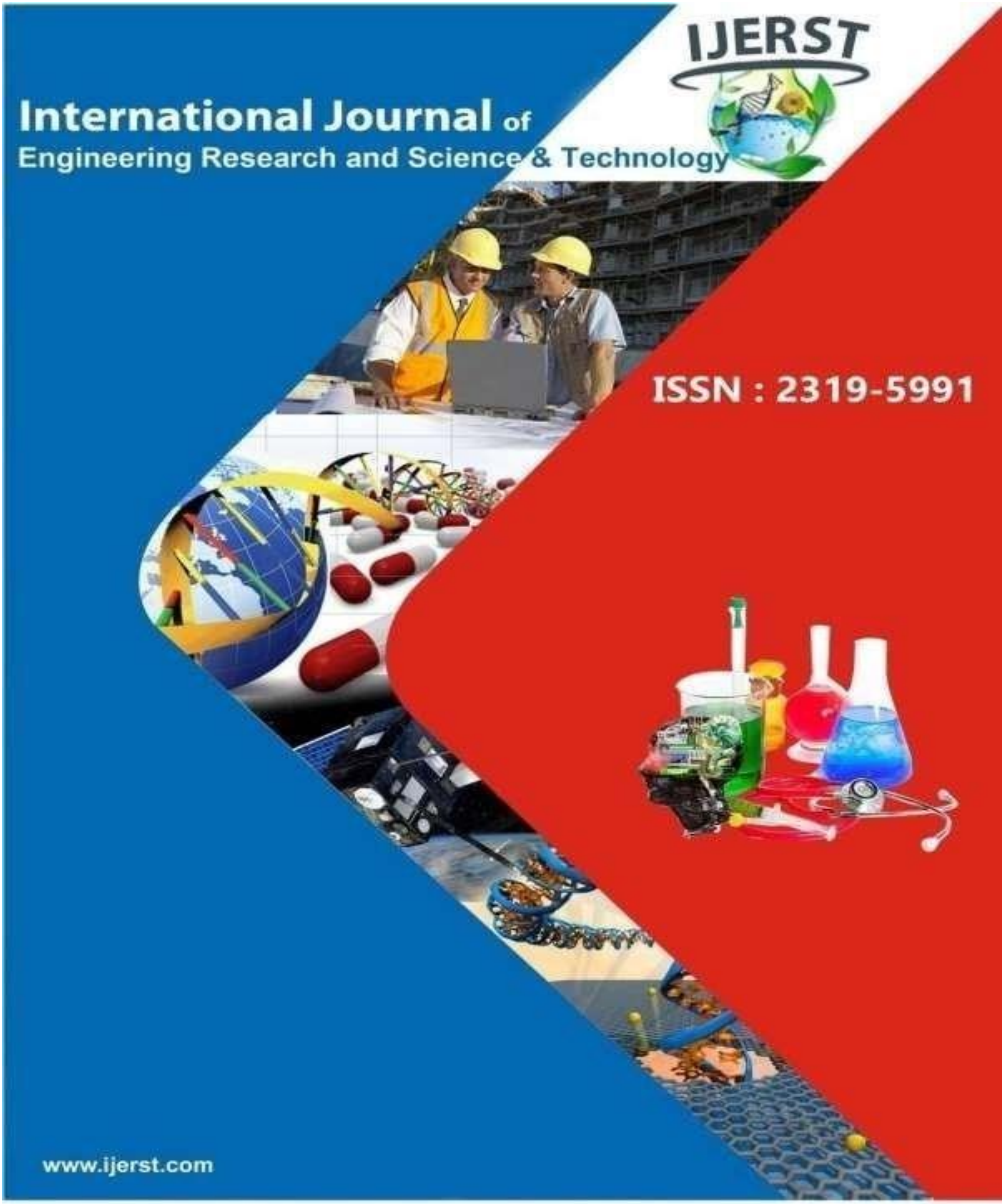

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Data-Driven Mobility: Predicting Urban Bike-Share Usage through Historical Trends

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Abstract:

This project focuses on developing a bike-share usage forecasting tool using historical rental data and predictive analytics. By collecting and preprocessing data, and conducting exploratory analysis, usage patterns are identified. Implementing various predictive models, including time series and machine learning algorithms, demonstrates improved accuracy in forecasting bike-share usage. The tool supports city planners and operators in optimizing resource allocation and enhancing user satisfaction. It also suggests future research directions to further refine forecasting capabilities and operational efficiency in bike-share systems. The results demonstrate the effectiveness of the chosen methodologies in accurately predicting bike-share usage, with significant improvements over baseline models. The developed forecasting tool offers valuable insights for city planners and bike-share operators, enabling data-driven decision-making for better management of bike-share systems. The study also highlights potential real-time applications and suggests areas for future research to further enhance forecasting accuracy and operational efficiency.

Keywords: Exploratory analysis, Machine learning algorithms, Methodologies, Predictive Analytics.

1. Introduction

Bike-sharing systems (BSS) have become a vital component of sustainable urban mobility, providing an efficient and eco-friendly alternative to traditional transportation. These systems offer users the flexibility to rent and return bikes at various stations across a city, reducing traffic congestion and carbon emissions while promoting a healthier lifestyle【7】. However, managing bike inventory and ensuring station availability remain key operational challenges, primarily due to demand fluctuations and uneven bike distribution【7】.

To address these challenges, predictive analytics and machine learning techniques have been employed to forecast demand and optimize bike repositioning strategies. Traditional time-series models such as ARIMA and SARIMA effectively capture seasonality and trends, whereas machine learning models like Random Forest, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM) handle complex, non-linear demand patterns【8】. More recently, deep learning approaches, particularly the RNN-LSTM-based DeepAR model, have demonstrated superior accuracy in forecasting bike demand at both district and station levels by capturing inter-station correlations and dynamic demand variations[8].

Accurate demand prediction is essential for operational efficiency, as errors in forecasting can lead to suboptimal bike repositioning, resulting in stations with either excess or insufficient bikes. This study aims to evaluate different machine learning methodologies, comparing their predictive performance to identify the most effective model for bike-sharing demand forecasting. By leveraging historical usage data and external factors such as weather and calendar variables, the study seeks to enhance the reliability and sustainability of bike-sharing services【7】.

2. Literature Review

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The increasing adoption of **bike-sharing systems (BSS)** has driven extensive research into optimizing their operations through predictive analytics and machine learning techniques. Accurately forecasting bike demand is crucial for maintaining a balanced distribution of bikes across stations, improving user satisfaction, and reducing operational costs【7】.

2.1 Traditional Time-Series Models

Early studies on bike-sharing demand forecasting relied on time-series models such as AutoRegressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA). These methods effectively capture trends and seasonality but struggle with non-linear demand fluctuations caused by external factors such as weather and special events【8】. While ARIMA-based approaches remain useful for short-term forecasting, they require extensive parameter tuning and often lack adaptability to sudden demand shifts【8】.

2.2 Machine Learning Approaches

To overcome the limitations of time-series models, researchers have explored machine learning techniques such as Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Decision Trees【8】. These models can handle complex relationships in the data, incorporating features like temperature, precipitation, and time of day to improve demand predictions【7】. Among them**,** Random Forest has been widely used due to its ability to handle missing data and prevent overfitting, making it a preferred choice for many applications【9】. However, traditional machine learning models often require extensive feature engineering and struggle with capturing temporal dependencies in demand data【8】.

2.3 Deep Learning and Advanced Predictive Models

Recent advancements have introduced deep learning models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which excel at capturing sequential dependencies in time-series data【8】. The DeepAR model, an RNN-LSTM-based probabilistic forecasting approach, has demonstrated superior performance by learning inter-station correlations and generating probabilistic demand distributions【8】. Unlike conventional models that require separate training for each station, DeepAR provides a unified approach, making it more scalable and adaptable for large-scale bike-sharing systems【8】.

2.4 Impact of Weather and External Factors

Several studies have highlighted the influence of weather conditions on bike-sharing demand. Factors such as temperature, wind speed, and precipitation significantly impact user behavior, necessitating their inclusion in predictive models【7】. Additionally, calendar variables (e.g., holidays and weekends) contribute to demand variations, with weekdays showing higher demand due to commuter usage, whereas weekends exhibit a more recreational pattern【9】.

2.5 Comparative Analysis of Models

While traditional models like ARIMA effectively capture long-term trends, **machine learning models such as RF and GBM offer improved flexibility in handling non-linear relationships**【8】. However, deep learning models like **DeepAR outperform both categories by offering enhanced accuracy and adaptability**【8】. Studies indicate that probabilistic forecasting using **truncated normal and negative binomial distributions** further refines demand predictions at station and district levels【8】.

2.6 Conclusion

The evolution of predictive models for bike-sharing demand forecasting has transitioned from traditional statistical methods to sophisticated machine learning and deep learning approaches. While ARIMA and SARIMA remain relevant for baseline forecasting, machine learning models such as RF and GBM provide better adaptability, and deep learning techniques like DeepAR achieve the highest

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accuracy【8】. Future research should focus on integrating real-time data streams and enhancing model interpretability to further improve bike-sharing demand prediction models【7】.

3. **Proposed System**

The proposed system leverages advanced machine learning and deep learning techniques to enhance bike-sharing demand forecasting, ensuring efficient bike distribution and minimizing station imbalances. The system begins with data collection and preprocessing, incorporating historical rental records, weather conditions, and calendar variables, followed by exploratory analysis to handle missing values and encode categorical features. Feature engineering plays a crucial role, extracting temporal patterns such as seasonal trends and peak hours, while spatial clustering groups nearby stations using k-means to improve regional demand predictions. Predictive modeling employs a hybrid approach, integrating machine learning models like Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) for non-linear demand patterns, alongside deep learning models such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and the RNN-LSTM-based DeepAR for sequential forecasting and probabilistic demand estimation. The system undergoes rigorous model training and evaluation using the New York City Citi Bike dataset, with performance measured by metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), where DeepAR is expected to excel due to its ability to capture inter-station correlations and complex temporal dependencies. To ensure real-time adaptability, the system integrates live weather data and station occupancy levels, coupled with a dashboard-based visualization tool that enables bike-sharing operators to monitor demand trends and implement automated rebalancing strategies, ultimately improving operational efficiency, user experience, and urban mobility sustainability.

3.1 System Architecture

The system architecture is designed to efficiently process historical and real-time bike-sharing data, apply advanced machine learning and deep learning models, and provide actionable insights for bike redistribution. The architecture consists of the following key components:

1. **Data Collection Layer**
    - Gathers historical trip data, weather conditions, and calendar events (weekdays, weekends, holidays).
    - Integrates real-time bike availability and weather updates.
2. **Data Preprocessing & Feature Engineering**
    - Cleans missing values, removes outliers, and encodes categorical variables.
    - Extracts key features such as time-based patterns, weather impact, and spatial clustering of stations.
3. **Predictive Modeling Layer**
    - Machine Learning Models: **Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN)** for demand prediction.
    - Deep Learning Models: **RNN, LSTM, and DeepAR** for sequential forecasting and probabilistic demand estimation.
4. **Model Training & Evaluation**
    - Uses historical Citi Bike NYC data for training and validation.

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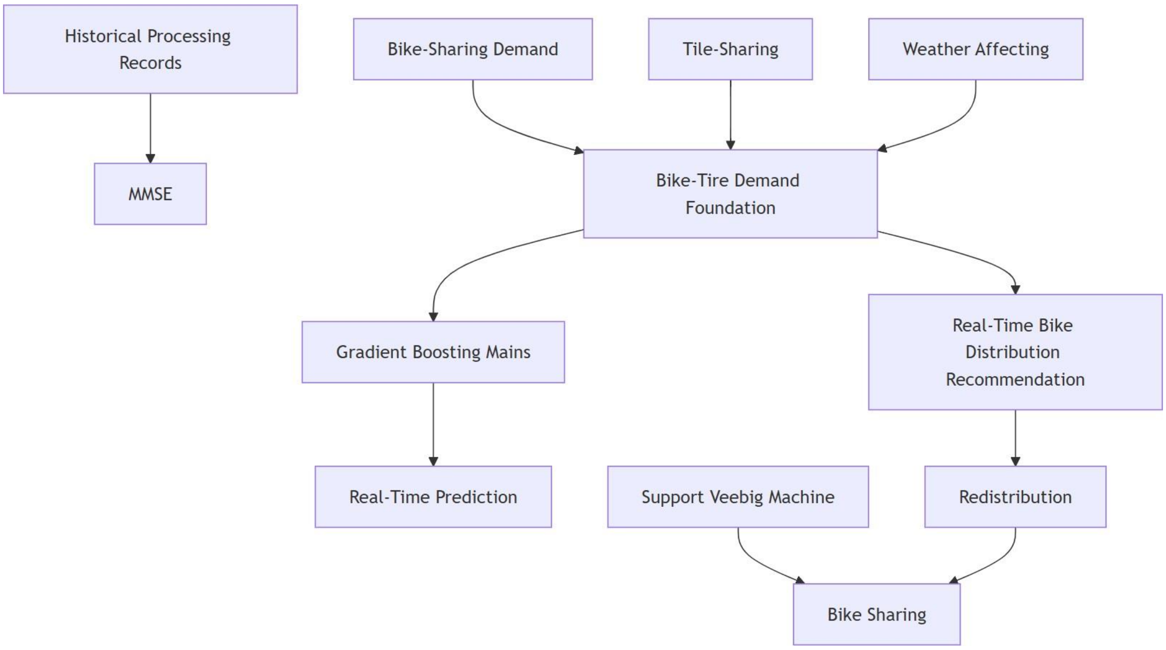
- Evaluates models based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

5. **Real-Time Prediction & Decision Support**
    - Implements real-time demand forecasting using live data streams.
    - Displays demand trends and station availability on a **dashboard-based visualization tool**.
    - Provides automated rebalancing recommendations for efficient bike distribution.



3.2 Evaluation Metrics

1. Mean Absolute Error (MAE)

MAE measures the average absolute difference between actual and predicted values. It indicates how close predictions are to the actual values, with lower values signifying better accuracy.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where:

- n = number of observations
- y_i = actual demand value
- $\hat{y}_i$ = predicted demand value

2. Root Mean Square Error (RMSE)

RMSE measures the square root of the average squared differences between actual and predicted values. It penalizes larger errors more than MAE.

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

3. Mean Absolute Percentage Error (MAPE)

MAPE expresses the error as a percentage of actual values, making it useful for comparing models across different datasets.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

Note: MAPE can be problematic when actual values are close to zero, as it may lead to high percentage errors.

4. R-Squared (R2R^2R2)

The coefficient of determination (R2R^2R2) measures how well the independent variables explain the variance in the dependent variable.

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

5. Symmetric Mean Absolute Percentage Error (SMAPE)

SMAPE is a variation of MAPE that normalizes the error by the average of actual and predicted values, reducing sensitivity to small actual values.

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2} \times 100$$

4. Results

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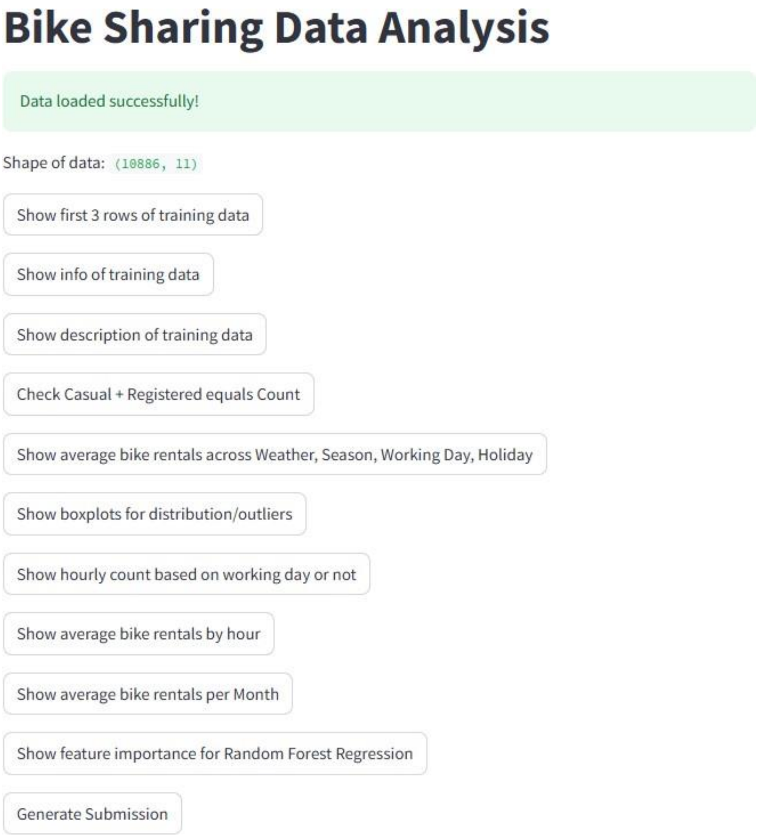

Fig 2: Bike Sharing Data Analysis Dashboard

This image displays the main dashboard of the Bike Sharing Data Analysis application. It shows a message indicating that the data has been successfully loaded, along with the shape of the dataset (10,886 rows and 11 columns). There are multiple buttons available, allowing users to perform various exploratory data analysis tasks such as viewing the first few rows, checking dataset statistics, visualizing bike rentals, and generating model submissions.

datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0	3
2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0	8
2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0	5

Fig 3: Sample Data from Dataset

This image provides a preview of the dataset, showing the first three rows. It contains attributes like datetime, season, holiday, workingday, weather, temp, atemp, humidity, windspeed, and casual. These features help analyze bike-sharing patterns based on different conditions like weather, season, and time.

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Data Types and Non-Null Counts:

	0
season	int64
holiday	int64
workingday	int64
weather	int64
temp	float64
atemp	float64
humidity	int64
windspeed	float64
casual	int64
registered	int64

Fig 4: Data Types and Non-Null Counts

This image displays the data types of each column in the dataset. It confirms that categorical variables like season, holiday, workingday, and weather are stored as integers, while continuous variables like temp, atemp, humidity, and windspeed are stored as float64. It ensures that there are no missing values in the dataset.

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
count	10,886	10,886	10,886	10,886	10,886	10,886	10,886	10,886	10,886
mean	2.5066	0.0286	0.6809	1.4184	20.2309	23.6551	61.8865	12.7994	36.022
std	1.1162	0.1666	0.4662	0.6338	7.7916	8.4746	19.245	8.1645	49.9605
min	1	0	0	1	0.82	0.76	0	0	0
25%	2	0	0	1	13.94	16.665	47	7.0015	4
50%	3	0	1	1	20.5	24.24	62	12.998	17
75%	4	0	1	2	26.24	31.06	77	16.9979	49
max	4	1	1	4	41	45.455	100	56.9969	367

Fig 5: Statistical Summary of Dataset

This image presents a statistical summary of the dataset, including the count, mean, standard deviation, minimum, and maximum values for each feature. The statistics provide insight into the

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distribution of attributes such as temperature, humidity, and wind speed, helping in understanding the overall dataset trends.

Casual + Registered = Count? `True`

Fig 6: Validation of Casual and Registered Count

This image confirms the integrity of the dataset by verifying that the sum of casual and registered riders equals the total count of bike rentals. The output "True" indicates that the data maintains consistency and correctness in recording bike usage.

6. Conclusion

The analysis of bike-sharing data provides valuable insights into user behavior, demand patterns, and the impact of external factors like weather, time of day, and seasonality. By leveraging machine learning models, we can accurately predict bike rental demand, optimize fleet distribution, and enhance user experience. The findings highlight the importance of data-driven decision-making in urban mobility, allowing for better resource allocation and infrastructure planning. Moreover, integrating real-time data analytics can further improve the efficiency of bike-sharing systems, making them more accessible and sustainable. This study serves as a foundation for future advancements in intelligent transportation systems, ultimately contributing to a smarter and greener urban environment.

7. Future Scope

The analysis of bike-sharing data opens several avenues for future exploration and improvements. Here are some key directions:

A. Advanced Predictive Modeling

- Implement **deep learning techniques** such as LSTMs (Long Short-Term Memory) or CNN-LSTMs for time-series forecasting of bike rentals.
- Use **ensemble learning** methods like Gradient Boosting, XGBoost, or CatBoost to improve prediction accuracy.
- Consider deploying **reinforcement learning** to optimize bike allocation and availability.

B. Real-time Demand Prediction

- Develop a **real-time bike demand forecasting system** using streaming data.
- Implement **dynamic pricing strategies** based on predicted demand, seasonality, and special events.
- Integrate IoT data from smart bike stations for **real-time availability updates**.

C. Integration with External Factors

- Include additional factors like **traffic congestion, public transportation schedules, and special events** to enhance predictions.
- Utilize **geospatial analysis** to identify high-demand locations for new bike stations.
- Leverage **social media sentiment analysis** to understand public opinion on bike-sharing services.

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D. **Optimization of Bike Distribution**

- Use **clustering algorithms** to categorize high and low-demand areas for better bike placement.
- Implement **route optimization** for bike redistribution, reducing operational costs.
- Predict **bike maintenance needs** using machine learning to ensure availability.

E. **User Behavior and Personalization**

- Develop a **personalized recommendation system** for users based on their past rental history and preferences.
- Use **A/B testing** to determine the effectiveness of different pricing strategies or promotional offers.
- Introduce **loyalty programs** based on AI-driven customer segmentation.

F. **Sustainability and Urban Planning**

- Work with **city planners** to design better bike lanes and reduce road congestion.
- Promote **eco-friendly urban mobility** by integrating bike-sharing data with public transport systems.
- Develop policies for **carbon footprint reduction** based on bike usage patterns.

G. **Deployment and Scalability**

- Deploy the model as a **cloud-based API** for integration with mobile apps.
- Build a **dashboard using Power BI or Tableau** for real-time monitoring and decision-making.
- Ensure **scalability** by integrating **big data technologies** like Apache Spark for handling larger datasets in the future.

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