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Predictive Machine Learning Algorithms for Metro Ridership Based on Urban Land Use Policies in Support of Transit-Oriented Development

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Abstract: The endeavors toward sustainable transportation systems are a key concern for planners and decision-makers where increasing public transport attractiveness is essential. In this paper, a machine-learning-based predictive modeling approach is proposed for metro ridership prediction, considering the built environment around the stations; it is in the best interest of sustainable transport planning to ultimately contribute to the achievement of Sustainable Development Goals (UN-SDGs). A total of twelve parameters are considered as input features including time of day, day of the week, station, and nine types of land use density. Hence, a time-series database is used for model development and testing. Several machine learning (ML) models were evaluated for their predictive performance: ridge regression, lasso regression, elastic net, k-nearest neighbor, support vector regression, decision tree, random forest, extremely randomized trees, adaptive boosting, gradient boosting, extreme gradient boosting, and stacking ensemble learner. Bayesian optimization and grid search are combined with 10-fold cross-validation to tune the hyperparameters of each model. The performance of the developed models was validated based on the test dataset using five quantitative performance measures. The results demonstrated that, among the base learners, the decision tree showed the highest performance with an R^2 of 87.4% on the test dataset. KNN and SVR were the second and third-best models among the base learners. Furthermore, the feature importance investigation explains the relative contribution of each type of land use density to the prediction of the metro ridership. The results showed that governmental land use density, educational facilities land use density, and mixed-use density are the three factors that play the most critical role in determining total ridership. The outcomes of this research could be of great help to the decision-making process for the best achievement of sustainable development goals in relation to sustainable transport and land use.

Keywords: sustainable transportation; metro ridership; time series models; machine learning; urban planning; land use policy; sustainable development

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1. Introduction

Sustainable transport includes the application of the sustainable development concept in the process of planning and development of transport infrastructure. Refs. [1–3] suggested that sustainable transportation systems evolve the application of sustainable development planning strategies; for instance, transportation sustainability is defined as "meeting the current mobility and transport needs nevertheless not compromising the future generations to meet those needs". According to OECD, Taiwan Transport Institute, and ref. [4], sustainable transport must be able to meet long-term and simultaneous environmental, social, and economic needs and impacts. There are three aspects of sustainable transport: environmental, social, and economic. Environmental aspect requires taking into account the external effects of the transport process; the social aspect also requires considering the interests of residents at different socio-economic levels while improving transport; economic aspects require efficient use and conservation of resources [1].

In this respect, to sustain the public transportation resources, planners should address the transportation systems operations with respect to the built environment around stations; in other words, they are expected to assure the highest efficiency of the transport service by increasing transport accessibility to as many residents as possible [4]. The trade-offs between transportation operation needs and built environment considerations could easily be solved by having high-density urban areas centered on transit service, yet an acceptable economic aspect should be maintained [5]. While the socio-economic attribute of sustainable development can be improved through transport infrastructure through logistics and multimodal capacity planning, intra-regional accessibility of the transport infrastructure promotes economic dimensions and other social interactions. Accessibility plays an undeniable role in urban areas and also ensures infrastructure efficiency combined with the multimodality of public transport [2].

With the rapid development of urbanization, the metro has become one of the main drivers of public transport due to its various advantages, such as high efficiency, high capacity, convenience, etc. [1]. During the planning phase of urban transport and construction, it is important to examine many urban indicators from a systemic point of view to cover urban-transport phenomena, such as density, ridership, and accessibility. Metro ridership at the station level is an important factor in determining the size of stations and access to facilities. Various components of the urban system (e.g., land use and socioeconomic aspects) require the kind of modeling presented in this paper, which could be of help to accurately estimate and predict the number of passengers, as well as analyze influencing factors. Recently, with the development of artificial intelligence and computational capabilities, machine learning (ML) techniques have gained considerable attention owing to their ability to effectively determine the relationship between the response variable and its predictors in a complex system [6]. In spite of their great efficacy, the literature lacks the application of machine learning models to the metro transportation system ridership, considering the built environment.

To this end, this study mainly focuses on metro transportation system ridership on a station level, and the land use density component of the urban system. The research contributes to both theory and practice as follows. The proposed methods examined in this research enable a time series prediction of metro ridership, considering the built environment and transportation sustainability. On the practical aspect, the examined model outcomes are applied to the case of Doha Metro and could be similarly applied to similar regions and cases. Furthermore, the outcomes of this research have numerous implications for both transportation operation and urban planning policymakers, which significantly bridge the gaps between theory and practical urban-transport models.

1.1. Public Transportation Sustainability

Integrated, strategic, and society-supported policies are required for the process of shifting toward sustainable transportation systems and behavior [7–9]. As per refs. [10,11], sustainable transportation measures do not seem to be restricted to mobility standards wherever the majority of transportation studies comprise. Sustainable transportation has to be thought of from an exceedingly additional holistic vision, therefore social, environmental, and economic impacts of high vehicle dependency as a transportation mode alternative may be given [3]. The study by [12] highlighted the importance of a holistic method that comprises institutional reforms, changes in land use (urban fabric), and economic incentives over individual technology solutions (vehicle-based) with a distorted perspective to achieve sustainable transport goals. It is well known that urban transport must play a central role in the development of today's urban structures that occupy huge areas and require excessive travel to meet basic needs, worker travel, etc. Qatar has very limited expertise with public transport and transit-oriented systems, resulting in additional resistance to changes from a vehicle-oriented society to a TOD [13]. Moreover, ref. [14] in their study examined the spatiotemporal heterogeneity in the nonlinear influence of transit-oriented development (TOD) on metro ridership. The findings have led to a better understanding of the spatiotemporal heterogeneity in the nonlinear influence of TOD on metro ridership.

In addition to the current macro-level literature, a number of survey-based studies have provided overlapping results, as they have recognized anomalies in the existing paradigm. Ref. [15] pointed out that the influences of travel time and financial costs on modality alternatives are independent of land use influences. In addition to the infrastructure of the city, demographic information, and the choice of transportation mode could be a matter of higher cognitive processing on the part of citizens, and this decision is plagued by psychological and emotional patterns. Ref. [2] accepts this as true, with ref. [3] thereon stating that urban fabric and transportation interactions may be accomplished by observing past tendencies in the urban fabric and a stripped-down upsurge in the ridership of public transportation. Despite the inflated federal investments in public transportation in several societies, such as the state of Qatar, the shared idea, implicit assumptions, and perceptions push right up against public transportation participation.

1.2. Transport-Related Sustainable Development Goals (SDGs)

According to Sustainable Development Agenda 2030, sustainable transport systems offer the world access to sustainable, reliable, affordable, and up-to-date energy facilities, resilient and quality infrastructure, and strategies that provide highly helpful capacities that can strengthen the foundations of the country's economy [16]. However, twelve targets are enclosed within the 2030 Agenda for sustainable development, which is associated with transportation (Figure 1), and five of them are directly associated with transportation, whereas seven of them are indirectly associated with it. Moreover, the five targets that are directly associated with transportation are road safety (Target 3.6), energy efficiency (Target 7.3), sustainable infrastructure (Target 9.1), urban access (Target 11.2), and fuel subsidies (Target 12.c). However, this highlights that sustainable transport is critical to accelerating the accomplishment of sustainable development goals. In other words, the common relationship between land use and transportation is seen in (SDG 9, 11, and 12). For example, travel demand is stricken by land use, whereas the patterns of land use are conspicuously wedged by transportation networks [17]. Thus, the connection between land use and transportation should be thought of in addressing urban planning efficiently, regarding sustainable development [17–19]. Transportation and land use have usually had a major role in the physical and economic development of contemporary cities. However, sustainable development advantages urban planners in supporting environmental, social, and economic goals, and managing infrastructures intellectually within the town [20,21]. Thus, for the exact purpose of accomplishing sustainable urban planning in cities, some approaches are established, similar to the Transit-Oriented Development (TOD) planning approach, which has been evidenced to be quite flourishing among varied existing projects [22].

1.3. Ridership Issues for Public Transportation

Considerable research work has been carried out with the aim of increasing the use of public transport; ref. [1,7] stated that, typically, seven key issues need to be addressed for transport to be sustainable in urban:

- Congestion in many urban areas is becoming more prolonged and intense. Urban speeds decline by 5% per decade, and congestion increases with city size [23].
- Increased air pollution has led to exceeding the national standards of air quality recommended by the (WHO, 2021) in many cities. Air pollution effect has a significant effect on health, reduces visibility, and destroys local structures and ecosystems, reducing the quality of urban life.
- Traffic noise has an impact on the entire life of the city. Ref. [24] estimated that about 15% of people in developed countries are most likely to be exposed to noise pollution, mainly from vehicles, trucks, and overnight deliveries.

- Degradation of the urban landscape due to new road construction and new vehicles on the roads, the historic buildings demolition, the reduction of open spaces, and urban sprawl [7].
- Space use by a vehicle enables the movement of car drivers but decreases other accessibility, as traffic routes turned out to be obstacles due to the fact that parked cars create difficulties for pedestrians, cyclists, and people who have disabilities, which leads to a predominance of traffic in urban environments.
- Global warming is the result of the usage of fossil fuels. Currently, transportation systems account for 25% of CO_2 emissions, and this level is increasing in both comparative and absolute terms. Moreover, transportation is entirely dependent on fuel, which is a non-renewable source of energy.
- Furthermore, transportation contributes to change in the urban fabric of the city, thus, development and land use factors should be added to the list above.
- Vehicle use has contributed to the city's decentralization, combined with efficient public transport. This significantly increases commuting time and the development of more dispersed movement patterns with a center in the city center, thereby increasing dependence on cars and reducing opportunities for developing an efficient public transport community; transport has become a driving force of change.
- Industry displacement and globalization (for instance, the information economy) have led to newfangled patterns of distribution and an increase in freight traffic at the global, regional, and local levels. Technologies and solutions that could be of help in promoting the relatively most efficient use of space and eliminating the total additional land allocated for the developments are highly needed. There is a sort of common agreement on these issues, and largely the variety of strategies existing is known, but progress has been made, and it's slow to integrate sustainability into everyday solutions.
- With the intensive transformation of the built environment in the state of Qatar from a traditional mixed-use, high-density fabric to inaccessible, car-oriented superblocks of the newly developed cities and closed communities on the periphery, urban mobility is noticeably affected. Along with the use of retail/commercial and office space, they benefit greatly from the country's sustainability [25]. Undoubtedly, based on the Transit Oriented Development (TOD) consensus, metro transport in the state of Qatar promises rapid and ambitious growth and is expected to become one of the main methods of connecting different districts. TOD is an auspicious tool that enhances greener mobility by switching from cars to the metro, encouraging short-distance walking, and using local public transport for long distances [25], and it can slow sprawl through the compact development of urban areas [26,27]. With the motivation to promote rail transport systems, studies looking at the factors influencing the number of passengers in transit have become interesting, but the impact of local communities on the number of passengers in transit is surprisingly different from the various contexts of the city.

a. Machine Learning-Based Ridership Prediction for Public Transportation

In general, optimization models are used for the planning of the transit network, as well as the optimum transfer, the orientation of the route, and, therefore, the ridership [28]. Ref. [29] outlined an empirically supported genetic algorithm to enhance the performance of the present networks by plummeting the vehicles while not penalizing the typical travel time. In this sense, it's been shown that heuristic algorithms are helpful in resolving numerous transport problems; for example, the matter of the road trafficker, the routing of multi-depot vehicles, or the shuttle network design [30–32], to simply call a couple of examples. Ref. [33] planned a computational tool for optimizing massive routes of transit networks that minimize transfers and optimize route openness through improved coverage of service. They tested the tool and functioned it to a significant and accurate network optimization drawback to the city of Miami. Ref. [34] investigated a three-tier hierarchic optimization method for resolving the mass transit network development problems that are typical of versatile large-scale mass transit choices and the exploitation of new technologies for passenger-vehicle communication. Ref. [35] deliberated on accessibility, which is a vital component of service delivery. Access sometimes has an approximate service associated with the cost, while access is expounded to the adequacy of the transit system to induce individuals from wherever they approach to where they are in an inexpensive period. In Australia, ref. [36] established a hybrid coverage model to concurrently expand access to services and, moreover, increase public transportation accessibility. The scholar suggested that the operation aspect of transport planning is the spatial effects of the service. Ref. [37] estimated rural mass transit traveler models that reply to public demand employing types of variables and derived helpful data for correct planning transport services that respond to local demand.

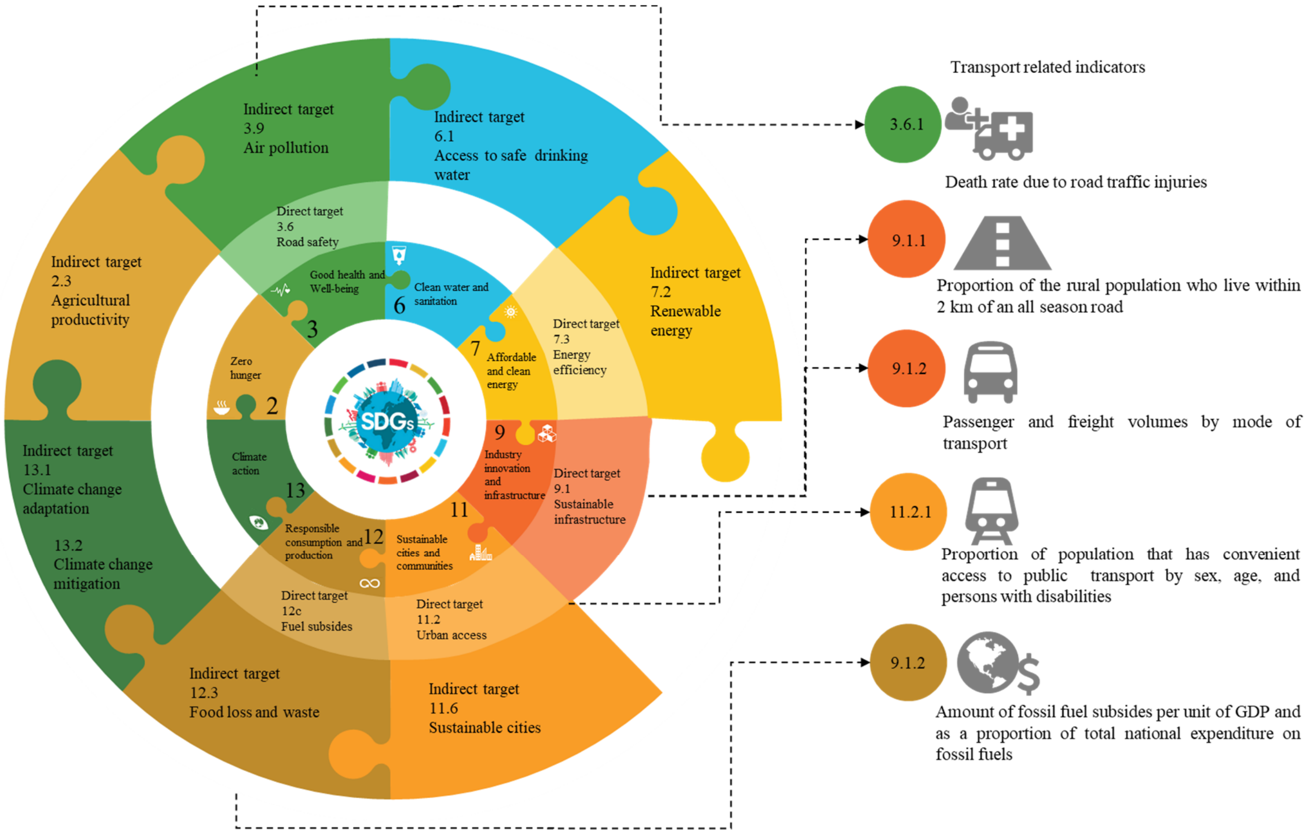


Figure 1. Transport-related sustainable development goals.

Ref. [38] addressed the requirement to quantify the trade-off amongst ridership and the way to enable public transport planning and choices regarding the balance between these priorities. This becomes a lot of vital given the participation of non-experts in the democratic planning of transportation [39,40]. In such a sense, the incorporation of people participation, quantitative analysis, and GIS methods, particularly Multi-Criteria Decision Analysis (MCDA), is proving to be useful in promoting joint and technically sound decisions [28]. In addition, though newer models are utilized to support the planning and design of recent DRST services [32,41], there's an absence of special analyzes and ways to integrate typical regular public transportation with flexible on-demand services. This might be taken into consideration as a primary stage in the planning of integrated, mounted, and versatile transport services supported by indicators of accessibility and social justice. It ought to be noted that although accessibility and equity do not embrace all of the essential operation and design features of public transportation (e.g., economical and operative public transportation intermeshed towards sustainability) [42].

b. Research Motivation and Knowledge Gap

Referring to recent studies discussed in Section 1.3(a), the previous studies have approached the ridership problem mainly from a purely operational perspective, utilizing several optimizations and regression models. To the best extent of the author's knowledge, no previous study has investigated the public transport ridership problem using urban fabric using machine learning-enhanced models. Thus, the current research is aimed to set up a comprehensive understanding of the public transportation operation considering built environment characteristics toward a Transit-Oriented Development, ending with the SDGs agenda achievement. A time-series data was utilized to examine simple machine learning techniques that may or may not capture the relationship between the response (ridership) and its predictors (land use densities), which could dictate the use of advanced techniques. Overall, the research attempts to develop machine learning-enhanced models that have the ability to accurately predict metro ridership concerning the built environment around the stations.

2. Methods

2.1. Data Collection

The State of Qatar is located on the east coast of the Persian Arabian Gulf. It is connected to the Arabian Peninsula and borders Saudi Arabia to the south. Qatar has been shaped by rapid globalization and urbanization. For the past five decades, notable economic change from a fishing and pearl collecting-based economy to a thriving and varied economy based on the production and export of natural gas/oil has been observed. Today, Qatar has almost 13% of the total international supply of natural gas reserves [43]. The country's growth and hosting of several mega-events, such as the 2006 Asian Games and the 2022 World Cup, led to intensive urban growth and development. The country witnessed a significant increase in population over the past two decades, from a projected urban population of 492 hundred thousand in 2000 to more than 2.4 million people in 2020. Consequently, the government confronted major challenges in the management of the growth, transport, infrastructure, accommodations, and preservation of the ecosystems.

The changes included the construction of a sophisticated road network, including road extensions and a ring road/expressway system. The traditional low-rise housing was almost abandoned for modern residential villas, typically three-story and high-rise apartments [44–46]. In parallel with its rapid urbanism growth. Sustainable development of transport systems is a core diminution in Qatar National Vision (QNV) 2030, which includes plans to develop a 300 km metro system with four lines and 98 stations connecting the international airport, stadiums, and urban areas [47]. In 2019, three lines and 38 stations are in operation.

2.2. Data Preprocessing

Figure 2 outlines a simplified procedure followed in this study. Firstly, a database of ridership is collected and pre-processed. Time-series data for metro ridership were collected from 38 different metro stations in the State of Qatar. The database was then randomly divided into train and test sets that consist of 80% and 20% of the entire dataset, respectively, as shown in Figure 2. The train set was used for the development and validation of the models, while the test set was used for the final appraisal of the models. A total of twelve white box and black box machine learning models were run to examine their predictive capabilities for the given problem. Furthermore, five different statistical performance metrics have been used for the evaluation of the predictive performance of the ML models and select the best-performing model among the twelve models considered in this study (Figure 2). Figure 3 demonstrates the total ridership distribution on weekdays and weekends. As shown in Figure 3, ridership during the weekdays is significantly higher than that for the weekend from 05:00 AM to 9:00 AM. Particularly, the ridership on Friday (the first weekend day in the State of Qatar) is zero between 05:00 AM and 12:00:00 AM; however, it was higher than on all other days after 3:00 PM (Figure 3). The peak ridership on each day was observed between 05:00 to 6:00 PM, after which it declines to less than 10,000 at 11:00 PM on Thursday and Friday and at 10:00 PM on Saturday and weekdays.

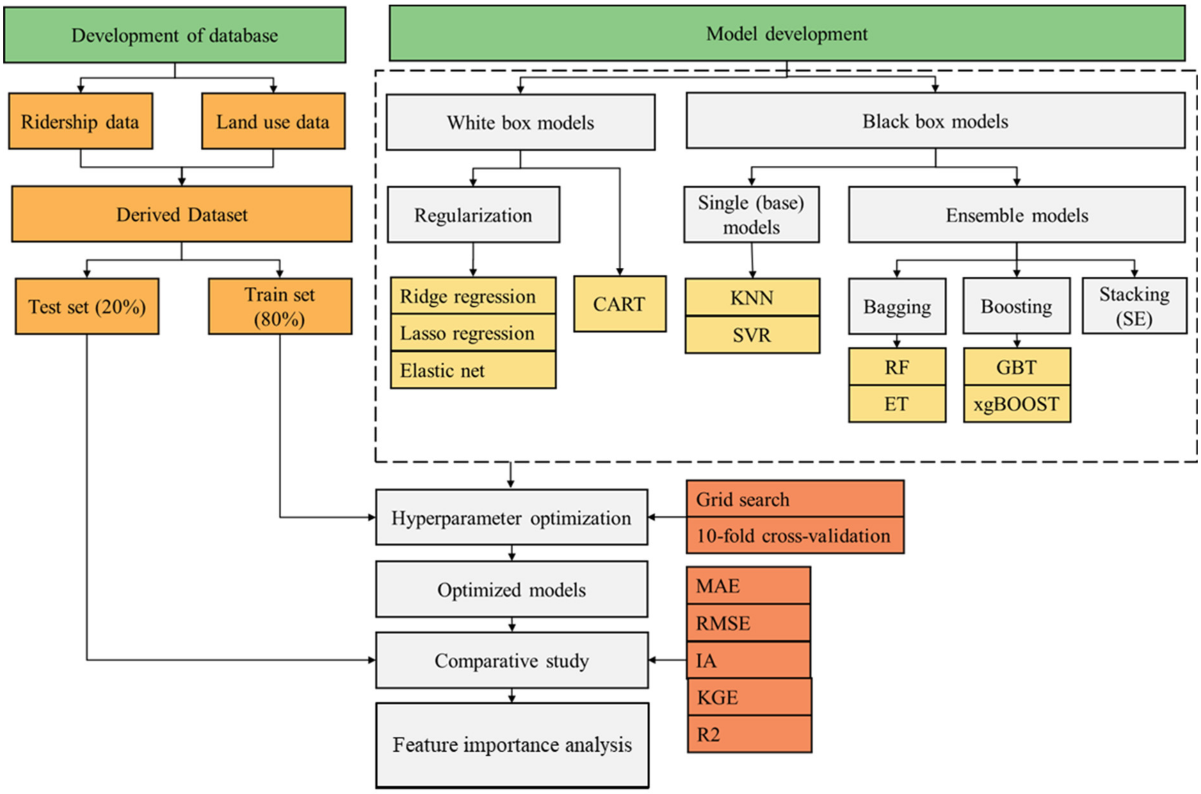


Figure 2. Research Framework.

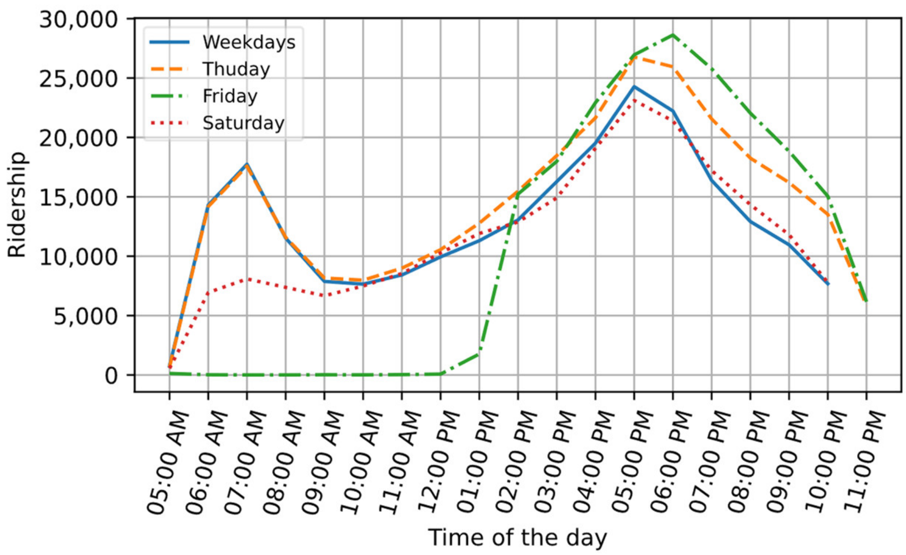


Figure 3. Distribution of ridership on weekdays and weekends.

The input features comprised a total of twelve parameters including time of day, day of the week, station, and land use density for open space and recreation facilities (indoor-outdoor), religious facilities, education facilities, retail/commercial, residential, special use, transportation, and government facilities. The distribution of the ridership for the complete dataset is shown in Figure 4 regardless of the land-use density. During the pre-processing stage, the database shown in Figure 4 is normalized based on Equation (1) below:

$$X_{i,\,n}^{j} = \frac{X_i^j - X_{min}^j}{X_{max}^j - X_{min}^j},\ j = 1,\ 2,\ \ldots,\ M;\ i = 1,\ 2,\ \ldots,\ N \tag{1}$$

where X_i^j is the ith observation of jth input features and $X_{i,\,n}^j$ is its corresponding normalized value, X_{max}^j and X_{min}^j are the maximum and minimum values of the jth input features, N represents the total observation numbers, and M is the number of input features.

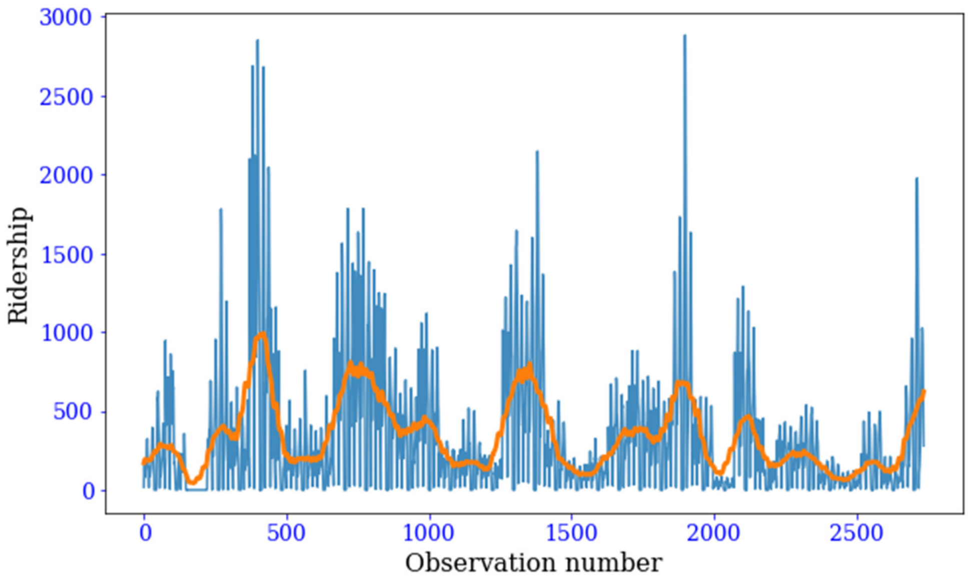


Figure 4. Ridership data was used for model development.

Figure 5 represents the diversity of land use within the 800 m catchment area at the 38 metro stations. It is clear from this figure that the majority of the land use in this area is High-Density Residential land use with a wide mix of offices, commercial, and recreation zones. The developed model utilized the data within the catchment areas at each station to predict the ridership at each metro station.

2.3. Predictive Models

2.3.1. Regularization

A regularization is an extended form of linear regression with an aim to enhance the generalization ability of the model. In contrast to linear regression, which computes the parameters estimates by minimizing the RMSE of the predictions, a regularization parameter that punishes the models with multiple model parameters is introduced in regularization, as illustrated below:

$$\min_{\beta_i}(RMSE + \varepsilon(\lambda,\ \beta)) \tag{2}$$

where λ controls the trade-off between bias-variance.

Ridge regression (RR), elastic net (EN), and lasso (short for least absolute shrinkage and selection operator) regression are the foremost usually used regularization algorithms. In ridge regression, the regularization function is taken into account because the total of the sq. of the constants, $\varepsilon(\lambda,\ \beta) = \lambda \sum_i \beta_i^2$, whereas the absolute values of the coefficient are employed in lasso regression, $\varepsilon(\lambda,\ \beta) = \lambda \sum_i |\beta_i|$. The penalty in lasso regression tends to set the model parameters to zero, while RR tends to scale back the absolute values of each parameter of the models. The penalty function in the elastic net is given by: $\varepsilon(\lambda,\ \beta) = \lambda_1 \sum_i \beta_i^2 + \lambda_2 \sum_i |\beta_i|$.

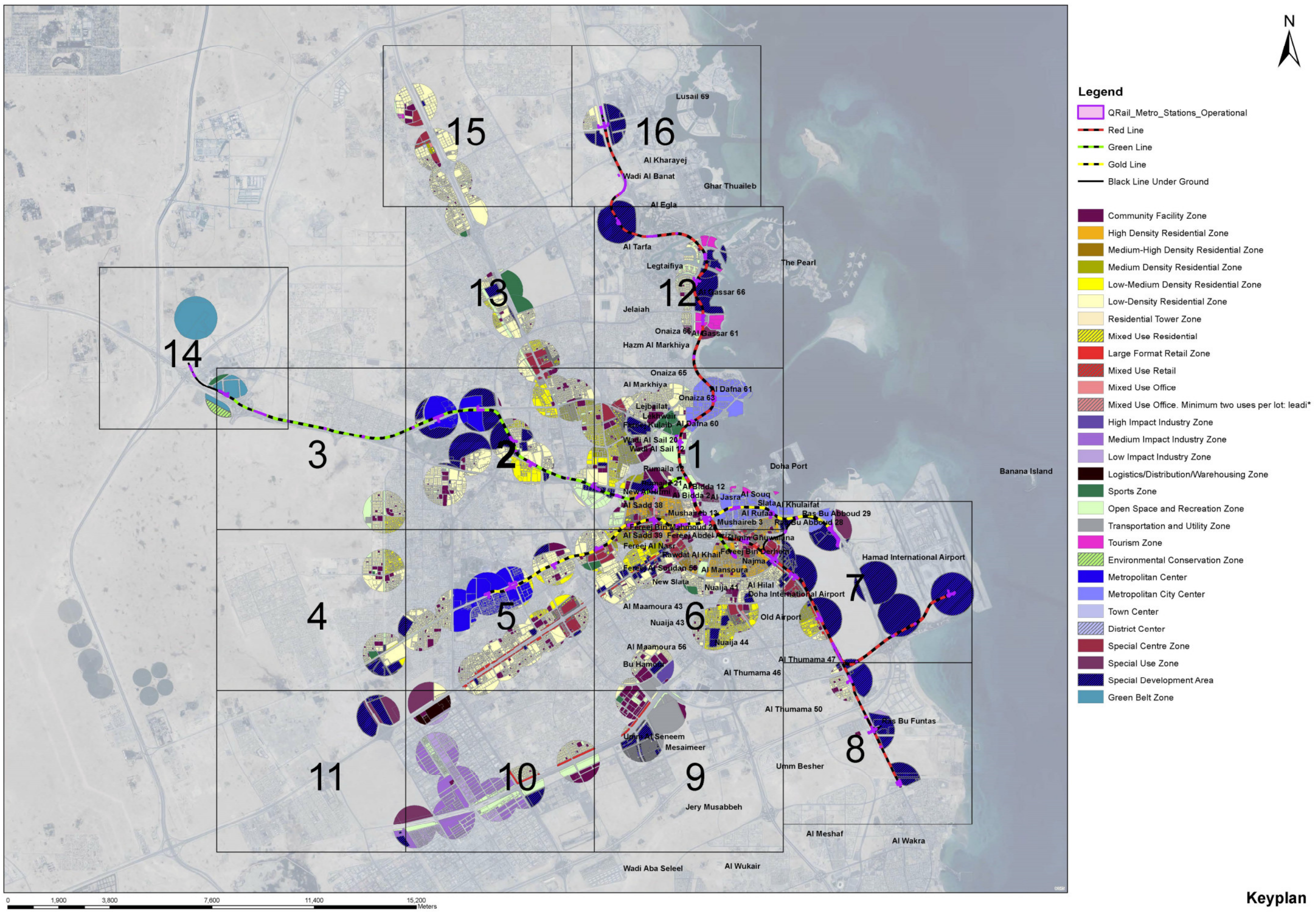


Figure 5. Land use in the stations' catchment area.

2.3.2. K-Nearest Neighbor

The K-nearest neighbor (KNN for short) is among the nonparametric supervised ML algorithms that can be used to solve classification as well as regression problems. The predicted output in KNN is evaluated as the mean of the predictions from the K data points nearest to the query point. Provided a training data set $\{(x_i,\ y_i)\}_{i=1}^{N}$ and a query point X_q, the K-nearest neighbor entails the determination of the points in the training dataset that are nearest to X_q [2]. The prediction of X_q is then computed as the weighted average of the predictions from the K observations nearest to X_q.

2.3.3. Support Vector Regression

Support vector regression (SVR) utilizes kernel functions to map the data into a wide-dimensional space, where linear separation is conceivable. Provided a training data set $\{(x_i,\ y_i)\}_{i=1}^{N} \epsilon\ \mathbb{R}^Q \times \mathbb{R}$, with N data points, where $x_i\ \epsilon\ X = \left\langle x_i^1,\ \ldots,\ x_i^Q \right\rangle \subseteq \mathbb{R}^Q$ are input parameters Q and y_i is the response, SVR the function f(x) in Equation (3).

$$f(x) = \sum_{i\epsilon\ SV} (\alpha_i - \alpha_i')\ K(x_i,\ x) + b \text{ subject to } \alpha_i, \alpha_i' \epsilon\ [0,\ C] \tag{3}$$

where C denotes the regularization parameter, $K(x_i,\ x)$ is the kernel function, SV represents support vectors, b is the bias, and α_i and α_i' are multipliers of Lagrangians of the inferior and superior SVs.

2.3.4. Decision Tree

The decision tree, also known as the classification and regression tree (CART), iteratively splits the feature space into D disjoint and distinct regions: $\{R_1, R_2, \ldots, R_D\}$ based on different measures, such as the mean squared error Gini Index [48] (L. Breiman et al., 1984) for regression and classification problems, respectively. The decision tree algorithm comprises three main components: (a) the topmost node referred to as the root node, (b) intermediate or internal nodes, and (c) the leaf or terminal node. Hence, the optimum decision tree model can be found by tuning the maximum depth of the tree, the minimum number of samples needed to split the internal node, and the minimum sample number required to be at the leaf node. Bayesian optimization is combined with a cross-validation technique to find the optimum values of the hyperparameters of each ML model in this study.

The CART algorithm is easy to visualize and interpret and not sensitive to outliers, but it has low generalization capability and is associated with high bias and variance. As a result, an ensemble of several CARTs can be used to enhance its generalization ability, as presented in the subsequent sections.

2.3.5. Bagging Ensemble: Random Forest, Extremely Randomized Trees

Bootstrap aggregation (Bagging) ensemble [49] (Leo Breiman, 2001) is one of the tree-based ensemble models that aggregate multiple decision tree models in parallel to form a strong model. Random forest (RF) and extremely randomized trees or extra trees (ET) are the two commonly utilized examples of bagging ensemble. RF independently trains T number of decision trees on randomly chosen samples with replacement referred to as bootstrap samples. The final prediction is then determined as the mean of the prediction from the T base learners (CART). Extremely randomized trees or extra trees (ET) is an additional form of bagging ensemble proposed by [50] Geurts et al., (2006). In ET, each base learner (CART) fits the entire training data set, unlike RF, which uses a bootstrap sample to construct CART. Similar to RF, the extremely randomized trees algorithm divides nodes with random subsets of input features, but the ET algorithm arbitrarily chooses an optimal split [50] (Geurts et al., 2006).

To find optimum RF and ET models, the following hyperparameters should be optimized: (a) the number of estimators or decision trees, (b) the minimum sample leaf, and (c) the maximum input features number required to split a node.

2.3.6. Boosting Ensemble: Adaptive Boosting, Gradient Boosting Trees, xgBoost

Boosting ensemble sequentially aggregates several base learners, typically CART in order to form a strong model. Adaptive Boosting (AdaBoost), gradient boosting trees (GBT), and extreme gradient boosting (xgBoost) are the three commonly used types of boosting ensemble. Provided a training set $\{(x_i, y_i), i = 1, 2, \ldots, N\}$, the AdaBoost algorithm [51] (Drucker, 1997) performs the following using T number of predictors (CART):

i. Initially, assign equal weights $\left\{ w_i^{(1)} = 1/N \right\}$ to each training example.
ii. For t = 1 to T, perform the following:
    (a) Train the weak learner $h_t : x \to y$
    (b) Compute the prediction from h_t: $y_i^{(t)}(x_i), i = 1, \ldots, N$
    (c) Determine the loss of model h_t: $L_i^{(t)} = L_t\left(\left|y_i - y_i^{(t)}(x_i)\right|\right)$, where $L_t \epsilon [0, 1]$ is the loss function. Linear, square, or exponential loss functions can be used as provided in Equations (4)–(6), respectively.

$$L_i^{(t)} = \frac{\left|y_i - y_i^{(t)}(x_i)\right|}{max\left|y_i - y_i^{(t)}(x_i)\right|}, \quad i = 1, \ldots, N \tag{4}$$

$$L_i{}^{(t)} = \frac{\left|y_i - y_i{}^{(t)}(x_i)\right|^2}{max\left|y_i - y_i{}^{(p)}(x_i)\right|},\ \ i = 1,\ \ldots,\ N \tag{5}$$

$$L_i{}^{(t)} = 1 - e^{\left(\frac{\left|y_i - y_i{}^{(t)}(x_i)\right|}{max\left|y_i - y_i{}^{(p)}(x_i)\right|}\right)},\ \ i = 1,\ \ldots,\ N \tag{6}$$

(d) Determine the mean of the loss:

$$\overline{L^{(t)}} = \sum_{t=1}^{n} L_i{}^{(t)}\, w_i{}^{(t)},\ L_t\, \epsilon\, [0,\ 1] \tag{7}$$

(e) Update the values of the weights:

$$w_i{}^{(t+1)} = w_i{}^{(t)} \beta_t{}^{1-L_i{}^{(t)}} \tag{8}$$

$$\beta_t = \frac{\overline{L^{(t)}}}{1 - \overline{L^{(t)}}} \tag{9}$$

The final prediction of the response is computed as the final cumulative predictions using T trees.

Gradient boosted trees as a more general form of boosting ensemble allows the usage of arbitrary loss functions, unlike AdaBoost. Provided a training set $\{(x_i,\ y_i),\ i = 1,\ 2,\ \ldots,\ N\}$, GBT performs the following:

(a) Start model with constant value: $F_o(x) = \underset{\gamma}{\arg\min} \sum_{i=1}^{N} L(y_i, \gamma)$ in which L, y_i and γ represent loss function, observed response value, and predicted response value.

(b) For $t = 1\ to\ T$ (where T denotes the total number of estimators):

i. Determine $g_i^t = -\left[\frac{\partial L(y_i, F(x_i)\ )}{\partial F(x_i)}\right]_{F(x) = F_{t-1}(x)},\ i = 1,\ \ldots,\ N$ which is the negative gradient descent.

ii. Train CART $h_t(x)$ using $\left\{\left(x_i,\ g_i^t\right)\right\}_{i=1}^{N}$ as training examples.

iii. Compute the value of γ_t by solving $\gamma_t = \underset{\gamma}{\arg\min} \sum_i L(y_i, F_{t-1}(x_i) + \gamma h_t(x_i))$.

iv. Update the model: $F_t(x) = F_{t-1}(x) + \gamma_t h_t(x)$.

(c) Finally, output $F_T(x)$.

Another variation of boosting ensemble, extreme gradient boosting (xgBoost) is introduced in 2016 by [52] (Chen & Guestrin, 2016) as an effective implementation of gradient boosting. A regularization term is introduced in the objective function of xgBoost for the purpose of minimizing the complexity of the model and overcoming the problem of overfitting, as given in Equation (10) [52] (Chen & Guestrin, 2016).

$$\sum_{i=1}^{N} L\left(y_i, \hat{y}_i{}^{(t)}\right) + \sum_{i=1}^{t} \Omega(f_i) \tag{10}$$

$$\Omega(f) = \gamma D + \frac{1}{2}\lambda \sum_{j=1}^{K} w_j^2 \tag{11}$$

The first term in Equation (10) denotes the loss function, while the second term denotes the complexity of the model. Moreover, λ and j represent the regularization parameters, D is the number of leaves, and γ and w_j denote the complexity and weight of each leaf.

2.4. Model Performance Evaluation

Five different statistical performance metrics are considered to assess the predictive performance of the ML models and select the best-performing model among the twelve models considered in this study. The statistical metrics include: (a) the root mean squared error (RMSE), (b) the mean absolute error (MAE), (c) the coefficient of determination (R^2),

(e) the index of agreement (IA), and (f) the Kling-Gupta efficiency (KGE), as given by Equation (12) through Equation (16). Low error (RMSE and MAE), and high IA, R^2, and KGE demonstrate the best predictive model. The KGE as an improvement of Nash-Sutcliffe efficiency considers three important measures: namely, correlation, bias, and variability in a more balanced way, as given in Equation (16). KGE = 1 shows a perfect agreement between the actual and predicted ridership. The same is true for R^2 and IA.

$$MAE = \frac{1}{N}\sum\nolimits_{i=1}^{N}|y_i - \hat{y}_i| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y})^2} \tag{14}$$

$$IA = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(|y_i - \overline{y}| + |\hat{y}_i - \overline{y}|)^2},\ 0 < IA \leq 1 \tag{15}$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \tag{16}$$

where y_i is the ith observed value of output variable, $\hat{y}_i$ is the ith the estimated value of the output variable, $\overline{y}$ is the average value of the output variable, r is the linear correlation between the actual and predicted response variable, $\alpha = \sigma_{\overline{y}}\ /\sigma_y$ is a measure of variability, $\beta = \mu_{\overline{y}}\ /\mu_y$, is a bias term, $\sigma_{\overline{y}}$ and σ_y are the standard deviation of the predicted and actual response variable, and $\mu_{\overline{y}}$ and μ_y are the mean of the predicted and actual response variable.

3. Results and Discussion

As discussed, twelve ML algorithms were examined with the objective to propose the best model that can accurately predict the response variable (ridership). The hyperparameters of each model were tuned using grid search and Bayesian optimization combined with 10-fold cross-validation. The optimized values of the hyperparameters are presented in Table 1 for all ML models except SE. The SE model combined the optimized ADB, GBT, and xgBoost models.

Table 1. Optimized hyperparameters of ML models.

Models	Parameters
RR	alpha = 0.1
LR	alpha = 0.001
EN	alpha = 0.001
KNN	Number of neighbors = 2
SVR	Kernel = RBF, C = 95, ε = 0.01, gamma = 'auto'
CART	Maximum depth = 10, maximum features = 7
RF	Number of estimators = 15, maximum features = 11, maximum depth = 13, minimum sample leaf = 1, minimum sample split = 2
ET	Number of estimators = 20, maximum features = 12, maximum depth = 13, minimum sample leaf = 1, minimum sample split = 2
ADB	Base learner = CART, number of estimators = 30, learning rate = 0.25, maximum depth of tree for base learner = 12, maximum features for base learner = 11
GBT	Number of estimators = 150, maximum depth = 8, learning rate = 0.25, subsample = 0.8, maximum features = 12
xgBoost	Number of estimators = 145, learning rate = 0.15, subsample = 0.5, maximum depth = 11, colsample by node = 1.0, colsample by level = 1.0, colsample by tree = 1

With the tuned optimal hyperparameters and the database, the prediction performance of each model was evaluated and compared against the other models. First, the simplest ML algorithms, namely, RR, lasso regression, and EN, are investigated for ridership prediction. Figure 6a–c represents the scatter plots for the actual ridership (R_{actual}) against the predicted ridership ($R_{predicted}$) using these models. Meanwhile, the five quantitative performance measures of the models on both the trained dataset and the tested dataset are shown in Table 2. It can be observed from Figure 6a–c and Table 2 that the simplest models (EN, LR, RR) are unable to capture the relationship between the independent variables and the response, which dictated the use of advanced ML models. Among the base learners that are investigated in this study, CART showed the best predictive performance followed by KNN and SVR, respectively, on the train as well as test, as can be observed in Figure 6a–f and Table 2. This is shown in Figure 7, which represents the values of the performance metrics for each base learner on the training and test datasets. For instance, the coefficient of determination, R^2, the value of CART was 87.4% on the test dataset which was reduced to 27.5%, 25.5%, 26.6%, 84.4%, and 67.7% in RR, LR, EN, KNN, and SVR, respectively, as listed in Table 2.

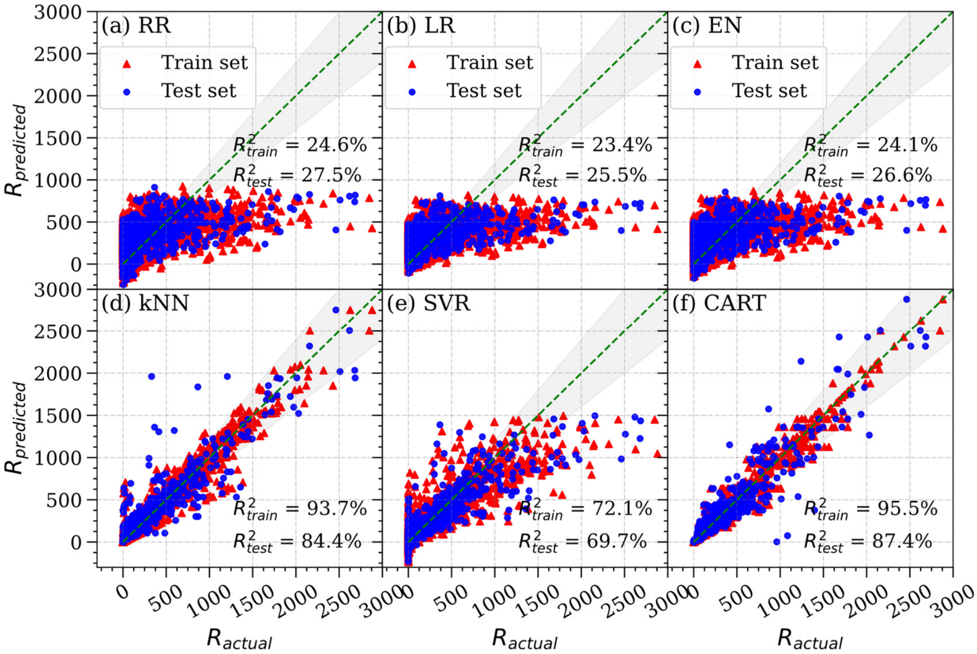
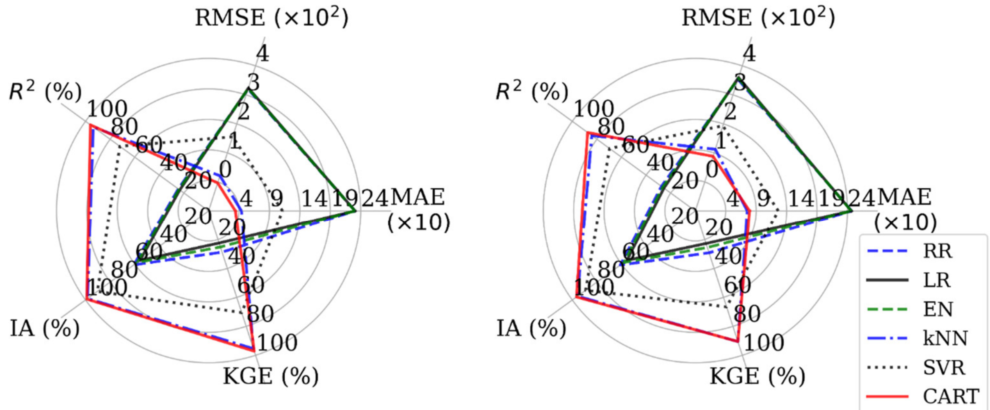


Figure 6. Predicted versus observed ridership based on single models.

Table 2. Performance measures.

Models	Train Set					Test Set				
	MAE	RMSE	R^2	AI	KGE	MAE	RMSE	R^2	AI	KGE
RR	231	336	24.6	60.71	28.75	247	363	27.5	60.91	29.18
LR	231	339	23.4	55.80	22.45	246	368	25.5	55.63	22.76
EN	231	337	24.1	58.09	25.20	246	365	26.6	58.07	25.54
KNN	52.0	97.2	93.7	98.35	95.39	80.7	169	84.4	95.80	90.77
SVR	117	204	72.1	90.37	70.51	131	235	69.7	89.11	66.55
CART	43.9	81.7	95.5	98.85	96.81	82.4	151	87.4	96.75	93.54
RF	24.4	43.5	98.7	99.68	97.27	51.5	91.9	95.4	98.77	94.56
ET	17.0	26.6	99.5	99.88	98.09	52.7	86.4	95.9	98.90	93.44
ADB	7.38	15.27	99.8	99.96	99.61	48.9	82.4	96.3	99.04	97.16
GBT	1.08	1.39	100	100	99.99	32.3	52.8	98.5	99.60	96.43
xgBoost	3.13	4.27	100	100	99.93	31.2	49.3	98.7	99.65	96.92
SE	2.25	3.10	100	100	99.80	28.8	46.5	98.8	99.69	96.93



(a) Train set (b) Test set

Figure 7. Performance measures for single models.

The performance of the CART model can be improved with the use of ensemble learners, as can be observed in Figure 8, which shows the scatter plots of the actual and predicted ridership based on the ensemble models. As noted in the figure, the ensemble learners showed good prediction performance with $R^2 \geq 95.4\%$ for both the test and train datasets. Among the five bagging and boosting algorithm-based ensemble models (i.e., RF, ET, ADB, GBT, and xgBoost), xgBoost exhibited the best predictive performance in terms of all the performance measures, as can be seen in Figure 9, which compares the ensemble models in terms of the five performance metrics on the train as well as test sets. Moreover, all ensemble models showed a better predictive performance compared with that of the base learners (see Figures 6 and 8 and Table 2). The performance of xgBoost was improved with the use of a stacking ensemble (SE) in which the best three models (xgBoost, GBT, and ADB) were stacked using linear SVR as a meta-model. Overall, via comparing the five quantitative performance measures, the proposed stacking ensemble was the best predictive model with the largest R^2, *KGE*, and *IA* and lowest RMSE AND MAE relative to the other models, as shown in Figures 6 and 8, and Table 2.

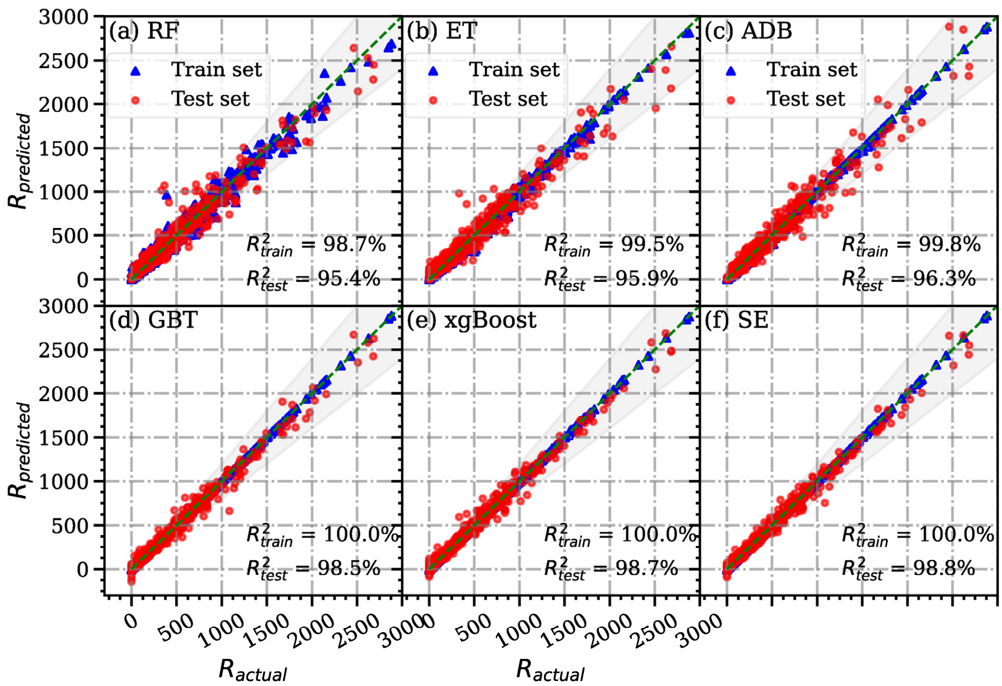


Figure 8. Predicted versus observed ridership based on ensemble models.

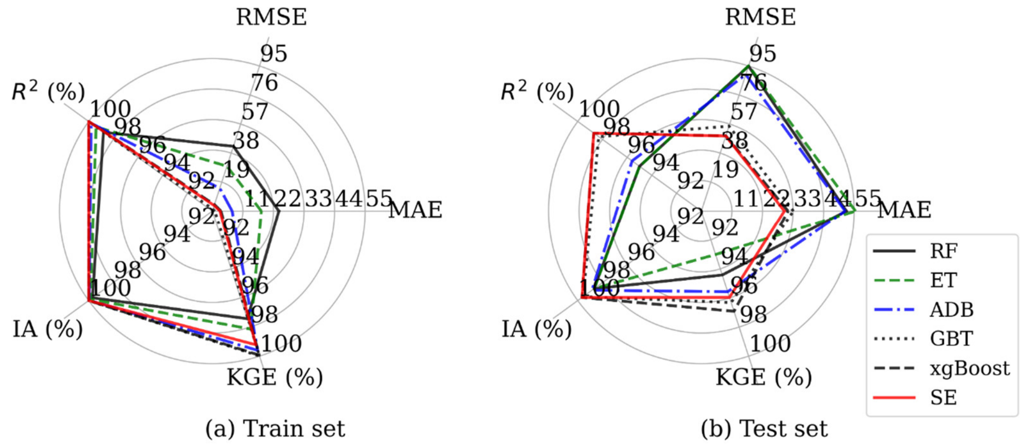


Figure 9. Performance measures for ensemble models.

Feature Importance Analysis

The effect of the input parameters is investigated using Permutation Feature Importance combined with the proposed gradient tree boosting ensemble model. The feature importance explains the relative contribution of each type of land use density to the prediction of the total metro ridership by assigning a score to each input parameter; in other words, these findings of the feature importance are used by transport-urban planners for land use allocation in the newly developed areas to maximize public transportation use. Figure 10 depicts the relative importance of several types of land use densities based on the results of the Permutation Feature Importance and gradient tree boosting model. The governmental land use density, educational facilities land use density, and mixed-use density are the three factors that play the most significant role in the determination of the total ridership and are the most dominant parameters, as shown in Figure 10.

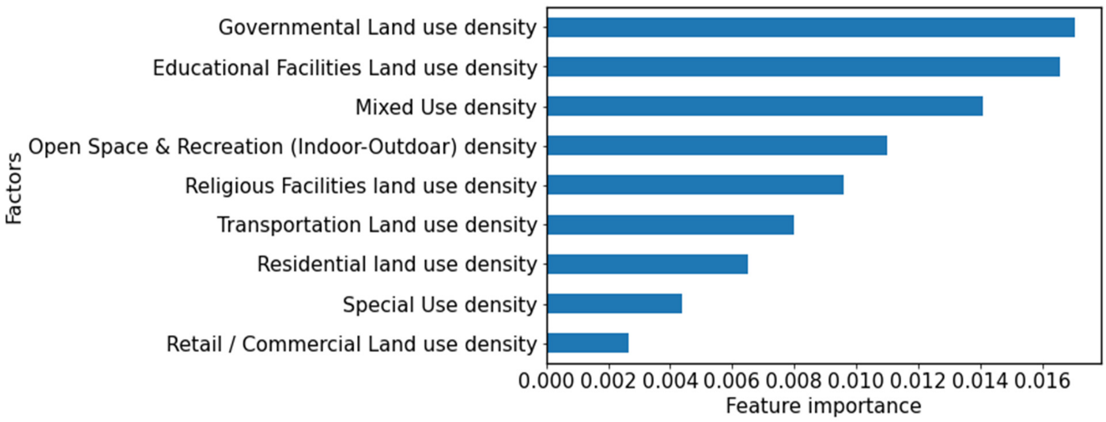


Figure 10. Feature importance analysis based on gradient tree boosting.

In contrast, the retail/commercial land use density has the least influence on the prediction of total ridership. These findings demonstrate the nature of the occupiers of the three most important land uses that tend to use metro transit, such as the governmental and educational sectors.

4. Model Implications on Policymaking

This section illustrates the relationship between the implications of the prediction urban-transport model investigated in this research and each related Sustainable Development Goal and pursues to make proposals for converting the transportation sector to a more "sustainable" one. Several SDGs rely on transportation to achieve their goals. Transportation might not show a large role in a destination, yet for the achievement of the destination and its objectives, transportation is essential and performs as an important "enabler". Hence, it has been shown that if one ignores sustainable transportation, it becomes much more problematic to meet most of the proposed SDGs. Figure 11 presents the urban-transport-related SDGs, and the following section suggests policy implications that could be in helping to achieve these goals, from this research study perspective:

SDG3: Ensure healthy lives and promote well-being for all of all ages

The integrated and significantly planned transport networks have the probability to enhance road safety using human-centered planning, transit-oriented development, or traffic improvement actions, such as speed maps. In developing countries, measures to build dimensions in road construction and transport policy and their execution are crucial elements in attaining this goal. To conclude the well-planned road network and the insurance of pedestrian safety will eventually be of great help in orienting people toward walkability and cycling for the best practice of TOD.

SDG7: Ensure access to affordable, reliable, sustainable, and modern energy for all

For the best achievement of Goal 7.3, the improvement of the fuel efficiency of vehicles will be crucial, as vehicle-oriented transport is still high in developing countries. Additionally, the decrease in private vehicle use by augmentation of public transport will efficiently achieve this goal. Thus, the assurance of the lowest energy consumption could be achieved by increasing public transportation ridership such as metro transit.

SDG9: Build resilience infrastructure, promote inclusive and sustainable industrialization, and foster innovation

Urban connectivity and traffic development play a decisive role in the achievement of sustainable industrialization. Reliable and resilient transportation infrastructure is an indispensable component for resilience to disturbance globally. Reliable transportation can increase social and economic resilience and meet the need for safety and emergency response. The aptitude of society, commerce, and economy to get ready for and recover from a disaster- such as the COVID-19 pandemic. The significance of public transport infrastructure in pre-and post-disaster evacuation is becoming ostensible and could save lives.

SDG11: Make cities and human settlement inclusive, safety, resilience and sustainable

Transport secures accessibility to all socio-economic needs of citizens. Dense urban planning could be of help in reducing the long travel time, in combination with an integrative and effective public transportation system that has better options for active mobility, more integrated transportation systems and land use, improving access to public transportation, and contributing to environmentally sustainable development.

SDG12: Ensure sustainable consumption and production pattern

The application of green processes and technologies in the transportation sector and logistics will be an essential part of the sophisticated strategies for better sustainable forms of demand and supply of goods and services across the economy. Metro transit is a great example of green transport that could significantly contribute to sustainable transport, the environment, and the economy.

SDG13: Take urgent action to combat climate change and its impact

Sustainable transportation systems could be of help in the considerable potential for mitigation for minimizing the effects of climate change. Inclusive sustainable transport systems should be pursued, including land use integration with transport planning. Moreover, the greening vehicle and infrastructure construction could be of help in the reduction of greenhouse gas emissions in the transportation industry, including preparedness, protection, response, and recovery. Climate change also has negative effects on the transport infrastructure—for example, extreme heat cracks on streets and winding train tracks or highways that are washed away by extreme weather events.

Figure 11. Urban-Transport direct and indirect related SDGs.

5. Conclusions and Recommendations

This paper investigates the use of machine learning-enhanced models, including the simplest model and advanced models for predicting metro ridership, considering the built environment around stations. A total of twelve parameters are considered as input features, including time of day, day of the week, station, and nine types of land use density, including land use density for open space and recreation (indoor-outdoor) facilities, religious facilities, education facilities, retail/commercial, residential, special use, transportation, mixed-use, and government land use densities. A time-series database is used for model development and testing. Twelve different ML models were evaluated for their predictive performance: ridge regression, lasso regression, elastic net, support vector machine, K-nearest neighbor, random forest, decision tree, extremely randomized trees, adaptive boosting, gradient boosting, extreme gradient boosting, and stacking ensemble learner. The model's performance was validated using the test set using five quantitative performance measures: (a) mean absolute error, (b) root mean squared error, (c) coefficient of determination, (d) agreement index, and (e) Kling Gupta efficiency. Based on the findings of this research, the following conclusions could be drawn:

- The simple machine learning techniques: particularly, RR, EN, and lasso regression cannot capture the relationship between the predictors and response variable (ridership), which dictated the use of advanced techniques.
- Among the base learners, classification and regression trees showed the highest performance, with an R^2 of 87.4% on the test dataset. The KNN and SVR were the second and third-best models among the base learners.
- The implementation of CART-based ensemble models considerably enhanced the prediction capability of the CART model. All ensemble models showed good prediction performance with $R^2 \geq 95.4$ on the train as well as in test sets.
- Overall, the stacking ensemble provided the best predictive performance. Thus, it is selected as the best model for predicting metro ridership with respect to the built environment around the stations.

In addition, this study presented the implications of the proposed urban-transport predictive ML model on SDGs and identified various strategies that could be applied to better achieve the SDGs. The discussion recommends that comprehensive sustainable transport solutions, such as metro transport, should be pursued, including the integration of land use and transport planning, prioritization of public transport, and non-motorized transport/active transport, as well as green vehicle and infrastructure construction, can help reduce greenhouse gas emissions from the transportation industry, including preparedness, protection, response, and recovery. Climate change also has negative effects on the transport infrastructure; thus, further studies are needed to investigate the correlation between effective and sustainable urban transport systems and climate change effects.

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