Enhancing Urban Bike Sharing with Machine Learning and Explainable AI Techniques

Brenda Nuwasiima
Department of Computer Science
Makerere University
2400721941, 2024/HD05/21941U
nuwabrenda@gmail.com

Rhoda Diana Ndibarekela
Department of Computer Science
Makerere University
2400721951, 2024/HD05/21951U
ndibalekera1620@gmail.com

***Abstract*—Bike-sharing services are emerging as a sustainable solution challenge that cities experience in the face of rapid urbanization and climate change. By providing accessible, eco-friendly transportation options, bike-sharing helps reduce traffic congestion, lowers greenhouse gas emissions, and encourages healthier lifestyles. bike-sharing programs still face a challenge in forecasting demand, improving resource allocation to improve efficiency.**

This paper investigates the application of machine learning techniques in predicting how bike-sharing system operates under certain conditions and highlights the need of explainable AI in urban mobility planning. . Regression models such as linear regression, Random Forest, Gradient Boosting, and XGBoost were implemented to classify data from the Seoul Bike Sharing dataset. We utilized techniques like LIME and SHAP to ensure explainability of the models. Results show that ensemble methods like XGBoost and Random Forest outperformed traditional Logistic Regression, achieving near-perfect classification accuracy.

***Index Terms*—Machine Learning, regression, Explainable AI, Urban Mobility, Bike Sharing.**

I. Introduction

With increasing urbanization and pollution [1], sustainable transport solutions are crucial.We reviewed a dataset that provides insights into usage patterns, offering opportunities to optimize operations. This study focuses on classifying whether a bike-sharing system is operational based on external and internal factors, using machine learning techniques. Explainable AI tools such as LIME and SHAP are employed to ensure model transparency, addressing community concerns about AI accountability. [2]

II. Background and Motivation

A. **Selecting a Template** Bike-sharing systems contribute to reducing urban congestion and rampat pollution [3] in African countries and the world at large. In Seoul, such systems depend on various factors like weather, holidays, and operational status. Classification models can predict operational conditions, aiding policymakers and businesses in resource allocation and decision-making. The increasing reliance on private vehicles in urban areas has caused a significant rise in fuel consumption, leading to adverse environmental effects and congestion. This has prompted governments and organizations to promote sustainable alternatives like bike-sharing systems. For example, South Korea's bike sharing program aims to address urban mobility problems while fostering a healthier and more environmentally friendly environment. These systems provide an affordable, sustainable transportation option for short trips and include the added benefit of health improvements through physical activity. The Seoul Bike Sharing System, supported by a network of docking stations, allows users to rent and return bikes conveniently. With advanced technology, users can track trip details like distance, duration, and calories burned, increasing the system's popularity. However, the growing demand for such services highlights the need for efficient resource management. This study leverages the Seoul Bike Sharing Demand dataset, which includes hourly rental counts alongside weather and holiday data for 12 months, from December 2017 to November 2018. Using this dataset, the report evaluates various machine learning models, such as Linear Regression, Decision Tree Regression, and Random Forest Regression, to predict hourly rental demand. The integration of AI and ML techniques into the analysis helps address critical challenges, such as optimizing bike availability across docking stations, forecasting demand fluctuations, and ensuring seamless user experiences. These predictive models enable proactive resource management and support the broader goal of fostering sustainable urban mobility solutions.

III. Literature Review

A. Existing Works

A bike-sharing system provides people with a sustainable mode of transportation and has beneficial effects for both the environment and the user. In recent days, Pubic rental bike sharing is becoming popular because of is increased comfortableness and environmental sustainability. [4]The imbalance in bike-sharing systems between supply and demand is significant. Therefore, these systems need to relocate bikes to meet customer needs. [5]Machine learning algorithms are utilized to overcome the challenges in forecasting the demand for hourly bike rentals. [6] Multiple evaluation indices such as 2 , Root Mean Square error are use to measure the prediction performance of the regression models. The performance of the model is vary with the time interval used in transforming data. [4] Ensemble model base on different predictors in combination with the current main streamdata prediction algorithms, including Linear Regression (LR),Ridge Regression (RR), Lasso Regression (Lasso), K-NearestNeighbor (KNN), Random Forest (RF), Decision Tree (DT),Support Vectors Machine (SVM), and Gradient Boosting Decision Tree (GBDT). [7]The Random Forests (RF) technique was among the best ensemble learning strategies for both classification and regression-based tasks [8] Regression analysis shows that the number of public transport stops, offices and schools are associated with a higher number of bike rentals, supporting the view that utilitarian travel is the main usage pattern. [9] The dominant machine learning methods to detect the transport mode are random forests and neural networks [10]. Logistic Regression offers interpretability but struggles with non-linear relationships. Random Forest and Gradient Boosting enhance performance but lack innate explainability, addressed by tools like LIME and SHAP. Regression models are important machine learning models for predicting total continuous values; this case is the number of bikes at a docking station. Good predictions can help dock station managers and service administrators make correct decisions based on the minimum number of bikes required [11] Explainable Artificial Intelligence (XAI) has emerged as a critical research area to address the opacity and lack of interpretability associated with complex machine learning models. [12] LIME offers local, instance-specific explanations that are intuitive for developers to understand, while SHAP provides a global perspective on feature importance across the entire dataset. Combining both methods allows for cross-validation of explanations. [13]

B. Research Gaps

Most studies lack focus on explainability and accountability in urban mobility AI models. Additionally, challenges include handling imbalanced datasets and ensuring scalability for real-time deployment.Most studies and publications reviewed in this domain do not adequately explain explainable AI and its relevance to their proposed models. [11] There is barely research work targeting transport prediction in Uganda and African countries as a whole.

C. Problem Statement

Despite the availability of this data, accurately predicting the hourly demand for bike rentals remains a challenge. This accuracy and explainability of AI prediction is crucial for optimizing bike distribution, managing inventory, and enhancing user satisfaction.

D. Contributions

Our work integrates advanced ensemble methods with explainable AI to classify operational status in Seoul's bike-sharing system, addressing the above gaps. The goal is to develop and refine regression models to predict the hourly rental demand for public bikes in Seoul, aiming to enhance operational efficiency and support sustainable transportation initiatives. The model is robust and non-exclusive, designed to accommodate diverse datasets and can be applied beyond Seoul to similar contexts, including African cities like Nairobi, Kampala etc.

IV. Methodology

A. Summary of the Methodology

This study followed a step-by-step approach starting from dataset identification, Exploratory data analysis/ data pre-processing, Machine learning model selection and evaluation, and model interpretation Exploratory data analysis (EDA) to clean and select relevant features. Regression models, including Linear Regression, Decision Tree Regression, Random Forest Regression, Gradient Boosting, and Support Vector Regression, were trained and tested. Model performance was evaluated using metrics such as Mean Absolute Error (MAE), R-squared (R^2), and Mean Squared Error (MSE), along with K-fold cross-validation for validation. To enhance model transparency, LIME and SHAP model were used interpret the predictions and understand the influence of various features like temperature, working day , solar radiation and time of day on bike demand.

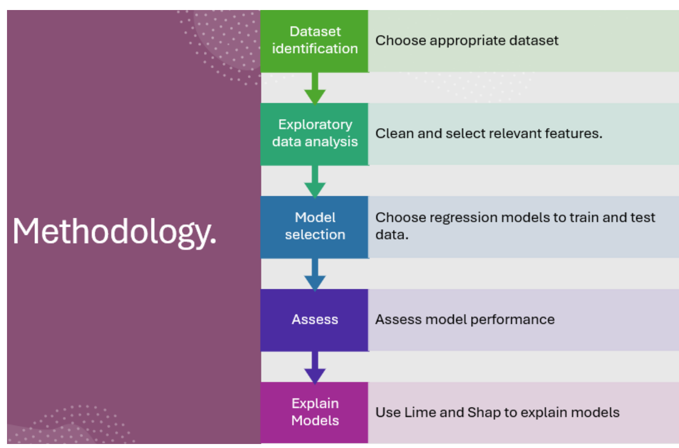


Fig. 1: Summary of Data and Attribute Description.

This approach enabled accurate prediction of bike-sharing demand, while providing valuable insights through interpretable AI techniques.

B. Dataset Description

The Seoul Bike Sharing dataset contains weather conditions, holidays, and operational status. Key features include temperature, humidity, rainfall, and holiday indicators. The data set was sourced from the UCI Machine Learning Repository at https://archive.ics.uci.edu/datasets/Seoul+Bike+Sharing... The has Date and time, the timestamp on which the observation was made, Weather data which includes information like the temperature, humidity, wind speed, and whether the weather was a clear or rainy.It captures the the season during the observation (e.g., winter, spring, summer, or autumn). Holiday, whether the day was a public holiday or not. Working day, whether it was a working day of the week (weekdays) or a weekend.The Rented bike count shows the number of bikes rented during that time period, which is the target variable for our predictive models.

ITEM	FEATURE	MEASURE	TYPE
1	Date		object
2	Rented Bike Count		int64
3	Hour	hour	int64
4	Temperature	(°C)	float64
5	Humidity	(%)	int64
6	Wind speed	(m/s)	float64
7	Visibility	(10m)	int64
8	Dew point temperature	(°C)	float64
9	Solar Radiation	(MJ/m2)	float64
10	Rainfall	(mm)	float64
11	Snowfall	10 (cm)	float64
12	Seasons		object
13	Holiday		object
14	Functioning Day		object

Fig. 2: Summary of Data and Attribute Description.

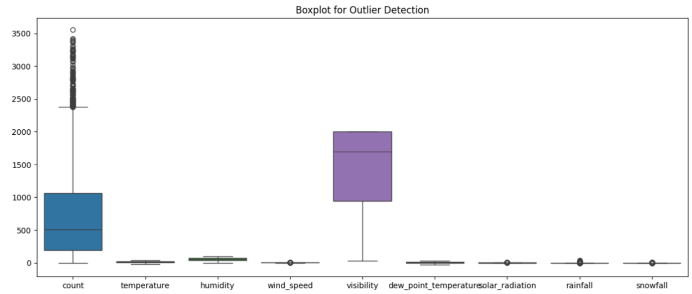


Fig. 3: Outlier detection

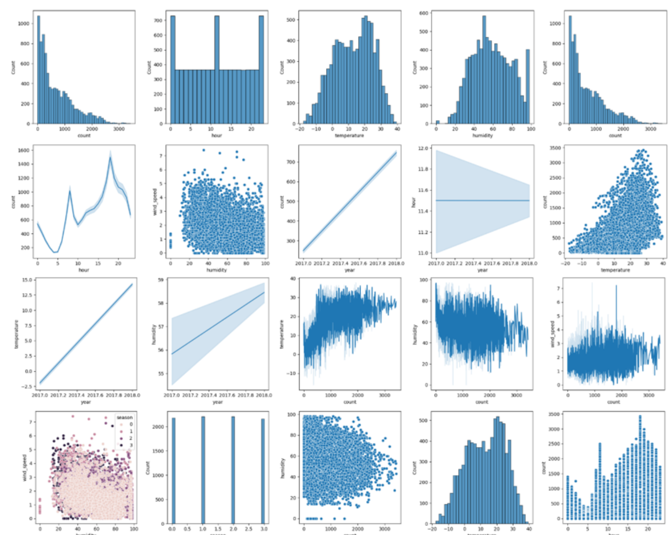


Fig. 4: clustering plot with two dimensions.

C. Data Preparation

Data cleaning is an essential first step in any data science project because raw data is often messy but highly valuable. It involves identifying and fixing incomplete, incorrect, or irrelevant entries in datasets. This process includes removing duplicates, correcting data types, and refining the dataset to ensure accuracy. Following data cleaning, exploratory data analysis (EDA) helps uncover patterns, relationships, and insights by using statistical and visualization techniques. For example, analyzing correlations can reveal relationships, such as a high correlation (0.91) between temperature and dew point, which can cause multicollinearity. In some cases, there are missing values that should be handled or outliers in the data set which are removed because they can distort analysis, skew results, and negatively impact model performance.

1) Exploratory analysis: included correlation matrices and visualizations.

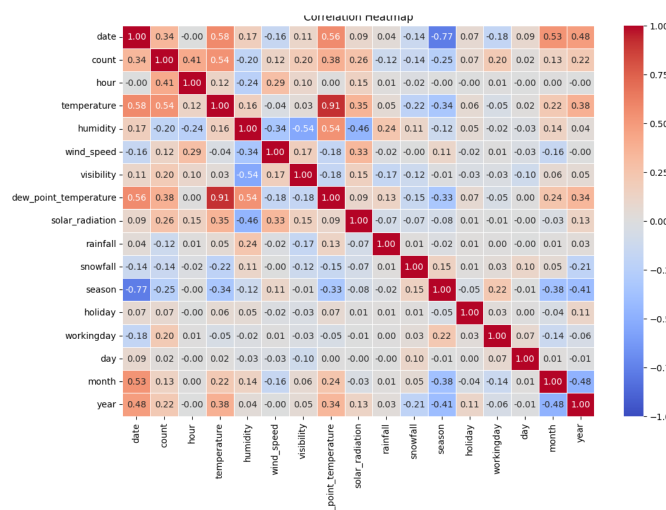


Fig. 5: Correlation Heat Map graph

D. Model Selection and Optimization

1) **Linear Regression**Is a simple model based on a straight-line relationship between features and target. It's simple fast, interpretable and easy to implement. sensitive to

outliers and quickly shows Linear relationships in small datasets, basic prediction tasks. The formula for linear regression is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$$

Where:

- y is the predicted value (dependent variable),
- $x_1, x_2, \ldots, x_n$ are the features (independent variables),
- β_0 is the intercept,
- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the features,
- ϵ is the error term.

2) **Random Forest** is a tree based Ensemble model that exploits multiple decision trees, bagging, random selection of non-linear data. It's robust to overfitting, no feature scaling required. The predicted value is the average of the predictions made by all individual trees in the forest:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} \hat{y}_t$$

Where:

- $\hat{y}$ is the final predicted value,
- T is the number of trees in the forest,
- $\hat{y_t}$ is the prediction made by the t^{th} tree.

3) **Gradient Boosting** is a sequential ensemble of decision trees, its quality of learning from errors of previous trees makes it high accuracy, handles complex relationships, works well with large datasets. The general form of the model is:

$$F(x) = \sum_{m=1}^{M} \eta \cdot h_m(x)$$

Where:

- $F(x)$ is the final prediction,
- $h_m(x)$ is the m^{th} weak learner (usually a decision tree),
- η is the learning rate,
- M is the total number of trees.

4) **Support Vector Regression (SVR)** is a non-linear kernel-based model Uses a hyperplane in a high-dimensional space to separate data points. Effective in high-dimensional spaces, works well for non-linear data and requires parameter tuning.SVR aims to find a function that deviates from the actual data by a margin of error ϵ. The formulation is:

$$f(x) = w^T \cdot x + b$$

Where:

- $f(x)$ is the predicted value,
- w is the weight vector,
- b is the bias term,
- x is the input vector.

For the non-linear case, a kernel function $K(x, x')$ is applied:

$$f(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x) + b$$

Where α_i are the support vectors' coefficients.

5) **ElasticNet** is a regular linear model that combines Lasso and Ridge regression penalties to show relationships between features are complex.

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{i=1}^{n} (y_i - X_i \beta)^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2 \right)$$

Where:

- $\hat{\beta}$ is the coefficient vector,
- y_i are the target values,
- X_i are the input features,
- λ_1 and λ_2 are the regularization parameters,
- $\|\beta\|_1$ is the L1 norm (Lasso penalty),
- $\|\beta\|_2^2$ is the L2 norm (Ridge penalty).

6) **KNN** Regression an instance based model that predicts based on the average of the nearest neighbors in feature space. It's simple, interpretable, works well with complex boundaries. Formula:

$$\hat{y}(x) = \frac{1}{k} \sum_{i=1}^{k} y_i$$

Where:

- $\hat{y}(x)$ is the predicted value,
- k is the number of nearest neighbors,
- y_i are the target values of the nearest neighbors.

7) **Ridge Regression** is a regularize linear model that adds L2 regularization to linear regression, penalizes large coefficients which prevents overfitting. The formula is:

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{i=1}^{n} (y_i - X_i \beta)^2 + \lambda \|\beta\|_2^2 \right)$$

Where:

- $\hat{\beta}$ is the coefficient vector,
- y_i are the target values,
- X_i are the input features,
- λ is the regularization parameter,
- $\|\beta\|_2^2$ is the L2 norm (penalty term).

Major focus was on these four models for the following reasongs

- **Logistic Regression**: Baseline model with linear decision boundaries.
- **Random Forest**: Ensemble model to handle feature importance.
- **Gradient Boosting**: Optimized using learning rate and depth tuning.
- **XGBoost**: Advanced boosting technique with hyperparameter optimization.

E. Explainable AI

AI accountability is the responsibility of AI systems to make decisions that are transparent (being able to understand how decisions are made by the AI system), fair (ensuring that AI decisions do not discriminate against certain groups), hold developers and organizations accountable for the actions and all decisions or predictions made by AI models should be understood by system stakeholders. In a nutshell AI systems should execute in away that aligns with ethical principles and human values, and that their outputs can be well understood and trusted.

LIME and SHAP were used to explain model predictions, ensuring accountability and transparency in feature contributions.To evaluate feature importance in our regression models using SHAP (SHapley Additive exPlanations), first installed the necessary libaries Iterate through the models, In this case such we chose regression models such as a Random Forest Regressor, Gradient Boosting Regressor, KNN and XGBoost Regressor. Use the scaled test data for SHAP analysis and choose an appropriate SHAP explainer based on your model type; for tree-based models, use shap.TreeExplainer, for linear models, use shap.LinearExplainer, and for neural networks, use shap.DeepExplainer. Finally calculate the SHAP values and Visualize the results on various SHAP plots to interpret feature contributions: the summary plot provides an overall view of feature importance and SHAP value distributions, the dependence plot shows the relationship between individual features and their SHAP values, and the force plot demonstrates how features contribute to a specific prediction.

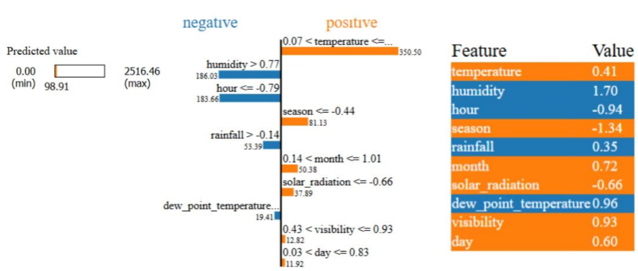


Fig. 6: LIME output as applied to the Random Forest Regressor model.

1) LIME: Predicted Value: The model's predicted value is shown on the left, ranging between 0.00 and 98.91, with the orange bar representing the predicted value based on the input features. Contribution to the Prediction: The plot shows positive and negative contributions from each feature: Positive Contribution: Features like temperature, dew point temperature, and visibility push the predicted value higher. Negative Contribution: Features such as humidity, hour, and season decrease the predicted value.

2) SHAP: The color gradient represents the feature values, with blue indicating lower values and red indicating higher values for each feature.The SHAP value indicates the influence of a feature on the model's prediction. Positive SHAP values push the model's prediction higher, and negative SHAP values push it lower.Feature Importance: Features like temperature, hour, and solar radiation have a wider distribution of SHAP values, indicating they have a larger impact on the model's predictions. Features like wind speed" and year have narrower distributions, suggesting they have a smaller influence.

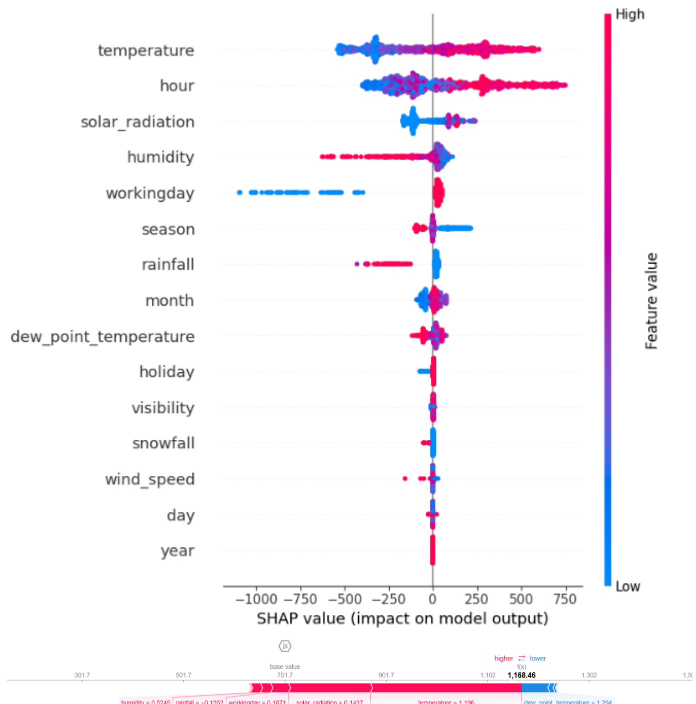
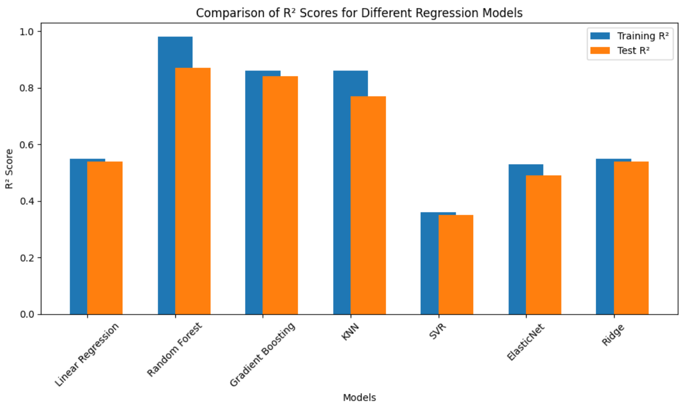
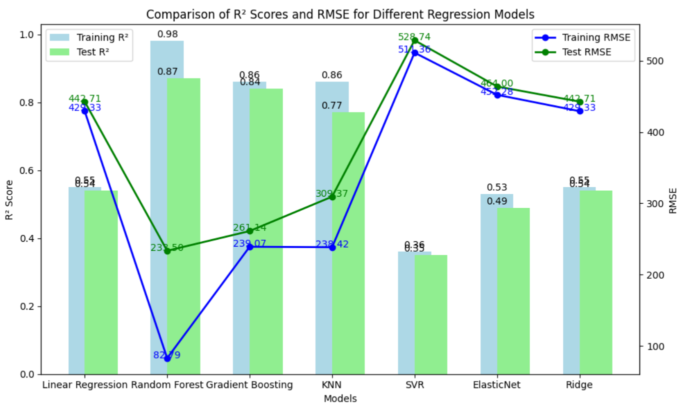


Fig. 7: SHAP summary plot that shows the impact of different features on the model's output. The SHAP values represent how much each feature contributes to the model's prediction for a given instance.

V. Results and Discussion

Based on the comparison of various machine learning models on the bike-sharing dataset, the Random Forest model demonstrated the best performance, with the lowest MAE, MSE, and RMSE values, as well as the highest R^2 score on both training and test datasets. In contrast, models like Support Vector Regression and Elastic Net performed less effectively, especially in terms of R^2, which were significantly lower compared to Random Forest. While models like Gradient Boosting and KNN performed well with relatively higher R^2 values, they were still outperformed by Random Forest in terms of prediction accuracy. Overall, Random Forest emerged as the most reliable model for predicting bike rental demand in this case.





MODEL	Training Results MAE	Training Results MSE	Training Results RMSE	Training Results R^2	Test Results MAE	Test Results MSE	Test Results RMSE	Test Results R^2
Linear Regression	319.4	184331.9	429.3	0.55	330.28	195993.4	442.71	0.541
Random Forest	48.85	68.87	82.79	0.98	140.33	54520.57	233.49	0.87
Gradient Boosting	160.6	57157.7	239.07	0.861	172.92	68194.61	261.14	261.14
KNN	148.51	56847.48	238.43	0.862	195.54	95711.84	309.37	0.776
Support Vector Regression	341.04	261494.39	511.36	0.365	350.82	279568.14	528.74	0.346
Elastic Net	328.69	204562.06	452.29	0.503	336.59	215296.78	0.496	0.496
Ridge Regression	319.48	184331.92	429.33	0.553	330.27	195994.38	442.71	0.54

Fig. 8: Evaluate of models to compute and return metrics MAE, MSE, RMSE, and R² for both training and test sets.

VI. Conclusion and Future Works

This paper showcases the potential of explainable AI in urban mobility. Future work will explore integrating real-time data and addressing scalability challenges in deployment. SHAP is a powerful tool for understanding the contribution of each feature to model predictions. Here's an implementation specifically for the regression models you trained. These visualizations can offer valuable insights into how features impact your model's predictions, making SHAP a powerful tool for interpretability. If needed, you can save the plots for reporting or documentation purposes.

Acknowledgment

We would like to express my sincere gratitude to all stakeholders; individuals and entities who have contributed to the successful completion of this project. Firstly, we would like to thank our supervisor, Mrs. Joyce Nabende, Department Of Computer Science, Makerere University for her valuable guidance, support, and expertise throughout the course from introduction to Machine learning to the experts we are today. We extend thanks to Mr. Sudi Murindanyi, his insights and encouragement have been instrumental in shaping our understanding. We thank Makerere University for providing computational resources and support. The creators and contributors of the Seoul Bike Sharing Demand dataset, available through the UC Irvine Machine Learning Repository. The data provided a solid foundation for conducting this research To the development teams behind the machine learning libraries used in this project, including Scikit-learn, NumPy, Matplotlib, Pandas, lime,shap and other related tools. Their efforts have made it possible to explore ML and AI. Lastly, our family and friends for their unwavering support. This project would not have been possible without great team effort.

References

[1] Eric Yankson. *Conceptualising an Urban Transport Framework for Enhanced Quality of Life in Sub-Saharan Africa: Case Studies of Ghana and Namibia*, pages 151–171. Springer International Publishing, Cham, 2022.

[2] Saravjeet Singh, Jaiteg Singh, S.B. Goyal, Sukhjit Singh Sehra, Farman Ali, Mohammed Ayad Alkhafaji, and Ramendra Singh. A novel framework to avoid traffic congestion and air pollution for sustainable development of smart cities. *Sustainable Energy Technologies and Assessments*, 56:103125, 2023.

[3] Eradius Edward Rwakarehe. Review of strategies for curbing traffic congestion in sub-saharan africa cities: Technical and policy perspectives. *Tanzania Journal of Engineering and Technology*, 40, April 6, 2022.

[4] Sarthak Arora, Jay Nandasana, Madhavi Mali, and Arshi Wani. Seoul bike sharing demand prediction, 09 2022.

[5] Kanokporn Boonjubut and Hiroshi Hasegawa. Accuracy of hourly demand forecasting of micro mobility for effective rebalancing strategies. *Management Systems in Production Engineering*, 30:246–252, 09 2022.

[6] Somay Verma, Lekha Bhambhu, Pradeepta Sarangi, and Ashok Sahoo. *Peak Hour Demand Prediction for Sharing Bikes: A Comparative Analysis of Performances of Machine Learning Models*, pages 47–64. 01 2024.

[7] Xinxue Lin and Chang Lu. A stacking-based ensemble model for prediction of metropolitan bike sharing demand. *American Journal of Information Science and Technology*, 04 2023.

[8]

[9] Michał Dziecielski, Alexandros Nikitas, Adam Radzimski, and Brian Caulfield. Understanding the determinants of bike-sharing demand in the context of a medium-sized car-oriented city: The case study of milton keynes, uk. *Sustainable Cities and Society*, 114:105781, 2024.

[10] Dina Bousdar Ahmed and Estefania Munoz Diaz. Survey of machine learning methods applied to urban mobility. *IEEE Access*, 10:30349–30366, 2022.

[11] Simon Onen, Marvin Ggaliwango, Samuel Mugabi, and Joyce Nabende. Interpretable machine learning for intelligent transportation in bike-sharing. In *2023 2nd International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN)*, pages 1–6. IEEE, 2023.

[12] M Arunika, S Saranya, S Charulekha, S Kabilarajan, and G Kesavan. A survey on explainable ai using machine learning algorithms shap and lime. In *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pages 1–6, 2024.

[13] Ishaya Gambo, Rhodes Massenon, Chia-Chen Lin, Roseline Oluwaseun Ogundokun, Saurabh Agarwal, and Wooguil Pak. Enhancing user trust and interpretability in ai-driven feature request detection for mobile app reviews: An explainable approach. *IEEE Access*, 12:114023–114045, 2024.