European Journal of Technique

journal homepage: https://dergipark.org.tr/en/pub/ejt

Vol.14, No.1, 2024

Research Article

Predicting Smart City Traffic Models using Adaboost and Gradient Boosting Method

Özlem BEZEK GÜRE[1*]

[1*] Batman University, Department of Medical Documentation, Secretariat Program Health Services Vocational School, Batman, Turkey. (e-mail:ozlem.bezekgure@batman.edu.tr)

ARTICLE INFO

Received: Feb., 13. 2024
Revised: May., 08. 2024
Accepted: May, 23. 2024

Keywords:
Smart City
Vehicle Traffic Prediction
Machine Learning
Ensemble Method
Adaboost Regression

Corresponding author:
Özlem Bezek Güre

ISSN: *2536-5010* | e-ISSN: *2536-5134*

DOI: https://doi.org/10.36222/ejt.1436180

ABSTRACT

In parallel with the population density in cities, noise, traffic congestion, parking problems and environmental pollution also increase. To address these problems, smart transportation and traffic systems have emerged, which benefit from internet technologies to offer solutions that concern nearly everyone. These systems generate a vast amount of data, often analyzed through machine learning methods. This study has utilized the Adaboost method and Gradient Boosting (GB) method from the ensemble methods family within the machine learning framework to predict a smart city's traffic model. This method is a combination of many weak learners randomly selected from the data set and created by applying machine learning algorithms to form a strong learner. Both methods have been applied on a smart city traffic models data set found in the Kaggle database. This data set consists of a total of 48,120 rows and 4 columns, including variables such as the number of vehicles, number of intersections, date and time, and ID number. New variables have been created from the date and time variable before starting to analyze the data. The analyses performed with the Adaboost and GB method were carried out in Orange, a free Python-based program. Performance indicators such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) have been used in the study. A 10-fold cross-validation method was used to ensure the validity of the model and to avoid overfitting. In conclusion, it has been observed that the Adaboost method performs successful predictions with low error rates. The Adaboost method, which estimates with minimum error, is also recommended for applications in areas such as smart grid, smart hospital, and smart home, in addition to smart traffic prediction.

1. INTRODUCTION

Transportation is one facet of urban life that affects almost all individuals in society. Particularly, with the increase in city populations and the consequent increase in the number of vehicles, transportation has become one of the most significant problems [1]. Dense urban traffic can lead to fatal, injurious, or financially damaging accidents. In addition to these, it can cause time loss, environmental pollution, and noise pollution [2]. Addressing these issues requires innovative solutions that go beyond traditional traffic management. For these reasons, there is a need for a traffic monitoring and reduction system in smart cities [3]. These systems utilize real-time data and predictive algorithms to optimize traffic flow, reduce congestion, and improve safety.

In smart cities, large amounts of data are collected as a result of using internet-based technologies [4]. These big data are not merely numerical values but represent a rich tapestry of urban life that can be harnessed for actionable insights. They are used both to determine past information and to predict the future, enabling authorities to make informed and proactive decisions. It is possible to plan for the future by developing action plans based on the results predicted with the analysis of big data [5].

The hidden patterns, complex, and nonlinear relationships within these massive data sets are analyzed using methods such as artificial intelligence, deep learning, and machine learning [6]. These sophisticated tools extend the capabilities of data analysis, enabling nuanced understanding and precise predictions. Using these methods, it is possible to predict traffic flow, classify vehicle images, and adjust traffic signal timing [7].

In this study, the Adaboot and GB method, one of the Ensemble methods family under the umbrella of machine learning methods, is used to predict the traffic model in a smart city. Upon reviewing the literature, although there are many studies related to traffic prediction in smart cities using machine learning methods, the use of this specific method (Adaboost and GB) has not been encountered. This research, therefore, presents a novel approach to addressing a pressing urban challenge, contributing to the ongoing discourse on smart cities and their potential to transform contemporary urban living.

The current study makes several contributions to the existing literature. The Adaboost and GB methods from the boosting family have been employed to predict the traffic model of smart cities. These methods, which aim to combine weak learners to produce a stronger learner, have been utilized to enhance predictive accuracy. The unique application of these methods in this context allows for a more dynamic adjustment to varying traffic conditions, potentially leading to more efficient urban mobility solutions. Furthermore, the adaptive nature of the boosting algorithms makes them particularly suitable for handling the non-linear and complex patterns often present in urban traffic data. The performance of these methods was assessed using various metrics, including mean square errors (MSE), root mean square errors (RMSE), mean absolute errors (MAE), and the determination coefficient (R^2). This evaluation helps in understanding the effectiveness of the methods in the context of smart city traffic modeling.

The rest of the paper is organized as follows: Section 2 discusses the literature related to traffic in smart cities. Section 3 presents the methods used in the study. Section 4 provides the analysis results, while Section 5 includes discussions and recommendations.

2. RELATED WORKS

Various machine learning methods have been employed in existing literature for traffic prediction within the context of smart cities. These studies have explored an array of algorithms and techniques, each providing unique insights into traffic prediction and modeling.

Oyewola, Dada, and Jibrin [8] utilized a dataset from the present study, exploring methods such as Bagging, K-Nearest Neighbors (KNN), Multivariate Adaptive Regression Spline (MARS), Bayesian Generalized Linear Model (BGLM), and Generalized Linear Model (GLM). They concluded that the GLM method yielded more accurate predictions with reduced error, highlighting the importance of model selection in achieving desired predictive outcomes. Furthermore, Ismaeel et al. [9] used the Recurrent Neural Networks (RNN) method in their study, which utilized the mentioned dataset for classification purposes. In contrast, a study by Mohammed and Kianfar [10] applied Neural Networks, Random Forest (RF), Gradient Boosting Machine (GBM), and GLM to anticipate traffic flow, finding a slightly superior predictive performance by the RF method. This study emphasizes the potential of ensemble methods in capturing complex patterns within traffic data. Navarro-Espinoza et al. [11] conducted a comprehensive study involving a variety of methods, including RNN, Multilayer Perceptron Neural Network (MLP), GBM, RF, and Stochastic Gradient. Their findings suggest that the MLP method shows more successful performance, reinforcing the adaptability of neural networks in handling non-linear relationships. Ramesh [12] used RF, Adaboost, and Logistic Regression methods, noting the more successful classification performance of logistic regression. The study underscores the effectiveness of Logistic Regression in binary classification problems within traffic prediction. Furthermore, Boukerche and Wang [13] implemented a hybrid method consisting of RNN and Graph Convolutional Network, an innovative approach that leverages the strengths of both techniques. An and Wu [14] added to this body of work by employing Neural Network methods, contributing to the ongoing exploration of neural architectures in traffic modeling. In the realm of incident classification, Devi, Alice, and Deepa [6] applied Support Vector Machine (SVM) and Logistic Regression methods to a similar dataset to classify incidents during heavy traffic times. Similarly, İbrahim and Hafez [15] achieved the best performance using the Decision Tree (DT) method among KNN, LR, SVM, Gaussian Naive Bayes (GNB), RF, and DT methods for classifying smart city traffic models. Lippmann et al. [16] used KNN, SVM, DT, and MLP methods and concluded that KNN and DT methods were more successful, offering valuable insights into the comparative performance of these popular algorithms. Saleem et al. [3] proposed a fusion-based intelligent traffic congestion control system, in conjunction with Artificial Neural Network and SVM methods. Their work represents an innovative approach to managing traffic congestion, stating that the proposed model had better classification performance. Other studies by Yıldırım, Birant, and Birant [17], Ozbayoğlu, Kucukayan, and Dogdu [18], and Niu et al. [19] have further contributed to the field by utilizing various machine learning algorithms to address different challenges within traffic prediction. Additionally, the literature includes studies that employ the Adaboost and Gradient Boosting methods used in the current study, illustrating the widespread adoption of these techniques in prediction and modeling.

Consequently, the related studies present a rich tapestry of approaches and methodologies in the domain of traffic prediction within smart cities. The collective insights from these works contribute to a better understanding of the complex dynamics of urban traffic and offer valuable guidance for future research and applications.

3. MATERIAL AND METHOD

In the present study, the smart city traffic models dataset, available in the Kaggle database, has been utilized [20]. The dataset, consists of traffic records from four junctions in a city between November 2015 and June 2017. Created to enhance city traffic management and increase the efficiency of services to citizens, the dataset aims to provide data that benefits future infrastructure planning [17]. Accordingly, the dataset, which includes variables such as ID number, date and time, vehicle count, and intersection count with 48,120 observation values, anticipates a robust traffic system for the city by preparing for heavy traffic. For this study, date and time information were reorganized as day, month, year, time slots (morning, afternoon, evening, and night), and weekdays/weekends. Predictions for Adaboost and GB were made using the free Python-based program Orange, and performance indicator values related to the predictions were obtained.

3.1.Adaboost Method

The Adaboost method is among the boosting algorithms. It is used to solve binary and multi-class classification problems as well as regression problems [21]. The method was developed by Freund and Schapire to enhance the performance of different learning algorithms. Adaboost is a method that combines numerous weak learners created by randomly selecting from the dataset and applying machine learning algorithms to create a strong learner [22]. In the training phase, weights are assigned to each observation value. The assigned weights are used to learn each hypothesis [23]. The weights used to calculate the hypothesis error are recalculated at each iteration. Then, incorrect predictions are identified and higher weights are given to incorrectly predicted samples [22]. At each iteration, the prediction error is compared to a threshold that is used to increase or decrease the weight of the sample for the next iteration [24].

3.2.Gradient Boosting Method

The GB (Gradient Boosting) method is also among the machine learning methods used in classification and regression problems. The method was developed by Friedman in 1999 [25]. GB is an iterative method that combines a series of weak regression learners iteratively to create a single strong regression learner [26]. Affected by the presence of overfitting, the method is not sensitive to data types [27]. The GB method aims to find a cumulative model that minimizes the loss function. For this purpose, it uses the mean squared error [28]. In this method, a model is built incrementally by minimizing the expected values of a specific loss function. Increasing the number of trees in the model can lead to a small training error. To minimize the risks associated with prediction, it is necessary to optimally determine the number of iterations or trees [29]. The working principle of the method is simple: Initially, a decision tree is created from the dataset worked on. Then, the error amount between the prediction values of this decision tree and the output values is calculated. Subsequently, these new output values are used as residuals, also known as errors, for other samples. Thus, a new decision tree is created with these errors, and the process is repeated until the error created by the previously built tree is minimized [30]. In the model, errors are trained, giving more importance to observations that have been misclassified. Here, a gradient optimization process is applied to minimize the general error of strong learning [31].

The detailed analysis of traffic modeling in smart cities reveals significant patterns and insights. Utilizing various machine learning methods, with a focus on the Adaboost and GB method, the study uncovers essential trends related to vehicle distribution, intersection count, and prediction accuracy.

Performance Metrics

In this study, the following performance metrics were used: MSE, RMSE, MAE, R^2. R^2, which takes values between 0 and 1, is an indicator of the goodness of fit in regression equations. It shows the proportion of the variance in the dependent variable that is predictable from the independent variables.

4. RESULTS

Analyses were conducted using the smart city traffic models dataset available in the Kaggle database. The traffic condition is affected by factors such as the number of vehicles and the number of intersections. A graph showing the distribution of vehicle numbers over the years, based on the variables used in the study, is provided in Figure 1.

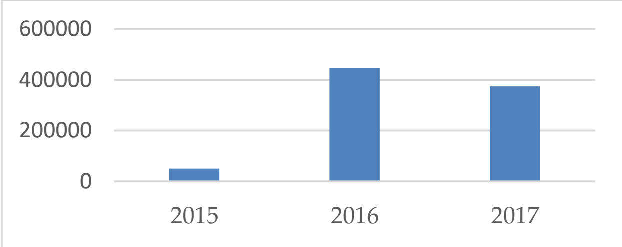

Figure 1. Vehicle count by year

Figure 1 illustrates the distribution of vehicles across different years, highlighting 2016 as the year with the highest number of vehicles and consequently the most traffic congestion. In contrast, 2015 is marked as the year with the lowest number of vehicles, leading to the least traffic congestion. These trends provide valuable insights into the fluctuations in traffic patterns over the observed period.

On the other hand Figure 2 shows a graph that illustrates the distribution of intersection counts over the years, which is another variable analyzed in the study.

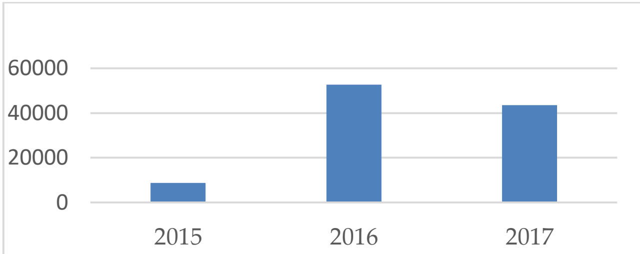

Figure 2. Number of junctions by year

Figure 2 shows a significant increase in the number of junctions between 2015 and 2016, followed by a decrease between 2016 and 2017.

Figure 3, 4, and 5 display the distributions of traffic density over time. Figure 3 presents a graph showing the number of vehicles by time for the year 2015.

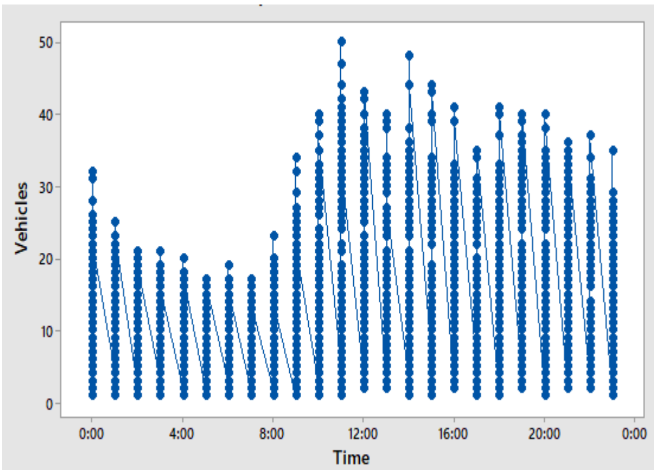

Figure 3. The distribution of vehicles over time in the year 2015

Figure 4 provides a graph showing the number of vehicles by time for the year 2016.

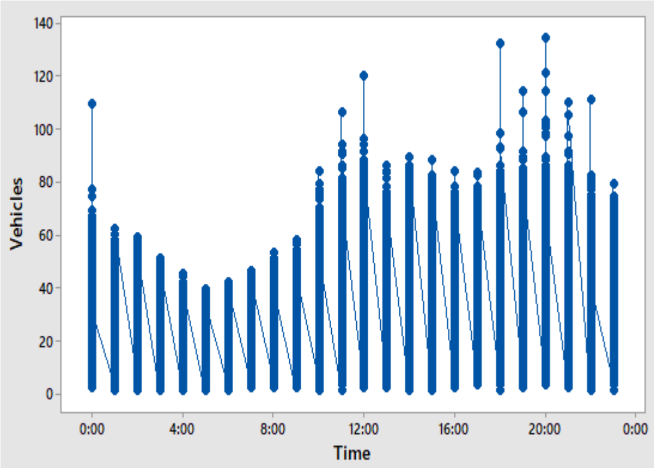

Figure 4. The distribution of vehicles over time in the year 2016

Figure 5 presents a graph showing the number of vehicles by time for the year 2017.

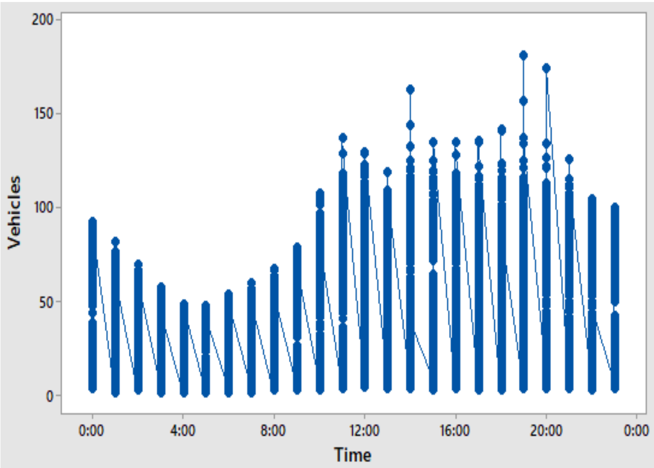

Figure 5. The distribution of vehicles over time in the year 2017

In the current study, the 10-fold cross-validation method is used for unbiased estimation. The cross-validation method is used to ensure the validity of the estimated model [32]. In the method, the data set is divided into 10 parts and one of them is used as test data and the other nine are used as training data. A different test data is used each time. Then, the overall error rate is calculated by averaging the error amounts of the 10 classes [33]. The performance indicators of the Adaboost and GB methods are given in Table 1.

TABLE 1.
PERFORMANCE METRICS

Method	MSE	RMSE	MAE	R^2
Adaboost	22.87	4.78	2.95	0.95
Gradient Boosting	42,61	6,53	4,10	0,90

Table 1 demonstrates that the Adaboost method achieves predictions with lower error amounts compared to the GB method. Additionally, the coefficient of determination measure shows that the independent variables used in the Adaboost method explain 95% of the variance in the dependent variable. This indicates a more successful prediction performance by the Adaboost method.

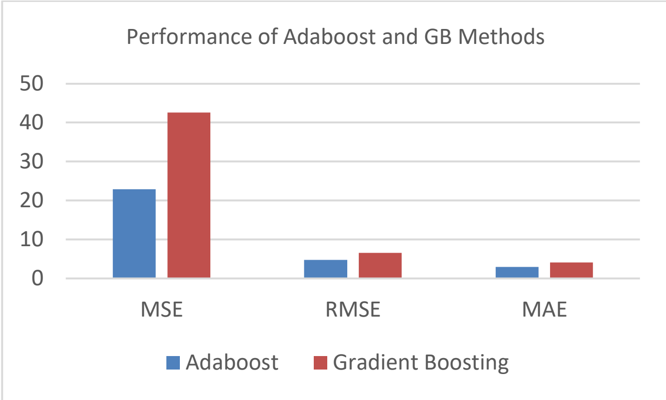

Figure 6. Performance of Adaboost and GB Methods

Based on Figure 6, it can be claimed that the AR method makes predictions with minimum error. As seen in Figure 6, the Adaboost method appears to make predictions with fewer errors compared to the GB method.

TABLE 2.
COMPARISON OF THE CURRENT STUDY WITH STUDIES IN THE LITERATURE

	Method	MSE	RMSE	MAE	R^2
The current study	Adaboost	22,87	4,78	2,95	0,95
	GB	42,61	6,53	4,10	0,90
Oyewola, Dada, and Jibrin [8]	Bagging	171,54	13,09	-	-
	KNN	85,30	9,23	-	-
	MARS	545,06	23,34	-	-
	BGLM	75,75	8,70	-	-
	GLM	75,34	8,68	-	-
Mohammed and Kianfar [10]	NN	-	8.63	5.95	0.93
	RF	-	5.56	3.57	**0.97**
	GBM	-	8.11	5.39	0.94
	GLM	-	9.94	6.74	0.92
Navarro-Espinoza et al. [11]	NN	-	9,80	7,24	0,95
	GB	-	9,66	7,12	0,94
	RF	-	9,57	7,05	0,94
	Stochastic Gradient	-	11,31	8,39	0,91
Zaman, Saha, and Abdelwahed [34]	Transformer	79.217	8.900	5.846	-
	LSTM	50.573	7.111	5.018	-
	BiLSTM	58.585	7.654	5.273	-
	Prophet	14208.68	119.20	102.81	-
Alekseeva et al. [35]	Bagging	-	2,99	1,66	50,8
	RF	-	3,38	2,19	34,2
	GB	-	**2,18**	1,43	60,2
	Bayesyen regression	-	2,25	1,49	49,7
	SVM	-	2,68	1,69	48,8
Tiwari [36]	LightGBM	-	4.14	2.49	-
	RF	-	3.95	2.36	-
	kNN	-	18.08	13.86	-
	XGBoost	-	18.25	14.12	-
Zheng et.al. [37]	CNN	-	24.52	13.01	
	Ensemble method	-	16.86	4.10	-
Savithramma, Sumathi & Sudhira [38]	SVM	8.30	2.88	0.92	-
	k-NN	9.14	3.02	1.20	-
	DT	16.07	4.00	2.00	-
	RF	9.00	3.00	1.36	-
	GB	**8.02**	2.83	**1.26**	-

5. CONCLUSION AND SUGGESTIONS

In this study, the Adaboost and GB method, a member of the Ensemble methods family within the scope of machine learning techniques, has been employed to predict the traffic model in a smart city. An examination of the existing literature reveals a multitude of studies that have utilized various machine learning methods to forecast traffic in smart cities. Nonetheless, the combined use of Adaboost and GB methods has not been previously observed in the context of smart city traffic modeling.

The literature includes studies that apply machine learning methods to traffic data. Table 2 compares the results of the current study with those from the literature.

As previously mentioned, Table 2 compares the results of the current study with those of the study conducted by Oyewola, Dada, and Jibrin [8], which used the same dataset. It is observed that the Adaboost and GB methods demonstrate a more successful prediction performance with fewer errors.

On the other hand, the best performance values from similar studies in the literature are highlighted in bold in Table 2. The lowest error amounts in terms of MSE and MAE were achieved by the study conducted by Savithramma, Sumathi & Sudhira [38] using the GB (Gradient Boosting) method. In terms of RMSE, the lowest error was also achieved with the GB method in the study by Alekseeva et al. [35] and in terms of R2, the best performance was achieved by the RF (Random Forest) method in the study by Mohammed and Kianfar [10].

In the current study, an attempt was made to determine the prediction performance of the Adaboost and GB method using a large traffic-related dataset. The method is found to make predictions with minimal error. Traffic congestion is considered one of the most significant problems in traffic management [34]. Therefore, due to the accuracy of the predictions made, measures implemented to reduce traffic density will prevent the formation of vehicle queues, facilitate quicker access to desired locations, and result in lower noise and environmental pollution. All these results will ultimately affect the quality of life for citizens.

In smart cities, the use of internet technology results in the collection of large amounts of data in traffic and other areas. Effectively analyzing and managing this vast data is crucial. Future studies could use the same dataset with different machine learning methods. The performance of these methods under various conditions can be compared.

REFERENCES

[1] Bawaneh, M., & Simon, V. (2023). Novel traffic congestion detection algorithms for smart city applications. Concurrency and Computation: Practice and Experience, 35(5), e7563.

[2] Balasubramanian, S. B., Balaji, P., Munshi, A., Almukadi, W., Prabhu, T. N., Venkatachalam, K., & Abouhawwash, M. (2023). Machine learning based IoT system for secure traffic management and accident detection in smart cities. PeerJ Computer Science, 9, e1259.

[3] Saleem, M., Abbas, S., Ghazal, T. M., Khan, M. A., Sahawneh, N., & Ahmad, M. (2022). Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. Egyptian Informatics Journal, 23(3), 417-426.

[4] Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., ... & Chiroma, H. (2016). The role of big data in smart city. International Journal of information management, 36(5), 748-758.

[5] Hemanth, D. J. (Ed.). (2022). Machine Learning Techniques for Smart City Applications: Trends and Solutions. Springer Nature.

[6] Devi, T., Alice, K., & Deepa, N. (2022). Traffic management in smart cities using support vector machine for predicting the accuracy during peak traffic conditions. Materials Today: Proceedings, 62, 4980-4984.

[7] Djenouri, Y., Michalak, T. P., & Lin, J. C. W. (2023). Federated deep learning for smart city edge-based applications. Future Generation Computer Systems, 147, 350-359.

[8] Oyewola, D. O., Dada, E. G., & Jibrin, M. B. (2022). Smart City Traffic Patterns Prediction Using Machine Learning. In Machine Learning Techniques for Smart City Applications: Trends and Solutions (pp. 123-133). Cham: Springer International Publishing

[9] Ismaeel, A. G., Janardhanan, K., Sankar, M., Natarajan, Y., Mahmood, S. N., Alani, S., & Shather, A. H. (2023). Traffic pattern classification in smart cities using deep recurrent neural network. Sustainability, 15(19), 14522.

[10] Mohammed, O., & Kianfar, J. (2018, September). A machine learning approach to short-term traffic flow prediction: A case study of interstate 64 in Missouri. In 2018 IEEE International Smart Cities Conference (ISC2) (pp. 1-7). IEEE.

[11] Navarro-Espinoza, A., López-Bonilla, O. R., García-Guerrero, E. E., Tlelo-Cuautle, E., López-Mancilla, D., Hernández-Mejía, C., & Inzunza-González, E. (2022). Traffic flow prediction for smart traffic lights using machine learning algorithms. Technologies, 10(1), 5.

[12] Ramesh, K. (2021). Smart Traffic Prediction and Congestion Reduction in Smart Cities. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(12), 1027-1033.

[13] Boukerche, A., & Wang, J. (2020). Machine learning-based traffic prediction models for intelligent transportation systems. Computer Networks, 181, 107530.

[14] An, C., & Wu, C. (2020). Traffic big data assisted V2X communications toward smart transportation. Wireless Networks, 26, 1601-1610.

[15] Ibrahim, A., & Hafez, A. (2023). Adaptive IEEE 802.11 ah MAC protocol for Optimization Collision Probability in IoT smart city data traffic Based Machine Learning models.

[16] Lippmann, R., Fried, D., Piwowarski, K., & Streilein, W. (2003, November). Passive operating system identification from TCP/IP packet headers. In Workshop on Data Mining for Computer Security (Vol. 40).

[17] Yıldırım, P., Birant, U. K., & Birant, D. (2019). EBOC: Ensemble-based ordinal classification in transportation. Journal of Advanced Transportation, 2019, 1-17.

[18] Ozbayoglu, M., Kucukayan, G., & Dogdu, E. (2016). A real-time autonomous highway accident detection model based on big data processing and computational intelligence. In 2016 IEEE international conference on big data (Big Data) (pp. 1807–1813).

[19] Niu, X., Zhu, Y., Cao, Q., Zhang, X., Xie, W., & Zheng, K. (2015). An online-traffic-prediction based route finding mechanism for smart city. International Journal of Distributed Sensor Networks, 11(8), 970256.

[20] Smart City Traffic Patterns. Available online: https://www.kaggle.com/datasets/utathya/smart-city-traffic-patterns/code (accessed on 15 June 2023).

[21] Shrestha, D. L., & Solomatine, D. P. (2006). Experiments with AdaBoost. RT, an improved boosting scheme for regression. Neural computation, 18(7), 1678-1710.

[22] Shanmugasundar, G., Vanitha, M., Čep, R., Kumar, V., Kalita, K., & Ramachandran, M. (2021). A comparative study of linear, random forest and adaboost regressions for modeling non-traditional machining. Processes, 9(11), 2015.

[23] Gupta, K.K.; Kalita, K.; Ghadai, R.K.; Ramachandran, M.; Gao, X.-Z. Machine Learning-Based Predictive Modelling of Biodiesel Production—A Comparative Perspective. Energies 2021, 14, 1122. [CrossRef]

[24] Kummer, N., & Najjaran, H. (2014). Adaboost. MRT: Boosting regression for multivariate estimation. Artif. Intell. Res., 3(4), 64-76.

[25] Dahiya, N., Saini, B., & Chalak, H. D. (2021). Gradient boosting-based regression modelling for estimating the time period of the irregular precast concrete structural system with cross bracing. Journal of King Saud University-Engineering Sciences.

[26] Gumaei, A., Al-Rakhami, M., Al Rahhal, M. M., Albogamy, F. R., Al Maghayreh, E., & AlSalman, H. (2021). Prediction of COVID-19 confirmed cases using gradient boosting regression method. Comput Mater Continua, 66, 315-329.

[27] Bentéjac, C., Csörgő, A., & Martínez-Muñoz, G. (2021). A comparative analysis of gradient boosting algorithms. Artificial Intelligence Review, 54, 1937-1967.

[28] Touzani, S., Granderson, J., & Fernandes, S. (2018). Gradient boosting machine for modeling the energy consumption of commercial buildings. Energy and Buildings, 158, 1533-1543.

[29] Zhang, Y., & Haghani, A. (2015). A gradient boosting method to improve travel time prediction. Transportation Research Part C: Emerging Technologies, 58, 308-324.

[30] Yangın, G. (2019). XGboost ve Karar Ağacı tabanlı algoritmaların diyabet veri setleri üzerine uygulaması (Master's thesis, Mimar Sinan Güzel Sanatlar Üniversitesi, Fen Bilimleri Enstitüsü).

[31] Islam, S., & Amin, S. H. (2020). Prediction of probable backorder scenarios in the supply chain using Distributed Random Forest and

Gradient Boosting Machine learning techniques. Journal of Big Data, 7(1), 65.

[32] Kaur, H., Malhi, A. K. & Pannu, H. S. (2020). Machine learning ensemble for neurological disorders. Neural Computing and Applications, 32, 12697-12714.

[33] Aksu, G. & Doğan, N. (2018). Learning Methods Used in Data Mining Comparison under Different Conditions. Ankara University Journal of Faculty of Educational Sciences (JFES). 51(3). 71-100.

[34] Zaman, M., Saha, S., & Abdelwahed, S. (2023, June). Assessing the Suitability of Different Machine Learning Approaches for Smart Traffic Mobility. In 2023 IEEE Transportation Electrification Conference & Expo (ITEC) (pp. 1-6). IEEE.

[35] Alekseeva, D., Stepanov, N., Veprev, A., Sharapova, A., Lohan, E. S., & Ometov, A. (2021). Comparison of machine learning techniques applied to traffic prediction of real wireless network. IEEE Access, 9, 159495-159514.

[36] Tiwari, P. (2024). The machine learning framework for traffic management in smart cities. Management of Environmental Quality: An International Journal, 35(2), 445-462.

[37] Zheng, G., Chai, W. K., & Katos, V. (2019, December). An ensemble model for short-term traffic prediction in smart city transportation system. In 2019 IEEE Global Communications Conference (GLOBECOM) (pp. 1-6). IEEE.

[38] Savithramma, R. M., Sumathi, R., & Sudhira, H. S. (2022). A comparative analysis of machine learning algorithms in design process of adaptive traffic signal control System. In Journal of Physics: Conference Series (Vol. 2161, No. 1, p. 012054). IOP Publishing.

BIOGRAPHIES

Özlem Bezek Güre graduated in Statistics from Anadolu University. She received her MSc in Biostatistics from Firat University, and her PhD from Van Yuzuncu Yil University in Statistics. She is currently an instructor at Batman University, working on machine learning, data mining, and statistic. She has studies published in national and international scientific platforms.

Copyright © European Journal of Technique (EJT)