then implemented, which entails grouping the arteries that belong to the same alley. Our comparison analysis will be based on the accessibility of parking spaces for the 101 arteries that are acquired after aggregation.

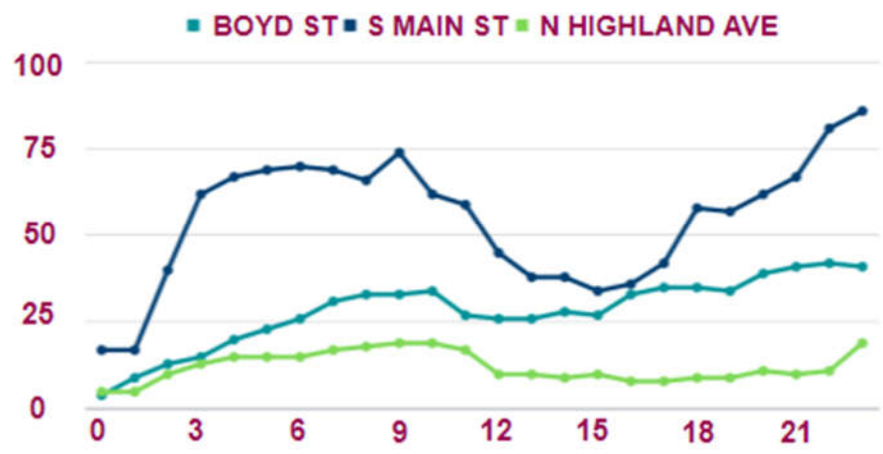

Figure 3. An outline of the hourly parking options at North Highland Avenue, South Main Street, and Boyd Street

Figure 3 shows an overview of the accessibility of parking spots by hour on the three main thoroughfares in the metropolitan area of Los Angeles on January 1, 2018.

Meteorological data

The Visual Crossing API was used to get Meteorological information for the city of Los Angeles [15]. Temperature, the atmosphere's pressure, and information about precipitation were all included within these hourly meteorological information retrievals. Converting the variables to their respective formats was the only processing that needed to be done on the data. The research we conducted considered the following meteorological data: temperature, atmospheric pressure, wind gusts, wind speed, the process of precipitation and transparency.

Data input for the various models

Based on the ARIMA approach and motivated by earlier research [16], the computation of autocorrelation as well as partial autocorrelation shown that the accessibility of parking spots during the past 24 hours is required to forecast the following three hours. The parking information at the lowest point of each artery is shown as a time series, with each hour being associated with the number of parking spots available, as shown in Figure 4.

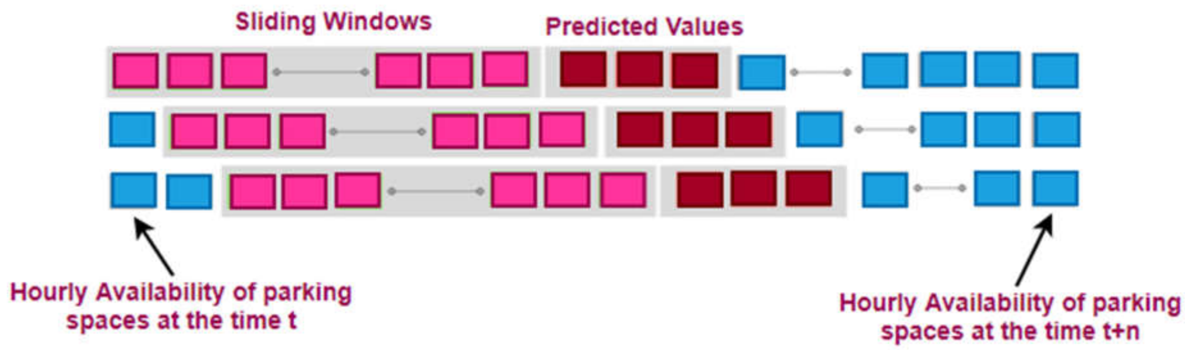

Figure 4. Data visualization for time series information on parking accessibility

The input matrix for the various models is created by traversing the time series with an adjustable window of 24 items at a time step of 1. Retrieve the following three availability-hours for each of the 24 items, which correspond to the projected values.

For our first method, the three subsequent hourly occupations reflect the goal values that can be forecasted for each one of the 24 items to be extracted that are designated as explained factors at the level of each artery. The 24 factors that were retrieved as well as the atmospheric variables— temperature, atmospheric pressure, wind gusts, wind speed, the process of precipitation and transparency. It define the variables that provide explanation for the second method.
The models' input matrix is made up of the collection of all retrieved explanatory variables, as well as the sequence of values to be forecasted is made up of the set of all three hourly accessibility.

Machine learning methods
The effectiveness and cost of training of several well-known machine learning algorithms in forecasting were used to contrast their performances. Furthermore, the capacity to forecast

Occupancy was evaluated during the following three hours. Our decision is supported by the knowledge that drivers can greatly benefit from long-term predictions, such those made three hours ahead of time, when planning their trips.
By giving drivers access to more sophisticated data, they may better plan their routes by learning how likely it is that they will find a parking spot on a certain street.

Multi-output prediction
The hypotheses that are compared in this research fall into two distinct categories: those any assistance multiple output prediction by nature, such as Random Forest [17], K Neighbors Regressor [18], Linear Regressor [19], Ridge Regression [20], and Decision Tree Regressor [21], and those that don't: Support Vector Machine Regression (SVR) [22], Stochastic gradient descent regression [23], Gradient Boosting Regression [24], Extra Tree [25], and Extreme Gradient Boosting Regression (XG-Boost) [26]. We employed an encapsulation strategy, which entails encapsulating multiple models to forecast each part of the output sequence, to get around the limitations of these later models. Furthermore, independent or dependent outputs can be predicted by encapsulating models. Each model independently forecasts a sequence element based on the input data for the models with independent outputs. On the other hand, Figure 5 shows the frameworks with driven output receive both the input data and the sequence element that had been anticipated by the prior model in order to forecast the current sequence component throughout the prediction.

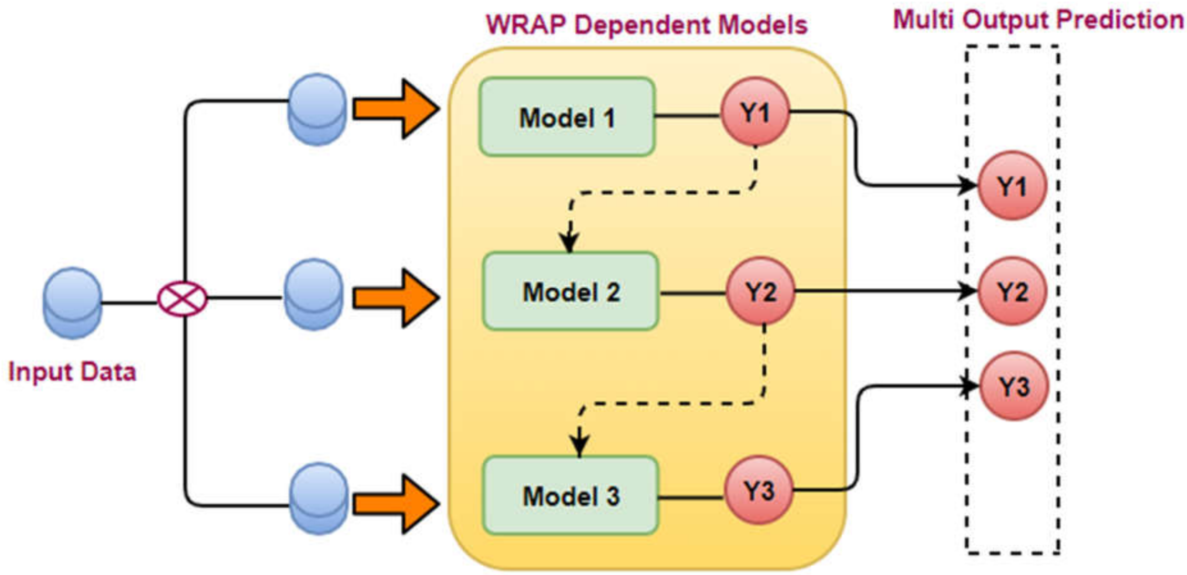

Figure 5. Multiple-output regression model encapsulation

However, in our situation, the presumption that the sequence element operates independently might not be accurate because there is most likely a dependency link between them and their parking accessibility for the following three hours. However, we considered both kinds of each model's variants in the comparison. Table 1 lists all of the models that were utilized in the above analysis.

Parameter optimization

Several hyperparameters in machine learning techniques need to be optimized in order to increase the predictive algorithm's effectiveness. Bayesian optimization is used in this research to identify the ideal parameters. To find the most important parameters, a thorough search is first done for every model.

The best values for the different parameters are then found using Bayesian optimization.

Table 1 displays the values obtained from Bayesian optimization for each parameter along with a brief discussion of the parameters utilized for each model.

Table 1. Models and ideal parameters taken into account in the comparison

Model Design	**Ideal parameters**
XG Boost combined with a unique output (XGB1)	Value of Gamma = 0.03, Maximum depth = 4, No of estimators = 99.4
XG Boost combined with adjustable output (XGB2)	
Unique output SVM Regressor (SVR1)	Maximum iterations = 1569, total= 0.2, epsilon = 0.08, Value of C = 5.7
Adjustable output SVM Regressor (SVR2)	
Stochastic gradient descent Regressor combined with the unique output (SGDR1)	Alpha value = 0.1, total = 0.59, power_t = 0.4, n_iter_no_change = 477, eta0 = 0.28
Stochastic gradient descent Regressor with variable output (SGDR2)	
Regressor with configurable output for extra trees (EXT2)	Minimum samples of leaf = 3, Minimum samples of split = 5, Maximum depth = 45,
Regressor with configurable output for extra trees (EXT1)	

	No of estimators = 652, Bootstrap = False
Random Forest Regressor (RF)	No of estimators = 353, maximum depth = 9, minimum samples of leaf = 3, minimum samples of split = 5
Ridge (RDG)	Typical values
Decision Tree Regressor (DTR)	Maximum features = 16, Maximum depth = 57, Minimum samples of split = 15, Maximum leaf nodes = 102, Minimum samples of leaf = 1
Gradient Boosting Regressor combined with the unique output(GBR1)	Maximum depth = 5, Minimum samples of split = 12, Minimum samples of leaf = 2, No of estimators = 273. random_state = 1, alpha = 0.3761, learning_rate = 0.081132
Gradient Boosting Regressor combined with the adjustable output(GBR2)	

Regardless of the parameter values taken into consideration, some models produced outcomes that were comparable. As a result, the default settings were chosen as these models' ideal settings.

5. Results and discussion

To evaluate the various models, as evaluation measures we have employed the R2 and the RAE. The model's level of fit to the expected job is indicated by the R2 metric. Equation (2) provides the formula for R2, and a maximum R2 value of 1 denotes a perfect match between the regression model's predictions and the data. According to equation (3), RAE represents the rate of inaccuracy among the actual and predicted values. Lastly, the models are evaluated and their resilience to data fluctuations is examined using k-fold cross-validation with k=5. Hence, this technique takes into account various configurations of the sets for training and testing purposes to produce a trustworthy estimate of the models' capacity for generalization.

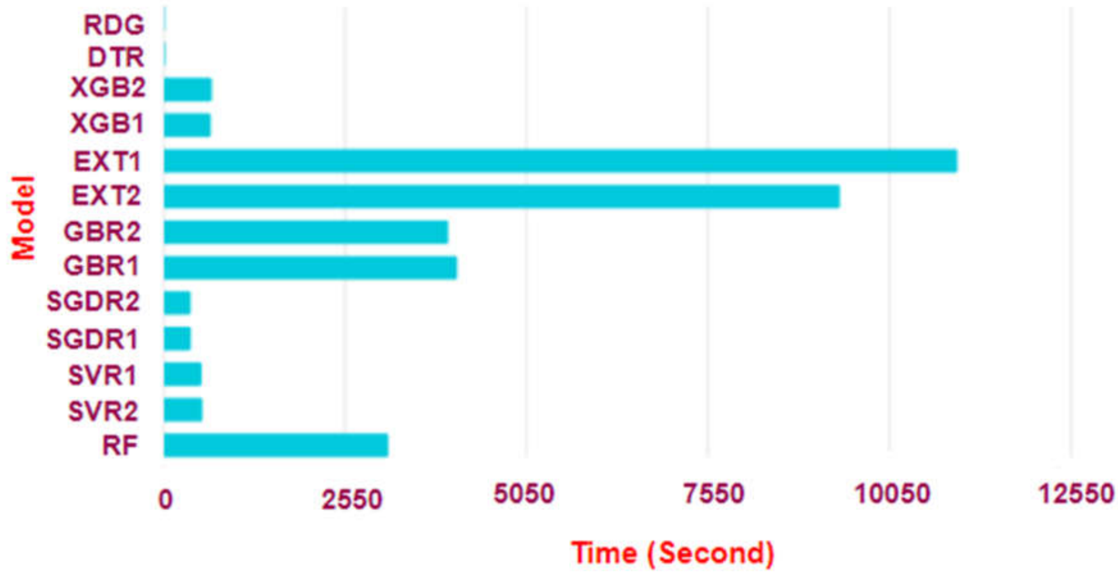

Figure 6. Each of the model's processing cost per second

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y_i} - y_i)^2}{\sum_{i=1}^{n} (y_i - y_i)^2} \quad (2)$$

$$RAE = \frac{\sum_{i=1}^{n} I y_i - \hat{y_i} l}{\sum_{i=1}^{n} l y_i - \hat{y_i} l} \quad (3)$$

where yi is the exact amount of parking spots accessible, Þi is the anticipated quantity of unoccupied parking spots, whereas ii is the average (mean).

For the implementation of the various learning models, we used the sklearn library as well as the Python programming language. Regarding the models' encapsulation, the Multi Output Regressor

For designs with irrespective outputs and models having dependent outputs, the RegressorChain and multioutput module functionalities of the sklearn package were utilized, accordingly. The application runtime environment was the Google Colab platform.
Table 2 displays the average value of R2 and RAE that each model produced throughout training on the driving data. Each one of R2 for the models was at least 0.6 on the parking data, which we observed, demonstrating the entirety of the algorithms fit the data well. In this, 10% more than the lowest R2 achieved inside the Ridge, with a maximal R2 of 0.70, the Extra Tree as well as Random Forest models were the most well-suited to the amount of parking space data that was taken into consideration.

We additionally noticed the fact that the more recent methods offered the highest possible accuracy having the least amount of error when we compared the RAE of the various algorithms. However, we found that the enclosed models with both autonomous and dependent output produced results that were nearly identical. This demonstrated that while the various models anticipated approximately three consecutive hours would be available in the future, most likely depending on one another, accounting for this knowledge did not considerably enhance the prediction.

The techniques which best corresponds to the data and produced the best predictions despite the addition of external information were the Extra Tree as well as Random Forest, according to Table 2, it displays the various algorithms' R2 as well as average RAE following the input of meteorological data.

Table 2. Model's performance

Model	Parking + weather		Parking	
	Mean R2	Mean RAE	Mean R2	Mean RAE
XGB1	0.67	0.46	0.68	0.45
XGB2	0.68	0.43	0.67	0.45
SVR1	0.66	0.50	0.62	0.51
SVR2	0.64	0.49	0.60	0.52
SGDR1	0.67		0.46	0.45
SGDR2	0.68		0.45	0.44
EXT2	0.69	0.45	0.69	0.44
EXT1	0.68	0.46	0.69	0.45
RF	0.68	0.46	0.69	0.46
RDG	0.67	0.50	0.64	0.51
DTR	0.61	0.53	0.64	0.53
GBR1	0.69	0.45	0.68	0.48
GBR2	0.67	0.46	0.69	0.48

It should be mentioned that after adding meteorological data, neither of the two SVR versions produced any results. As a result, Table 2 does not display these findings. Furthermore, when comparing the outcomes of the models with and without meteorological data, Table 2 reveals that the inclusion of meteorological data for certain models reduces R2 and RAE.

This demonstrates that adding weather information to the forecast does not enhance its accuracy. The algorithm that takes the longest to execute is the Extra Tree (Figure 6) when compared to the other algorithms. This is primarily because it requires a comparatively large number of parameters that must be learned during the algorithm's training phase. Consequently, in terms of computing both costs and effectiveness, the Random Forest technique is more often used than the Extra Tree.

6. Conclusion

In order to respond to the research question, "What is the current state of applied AI algorithms in IS, and how can existing research be synthesized?" this study does a systematic literature review. We offer a conceptual framework to improve transparency about the application domains, methodologies, and algorithms of applied AI in IS research by decomposing the research topic for examination. In this study, we examine 143 papers from top IS journals and discover that, throughout the observation period of our SLR, there was a significant increase in both the annual number of AI publications and the proportion of articles that addressed DL and xAI. Regarding the functional area and industry sector, the application of AI can be divided into different topic clusters. Our literature population is dominated by supervised algorithms that make predictions using textual or numerical inputs. Additionally, our SLR demonstrates that computer vision, semi-supervised learning, reinforcement learning, and generative algorithms are used in relatively few papers. There may be applications for these algorithm types in IS and management research generally. As a result, we label them as underrepresented and propose that they constitute interesting areas for future study.

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