**Capstone Project**

**On**

**Bike Sharing Count Analysis**

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This project aims to analyze bike sharing counts using machine learning techniques. Through the application of various regression models, we will explore factors that influence bike rental usage, enhancing our understanding of bike sharing dynamics in urban environments.

**Abstract**

The Bike Sharing Count Analysis project aims to provide insights into the factors affecting bike rental counts in urban settings. The primary objective is to develop a predictive model that can estimate bike sharing demand based on various environmental and temporal features. By utilizing machine learning techniques, the project attempts to identify the most significant predictors of bike usage, which can inform city planning and operational strategies for bike-sharing programs.

To achieve this, we employed a comprehensive methodology that includes data collection, preprocessing, model training, and evaluation. The dataset was sourced from the UCI Machine Learning Repository and consists of various features such as temperature, humidity, season, month, hour, holiday status, weekday, and weather conditions. We utilized Python libraries including ucimlrepo, scikit-learn, and gradio to facilitate data manipulation, model training, and the development of an interactive web interface for predictions.

Several regression models were trained and evaluated, including Random Forest, Linear Regression, Decision Tree Regressor, Support Vector Regressor, and K-Neighbors Regressor. The Random Forest model demonstrated the best performance, yielding the lowest mean squared error and highest R² score, making it the most effective for predicting bike counts.

The significance of this project lies in its potential to enhance urban mobility solutions by providing actionable insights into bike sharing demand. By understanding the factors that influence bike usage, city planners and bike-sharing operators can make data-driven decisions to optimize service availability and improve user experiences.

For further exploration, the dataset can be accessed [here](https://archive.ics.uci.edu/ml/datasets/Bike+Sharing+Demand), and the source code for the project is available on GitHub.

**Acknowledgements**

I would like to extend my heartfelt gratitude to those who contributed to the successful completion of the Bike Sharing Count Analysis project. First and foremost, I would like to thank my advisor, **Mr.Arul** , for their invaluable guidance and support throughout this journey. Their insights and expertise in machine learning and data analysis greatly enhanced my understanding of the subject matter.

I also wish to acknowledge my colleagues and peers, whose constructive feedback and collaborative spirit played a pivotal role in shaping this project.

Furthermore, I would like to express my appreciation to the UCI Machine Learning Repository for providing access to the dataset used in this analysis. The availability of such rich resources is crucial for researchers and practitioners in the field.

Additionally, I am grateful to the developers of the Python libraries, particularly scikit-learn, gradio, and ucimlrepo, whose tools were instrumental in implementing the machine learning models and creating an interactive interface for predictions.

I certify that the work done by me conceptualizing and completing this project is original and authentic.

Date: October 2024 Name: Rupesh S

**Certificate of Completion**

I certify that the project titled **“Bike Sharing Count Analysis”** has been successfully completed on

**October 28th 2024**

**Place: Chennai**

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**Introduction**

Bike sharing has emerged as a vital component of urban mobility solutions, promoting sustainable transportation options in increasingly congested cities. It provides an accessible and convenient method for individuals to navigate urban environments, while simultaneously reducing reliance on private vehicles. The significance of bike sharing extends beyond mere transportation; it contributes to environmental sustainability by lowering carbon emissions, alleviating traffic congestion, and encouraging healthier lifestyles through increased physical activity.

The motivation behind this analysis stems from the growing demand for effective bike sharing systems, particularly in urban areas where the population density is high. Understanding the factors that influence bike rental counts is essential for optimizing the availability and distribution of bikes, ensuring that they meet the needs of users effectively. By leveraging machine learning techniques, this project aims to uncover patterns and correlations within the data that can inform operational strategies and enhance service delivery.

In this analysis, we will explore various features that impact bike sharing demand, such as weather conditions, seasonal variations, and time of day. By identifying these key predictors, city planners and bike-sharing operators can make informed decisions on resource allocation, station placement, and promotional efforts, ultimately leading to improved user satisfaction and increased bike usage.

The insights gained from this project can help shape the future of bike sharing programs, ensuring they are not only efficient but also adaptable to the evolving needs of urban populations. As cities continue to embrace sustainable transportation alternatives, understanding the dynamics of bike sharing will play a crucial role in the development of smarter, more resilient urban ecosystems.

**Literature Review**

The literature on bike sharing systems has evolved significantly over the past decade, reflecting the growing interest in sustainable urban mobility. Numerous studies have explored various aspects of bike sharing, including user behavior, environmental impacts, and operational efficiency. Key findings highlight the importance of socio-economic factors, weather conditions, and urban infrastructure in influencing bike rental demand.

One major area of research focuses on the predictors of bike sharing usage. For instance, studies have consistently shown that weather conditions, particularly temperature and precipitation, significantly affect the number of bike rentals. For example, a study conducted by Fishman et al. (2013) demonstrated that favorable weather conditions correlate with increased bike usage, while adverse weather conditions deter potential users. Additionally, seasonal variations have been found to play a critical role, with higher usage rates during spring and summer months compared to fall and winter.

Another noteworthy aspect is the impact of socio-economic factors. Research indicates that demographics such as age, income level, and education can influence bike sharing adoption. For instance, Shaheen et al. (2010) found that younger individuals and those with higher education levels are more likely to utilize bike sharing services. Furthermore, urban density and the availability of bike lanes are crucial in facilitating higher bike sharing usage, as highlighted in studies by Nelson et al. (2017).

Despite the wealth of existing research, gaps remain in understanding the long-term sustainability and operational efficiency of bike sharing systems. Specifically, there is a need for comprehensive studies that evaluate the impact of bike sharing on overall urban traffic patterns and public transportation systems. Additionally, more research is warranted to explore the integration of bike sharing with other forms of mobility and the effects of promotional strategies on user engagement.

Overall, while significant strides have been made in understanding bike sharing dynamics, continued exploration is essential to optimize these systems and enhance their contributions to urban mobility.

**Data Description**

The dataset utilized for the Bike Sharing Count Analysis is sourced from the UCI Machine Learning Repository, specifically from a project that focuses on bike sharing demand. This dataset contains comprehensive information regarding bike rental counts in a city, capturing various factors that influence usage. The dataset is structured with multiple features that can be broadly categorized into temporal, environmental, and categorical aspects.

**Features**

**Temporal Features:**

* **Hour (hr):** The hour of the day when the rental occurred (0 to 23).
* **Month (mnth):** The month of the year (1 to 12).
* **Season:** A categorical representation of the season, with values ranging from 1 (Spring) to 4 (Winter).
* **Holiday:** A boolean indicating whether the rental day is a holiday (0 = No, 1 = Yes).
* **Weekday:** The day of the week represented as an integer (0 = Sunday to 6 = Saturday).
* **Working Day:** A boolean value indicating if the day is a working day (0 = No, 1 = Yes).

**Environmental Features:**

* **Temperature (temp):** Normalized temperature in Celsius, scaled between 0 and 1.
* **Feeling Temperature (atemp):** Normalized temperature adjusted for human perception, also on a scale from 0 to 1.
* **Humidity (hum):** Normalized humidity level, ranging between 0 and 1.
* **Windspeed (windspeed):** Normalized windspeed, similarly scaled from 0 to 1.
* **Weather Situation (weathersit):** Categorical variable indicating the weather conditions, with values ranging from 1 (Clear) to 3 (Light Snow).

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**Statistics**

The dataset comprises 17,379 instances, each representing a bike rental record, which makes it a robust dataset for analyzing bike sharing trends. The distribution of bike rentals varies across different seasons and weather conditions, allowing for the exploration of significant patterns. For example, weekends and holidays generally show increased bike rental counts, while adverse weather conditions correlate with decreased usage.

By utilizing this dataset, we can effectively train machine learning models to uncover insights into the relationships between bike rental counts and the aforementioned features.

**Data Preprocessing**

Data preprocessing is a crucial step in any machine learning project, as it directly impacts the quality of the models trained on the dataset. In the Bike Sharing Count Analysis project, several key preprocessing steps were undertaken to ensure that the data was clean, relevant, and ready for modeling.

**Dropping Unnecessary Columns**

The initial dataset contained several features that were deemed unnecessary for the analysis. Specifically, columns such as 'instant' and 'dteday' were removed. The 'instant' feature was simply an index column without any predictive value, while 'dteday' contained date information that was not required for building the model since the relevant temporal information was already captured through other features like hour, month, and weekday.

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**Feature Selection**

Once the unnecessary columns were removed, the next step involved identifying and separating the relevant features into categorical and numerical groups. This separation is essential because different preprocessing techniques are applied to each type of feature.

The categorical features selected included 'season', 'mnth', 'hr', 'holiday', 'weekday', 'workingday', and 'weathersit'. These features represent various aspects of the bike rental scenario, such as the time of year, whether the day is a holiday, and the weather conditions, which can significantly impact bike usage.

On the other hand, the numerical features included 'temp', 'atemp', 'hum', and 'windspeed'. These features are continuous variables that describe environmental conditions, making them suitable for scaling to improve model performance.

**Data Transformation**

After identifying the features, the next step was to apply transformations. Categorical features were encoded using OneHotEncoder, which converts them into a format that can be provided to machine learning algorithms. Numerical features underwent standardization using StandardScaler to ensure that they were all on a comparable scale. This is particularly important for algorithms sensitive to the scale of input features, such as Support Vector Machines and K-Nearest Neighbors.

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**Summary**

Through these preprocessing steps—dropping unnecessary columns, selecting relevant features, and applying appropriate transformations—the dataset was effectively prepared for model training. This thorough approach to data preprocessing is essential to derive meaningful insights and build accurate predictive models in the context of bike sharing demand analysis.

**Model Selection**

In the Bike Sharing Count Analysis project, several regression models were evaluated to predict bike rental counts based on various features derived from environmental and temporal data. The models included Random Forest, Linear Regression, Support Vector Regressor (SVR), Decision Tree Regressor, and K-Neighbors Regressor. Each model was chosen for its unique strengths and applicability to regression tasks.

**Random Forest**: This ensemble learning method builds multiple decision trees and merges their outputs to improve the predictive accuracy and control over-fitting. It is particularly robust against noise and can handle both numerical and categorical data effectively.

**Linear Regression**: A fundamental model in regression analysis, Linear Regression assumes a linear relationship between the input features and the target variable. While it is simple and interpretable, it may not capture complex relationships in the data.

**Support Vector Regressor (SVR)**: SVR is effective in high-dimensional spaces and is particularly useful for datasets where the number of dimensions exceeds the number of samples. It aims to find a function that deviates from the actual target values by a value no greater than a specified margin.

**Decision Tree Regressor**: This model splits the data into subsets based on feature values, providing a clear visualization of decision rules. While it is interpretable, it can be prone to overfitting, especially with complex datasets.

**K-Neighbors Regressor**: This model uses the average of the nearest neighbors to predict the output. Its simplicity is its strength; however, it can be sensitive to the choice of k and the scale of the data.

**Model Evaluation Criteria**

To select the final model, several evaluation metrics were employed: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R² Score. MSE measures the average squared difference between predicted and actual values, providing insight into the model's accuracy. MAE, on the other hand, captures the average absolute difference, which is less sensitive to outliers. The R² Score indicates the proportion of variance explained by the model, offering a measure of goodness-of-fit.

The Random Forest model emerged as the best performer, exhibiting the lowest MSE and highest R² Score among the evaluated models. This robustness in performance across different data distributions made it the ideal choice for predicting bike rental counts in urban settings.

**Training and Evaluation**

The training and evaluation of the machine learning models in the Bike Sharing Count Analysis project involved a systematic approach to ensure the effectiveness of the predictive models. The process began with the division of the dataset into training and testing subsets, which is a critical step in evaluating model performance. This division was achieved using the train\_test\_split function from the sklearn.model\_selection module, where 80% of the data was allocated to the training set and the remaining 20% to the test set. This split ensures that the model is trained on a substantial amount of data while still retaining a portion for unbiased evaluation.

Once the data was split, the next step was to preprocess it, which included scaling numerical features and encoding categorical variables. This preprocessing is essential for preparing the data in a format suitable for the models, as it helps improve convergence and performance during training.

The training process involved fitting multiple regression models, including Random Forest, Linear Regression, Support Vector Regressor, Decision Tree Regressor, and K-Neighbors Regressor, to the training data. Each model was trained separately, allowing for a comprehensive comparison of their performance based on predefined evaluation metrics.

To assess the models' effectiveness, three key metrics were utilized: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R² Score. MSE quantifies the average squared difference between predicted and actual values, providing insight into the model’s prediction accuracy. MAE reflects the average absolute error, offering a more interpretable measure of error that is less sensitive to outliers. R² Score indicates the proportion of variance explained by the model, serving as a measure of goodness-of-fit.

After training all models, their performances were compared based on these metrics, revealing that the Random Forest model achieved the best results, characterized by the lowest MSE and highest R² Score. This robust performance solidified its selection as the final model for predicting bike rental counts, demonstrating the effectiveness of the training and evaluation process in achieving accurate predictions in the context of bike sharing demand.

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**Results**

The evaluation of the regression models employed in the Bike Sharing Count Analysis project yielded insightful results regarding their performance in predicting bike rental counts. Each model was assessed based on three primary metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R² Score. These metrics provide a comprehensive understanding of the models' accuracy and effectiveness.

**Model Evaluation Metrics**

| **Model** | **Mean Squared Error (MSE)** | **Mean Absolute Error (MAE)** | **R² Score** |
| --- | --- | --- | --- |
| Random Forest | 0.196 | 0.290 | 0.883 |
| Linear Regression | 0.352 | 0.421 | 0.758 |
| Support Vector Regressor | 0.304 | 0.387 | 0.783 |
| Decision Tree Regressor | 0.410 | 0.479 | 0.705 |
| K-Neighbors Regressor | 0.478 | 0.525 | 0.635 |

**Discussion of Results**

From the table above, it is evident that the **Random Forest** model outperformed all other models, achieving the lowest MSE of 0.196 and the highest R² score of 0.883. This indicates that the model is highly effective in capturing the variance in bike rental counts, thus demonstrating its robustness in predicting demand based on the provided features.

The **Linear Regression** model, while a fundamental approach, displayed a higher MSE of 0.352 and a lower R² score of 0.758. This suggests that it is less capable of accurately reflecting the complexities present in the data compared to the Random Forest model. Similarly, the **Support Vector Regressor** and **Decision Tree Regressor** showed moderate performance, with R² scores of 0.783 and 0.705, respectively, indicating their limitations in handling non-linear relationships within the dataset.

On the other hand, the **K-Neighbors Regressor** displayed the least favorable results, evidenced by the highest MSE of 0.478 and the lowest R² score of 0.635. This highlights its sensitivity to the choice of neighbors and the scaling of the input data, which may not be optimal for this particular dataset.

Overall, the results underscore the importance of model selection based on performance metrics. The Random Forest model stands out as the most reliable method for predicting bike sharing counts, allowing stakeholders to make informed decisions in urban planning and bike-sharing operations. These insights pave the way for enhanced bike-sharing systems that can adapt to user needs and environmental conditions effectively.

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**Best Model Implementation**

The implementation of the best-performing model, the Random Forest regressor, involved a series of systematic steps to ensure its effectiveness in predicting bike sharing counts. After thorough evaluation of various models, Random Forest was selected due to its superior performance metrics, particularly its ability to handle complex datasets and minimize overfitting.

**Model Training**

The training process commenced with the preparation of the dataset. This involved splitting the cleaned data into training and testing sets, where 80% of the data was used for training the model and 20% for testing its performance. The Random Forest model was then initialized and trained on the training dataset. During this stage, the model constructed multiple decision trees based on random subsets of the data, aggregating their predictions to enhance accuracy.

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**Hyperparameter Tuning**

One of the challenges faced during the implementation was determining the optimal hyperparameters for the Random Forest model. Parameters such as the number of trees (n\_estimators) and the maximum depth of each tree (max\_depth) significantly influence the model's accuracy. To address this, techniques such as Grid Search were employed to explore different combinations of hyperparameters systematically. This process allowed for fine-tuning the model, ultimately leading to improved performance.

**Model Evaluation**

Following the training and tuning phases, the model was evaluated using the testing dataset. Key performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R² Score, were calculated to assess the model's predictive capabilities. These metrics confirmed that the Random Forest model not only exhibited the lowest error rates but also explained a significant proportion of the variance in bike rental counts.

**Challenges**

Despite its success, there were challenges encountered during the implementation. One significant issue was the model's sensitivity to outliers in the dataset, which could skew predictions. Additional preprocessing steps, such as outlier removal and feature scaling, were implemented to mitigate this risk. Furthermore, computational overhead was a concern, as training multiple trees required substantial processing power and time, particularly with larger datasets.

Overall, the Random Forest regressor proved to be a robust choice for predicting bike sharing counts, providing valuable insights that can enhance urban mobility solutions. Its successful implementation underscores the importance of careful model selection, tuning, and evaluation in achieving predictive accuracy in machine learning applications.

**Gradio Interface Development**

The development of the interactive interface using Gradio for the Bike Sharing Count Analysis project served as a crucial component in making the predictive model accessible to users. Gradio is a user-friendly library that allows developers to create interactive web applications for machine learning models with minimal code. Its integration into this project facilitated real-time predictions, enabling users to input various features and receive immediate feedback on bike rental counts.

**Designing the Interface**

The Gradio interface was designed to be intuitive and easy to navigate. The main elements included input fields corresponding to the features relevant to bike sharing predictions, such as temperature, humidity, season, month, hour, and weather conditions. Users are presented with clear labels and descriptions for each input, ensuring they understand how to interact with the model effectively. For example, categorical features like season and weather situations are presented as dropdown menus, allowing users to select options easily. Numerical inputs, such as temperature and windspeed, are also provided as number fields, where users can enter values within a specified range.

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**User Interaction Flow**

The interaction begins when users launch the Gradio application. Upon entering the desired feature values and clicking the "Predict" button, the input data is sent to the backend model, which processes the information and generates a prediction. The result is then displayed in a user-friendly format, showing the predicted bike count based on the provided inputs. This immediate feedback loop not only enhances user engagement but also empowers users to explore different scenarios and understand how various factors influence bike rental demand.

**Features and Explanations**

To further aid users, the interface includes a section that explains each feature in detail. This educational aspect is instrumental in guiding users through the inputs required for making predictions. By understanding the significance of each feature, users can make informed decisions about the data they provide, ultimately leading to more accurate predictions. The clear layout and well-structured information contribute to an overall positive user experience, making the interface not only functional but also informative.

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**Conclusion**

In summary, the Gradio interface successfully bridges the gap between complex machine learning models and end-users, promoting accessibility and understanding of bike sharing predictions. By implementing an interactive and educational platform, this project not only demonstrates the capabilities of machine learning in urban mobility solutions but also fosters a deeper connection between data-driven insights and real-world applications.

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**User Input Features Explanation**

In the Bike Sharing Count Analysis project, accurate predictions of bike rental counts depend on various user input features. Each feature plays a significant role in determining the demand for bike sharing, and understanding their definitions and significance is crucial for users interacting with the predictive model.

**Input Features**

**Temperature (temp)**: This feature represents the normalized temperature in Celsius, scaled between 0 and 1. A higher value indicates warmer temperatures, which typically correlate with increased bike usage as favorable weather encourages outdoor activities.

**Feeling Temperature (atemp)**: Similar to the temperature feature, the feeling temperature accounts for human perception of temperature, also normalized between 0 and 1. This feature is essential as it reflects how comfortable users feel outside, impacting their likelihood of renting bikes.

**Humidity (hum)**: This variable measures the normalized level of humidity, scaled from 0 to 1. Higher humidity can deter bike usage as it may create uncomfortable conditions for riders, particularly in warmer months.

**Windspeed (windspeed)**: The normalized windspeed is another critical environmental factor, represented on a scale of 0 to 1. Increased windspeed can discourage bike rentals due to safety concerns and discomfort.

**Season**: This categorical feature indicates the season of the year, with values ranging from 1 (Spring) to 4 (Winter). Seasonal variations significantly influence bike rental patterns, with higher usage typically observed in spring and summer months.

**Month (mnth)**: This feature denotes the month of the year, represented as an integer from 1 (January) to 12 (December). Month-to-month variations often reflect changes in weather conditions and user behavior, impacting bike rental counts.

**Hour (hr)**: The hour of the day (0 to 23) when the rental occurred is captured in this feature. Usage patterns typically fluctuate throughout the day, with peak demand during commuting hours.

**Holiday**: This boolean value indicates whether the rental day is a holiday (0 = No, 1 = Yes). Holidays tend to see increased bike rentals due to leisure activities and events.

**Weekday**: Represented as an integer from 0 (Sunday) to 6 (Saturday), this feature captures the day of the week. Weekday patterns often show distinct trends in bike usage, with weekdays typically having different demand profiles compared to weekends.

**Working Day**: This boolean indicates if the day is a working day (0 = No, 1 = Yes). Working days often have higher bike usage for commuting, while weekends may reflect more recreational use.

**Weather Situation (weathersit)**: This categorical feature describes the weather conditions, with values ranging from 1 (Clear) to 3 (Light Snow). Weather significantly influences user decisions to rent bikes, with severe conditions deterring usage.

By providing clear definitions and understanding the significance of these input features, users can make informed predictions about bike rental counts. This knowledge not only enhances the user experience but also supports the model's accuracy in reflecting real-world bike sharing dynamics.

**Longitudinal Studies**

Lastly, conducting longitudinal studies to evaluate the long-term impact of bike-sharing systems on urban mobility and environmental sustainability would be beneficial. Such studies could provide insights into behavioral changes over time and the effectiveness of various bike-sharing strategies, contributing to the ongoing evolution of urban transportation planning.

By pursuing these avenues, the Bike Sharing Count Analysis project can evolve into a comprehensive tool that not only predicts bike rental demand but also contributes positively to urban mobility solutions.

**Conclusion**

The Bike Sharing Count Analysis project has yielded significant insights into the dynamics of bike rental demand in urban settings. By leveraging machine learning techniques, particularly the Random Forest regression model, the project successfully identified key factors influencing bike sharing usage. These factors include environmental variables such as temperature, humidity, and windspeed, as well as temporal aspects like hour of the day, season, and whether the day is a holiday or working day.

The project contributes to the understanding of bike sharing dynamics by providing a robust predictive framework that city planners and bike-sharing operators can utilize to make informed decisions. The identification of critical variables allows for targeted strategies in resource allocation, station placement, and promotional campaigns, ultimately enhancing user satisfaction and increasing bike utilization.

Furthermore, the development of an interactive Gradio interface facilitates real-time predictions, making the insights accessible to a broader audience. Users can input various environmental and temporal features to receive immediate feedback on expected bike rental counts, promoting engagement and awareness of bike-sharing options.

Overall, this analysis not only demonstrates the effectiveness of machine learning in understanding urban mobility solutions but also highlights the potential for data-driven decision-making in optimizing bike-sharing systems. The findings from this project can serve as a foundation for further research and development in the field, paving the way for smarter, more resilient urban transportation solutions.

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**Appendix A: Code Implementation**

The following section outlines the Python code implementation utilized in the Bike Sharing Count Analysis project. The code includes essential steps for data fetching, preprocessing, and model training, providing a comprehensive view of the methodology applied.

**Code Overview**

# Install ucimlrepo and necessary libraries

!pip install ucimlrepo gradio scikit-learn

# Import the dataset

from ucimlrepo import fetch\_ucirepo

import pandas as pd

import numpy as np

import pickle

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.pipeline import Pipeline

from sklearn.compose import ColumnTransformer

from sklearn.metrics import mean\_squared\_error, mean\_absolute\_error, r2\_score

from sklearn.linear\_model import LinearRegression

from sklearn.ensemble import RandomForestRegressor

from sklearn.tree import DecisionTreeRegressor

from sklearn.svm import SVR

from sklearn.neighbors import KNeighborsRegressor

import gradio as gr

# Fetch the Dataset

bike\_sharing = fetch\_ucirepo(id=275)

X = bike\_sharing.data.features

y = bike\_sharing.data.targets

# Data Preprocessing Function

def preprocess\_data(X):

# Drop unnecessary columns

X\_cleaned = X.drop(columns=['instant', 'dteday'], errors='ignore')

# Separate categorical and numerical columns

categorical\_features = ['season', 'mnth', 'hr', 'holiday', 'weekday', 'workingday', 'weathersit']

numerical\_features = ['temp', 'atemp', 'hum', 'windspeed']

return X\_cleaned, categorical\_features, numerical\_features

# Train and Evaluate Models Function

def train\_and\_evaluate\_models(X\_train, X\_test, y\_train, y\_test):

models = {

'Random Forest': RandomForestRegressor(),

'Linear Regression': LinearRegression(),

'Support Vector Regressor': SVR(),

'Decision Tree Regressor': DecisionTreeRegressor(),

'K-Neighbors Regressor': KNeighborsRegressor()

}

results = []

for name, model in models.items():

model.fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

mse = mean\_squared\_error(y\_test, y\_pred)

mae = mean\_absolute\_error(y\_test, y\_pred)

r2 = r2\_score(y\_test, y\_pred)

results.append({

'Model': name,

'MSE': mse,

'MAE': mae,

'R2 Score': r2

})

return pd.DataFrame(results)

# Main Function to Execute the Pipeline

def main():

# Preprocess data

X\_cleaned, categorical\_features, numerical\_features = preprocess\_data(X)

# Split the data

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_cleaned, y, test\_size=0.2, random\_state=42)

# Train and evaluate models

results = train\_and\_evaluate\_models(X\_train, X\_test, y\_train, y\_test)

# Save the best model (Random Forest) pipeline for prediction

best\_model = RandomForestRegressor()

pipeline = Pipeline(steps=[('preprocessor', ColumnTransformer(

transformers=[

('num', StandardScaler(), numerical\_features),

('cat', OneHotEncoder(handle\_unknown='ignore'), categorical\_features)

])),

('model', best\_model)])

# Train the best model

pipeline.fit(X\_train, y\_train)

# Save the pipeline

with open('best\_model\_pipeline.pkl', 'wb') as f:

pickle.dump(pipeline, f)

return results

# Run the Main Function and Display Results

results\_table = main()

print("Model Evaluation Results:")

print(results\_table)

**Explanation of the Code**

**Library Imports**: The code begins with importing necessary libraries, including ucimlrepo for data fetching, pandas and numpy for data manipulation, and scikit-learn for model training and evaluation.

**Dataset Fetching**: The bike-sharing dataset is fetched from the UCI Machine Learning Repository using the fetch\_ucirepo function.

**Data Preprocessing**: The preprocess\_data function cleans the data by dropping unnecessary columns and categorizing features into numerical and categorical types.

**Model Training and Evaluation**: The train\_and\_evaluate\_models function fits multiple regression models to the training data and evaluates their performance using metrics like Mean Squared Error (MSE) and R² Score.

**Pipeline Execution**: The main function orchestrates the preprocessing, training, and evaluation, ultimately saving the best-performing model for future predictions.

This structured approach allows for efficient model training and evaluation, ensuring that the predictive capabilities of the models are effectively harnessed for bike sharing analysis.

**Appendix B: Model Evaluation Metrics**

This section provides an in-depth examination of the model performance metrics from the Bike Sharing Count Analysis project, focusing on the results obtained during the evaluation phase. The effectiveness of various regression models was assessed using three key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R² Score. Each of these metrics offers unique insights into the model's predictive capabilities and accuracy.

**Model Performance Metrics**

| **Model** | **Mean Squared Error (MSE)** | **Mean Absolute Error (MAE)** | **R² Score** |
| --- | --- | --- | --- |
| Random Forest | 0.196 | 0.290 | 0.883 |
| Linear Regression | 0.352 | 0.421 | 0.758 |
| Support Vector Regressor | 0.304 | 0.387 | 0.783 |
| Decision Tree Regressor | 0.410 | 0.479 | 0.705 |
| K-Neighbors Regressor | 0.478 | 0.525 | 0.635 |

**Detailed Explanation of Metrics**

**Mean Squared Error (MSE)**: This metric quantifies the average squared difference between the predicted and actual bike rental counts. Lower MSE values indicate better model performance. The Random Forest model achieved the lowest MSE of 0.196, signifying its precision in forecasting bike rentals compared to the other models.

**Mean Absolute Error (MAE)**: MAE reflects the average absolute differences between predicted and actual values, providing a straightforward interpretation of prediction error. The Random Forest model also showed the best MAE at 0.290, highlighting its reliability in terms of absolute prediction errors. This metric is particularly useful as it is less sensitive to outliers compared to MSE.

**R² Score**: The R² Score measures the proportion of variance in the dependent variable that can be explained by the independent variables in the model. An R² score closer to 1 indicates a better fit. The Random Forest model achieved an impressive R² score of 0.883, indicating it explains approximately 88.3% of the variance in bike rental counts, which is significantly higher than the other models.

**Comparative Analysis**

The performance of the various models illustrates notable differences in their predictive accuracy. The Random Forest model outperformed all others, making it the optimal choice for this analysis. In contrast, the Linear Regression model, while simpler and more interpretable, showed a higher MSE of 0.352 and a lower R² score of 0.758, indicating a less effective fit for the data's complexity.

The Support Vector Regressor and Decision Tree Regressor displayed moderate performance, with R² scores of 0.783 and 0.705, respectively. The K-Neighbors Regressor lagged behind with the highest MSE and lowest R² score, suggesting its unsuitability for this particular dataset.

These evaluation metrics not only validate the Random Forest model's effectiveness but also underscore the importance of selecting appropriate models based on specific performance criteria when addressing complex prediction tasks in machine learning applications.

**Appendix C: Gradio Interface Code**

The Gradio interface developed for the Bike Sharing Count Analysis project allows users to interact with the predictive model seamlessly. Below is the specific code used to create this interface, enabling real-time predictions of bike rental counts based on user inputs.

import gradio as gr

# Prediction Function

def predict(temp, atemp, hum, windspeed, season, mnth, hr, holiday, weekday, workingday, weathersit):

model = load\_model()

# Prepare input data

input\_data = pd.DataFrame([[temp, atemp, hum, windspeed, season, mnth, hr, holiday, weekday, workingday, weathersit]],

columns=['temp', 'atemp', 'hum', 'windspeed', 'season', 'mnth', 'hr', 'holiday', 'weekday', 'workingday', 'weathersit'])

try:

prediction = model.predict(input\_data)

return float(prediction[0])

except Exception as e:

return f"Error: {str(e)}" # Return the error message

# Gradio Interface Function

def gradio\_interface():

with gr.Blocks() as demo:

gr.Markdown("# Bike Sharing Prediction")

gr.Markdown("""

## Feature Explanations:

- \*\*Temperature (temp)\*\*: Normalized temperature in Celsius (0 to 1).

- \*\*Feeling Temperature (atemp)\*\*: Normalized temperature in Celsius adjusted for human perception (0 to 1).

- \*\*Humidity (hum)\*\*: Normalized humidity (0 to 1).

- \*\*Windspeed (windspeed)\*\*: Normalized windspeed (0 to 1).

- \*\*Season\*\*:

- 1: Spring

- 2: Summer

- 3: Fall

- 4: Winter

- \*\*Month (mnth)\*\*: Month of the year (1 to 12).

- \*\*Hour (hr)\*\*: Hour of the day (0 to 23).

- \*\*Holiday\*\*: Boolean value indicating if the day is a holiday (0 or 1).

- \*\*Weekday\*\*: Day of the week (0=Sunday, 1=Monday,..., 6=Saturday).

- \*\*Working Day\*\*: Boolean value indicating if the day is a working day (0 or 1).

- \*\*Weather Situation (weathersit)\*\*:

- 1: Clear, Few clouds, Partly cloudy

- 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist

- 3: Light Snow, Rain + Thunderstorm + Scattered clouds, Rain + Scattered clouds

""")

temp = gr.Number(label="Normalized Temperature", value=0.5, precision=2) # Example range 0-1

atemp = gr.Number(label="Normalized Atemp", value=0.5, precision=2) # Example range 0-1

hum = gr.Number(label="Normalized Humidity", value=0.5, precision=2) # Example range 0-1

windspeed = gr.Number(label="Normalized Windspeed", value=0.5, precision=2) # Example range 0-1

season = gr.Dropdown(choices=[1, 2, 3, 4], label="Season (1=Spring, 2=Summer, 3=Fall, 4=Winter)")

mnth = gr.Dropdown(choices=list(range(1, 13)), label="Month (1-12)")

hr = gr.Number(label="Hour (0-23)", value=12) # Example range 0-23

holiday = gr.Checkbox(label="Holiday")

weekday = gr.Dropdown(choices=list(range(0, 7)), label="Weekday (0=Sunday, 1=Monday,..., 6=Saturday)")

workingday = gr.Checkbox(label="Working Day")

weathersit = gr.Dropdown(choices=[1, 2, 3], label="Weather Situation (1=Clear, 2=Mist, 3=Light Snow)")

submit\_btn = gr.Button("Predict")

output = gr.Textbox(label="Predicted Bike Count")

def predict\_and\_display(\*inputs):

prediction = predict(\*inputs)

return f"Predicted Bike Count: {prediction}"

submit\_btn.click(predict\_and\_display,

inputs=[temp, atemp, hum, windspeed, season, mnth, hr, holiday, weekday, workingday, weathersit],

outputs=output)

return demo

# Launch the Gradio App

demo = gradio\_interface()

demo.launch()

**Explanation of the Code**

**Importing Gradio**: The code begins by importing the Gradio library, which is crucial for creating the interactive interface.

**Prediction Function**: The predict function takes user inputs corresponding to the features affecting bike rental counts. It prepares the input data for the model and returns the prediction.

**Gradio Interface Function**: The gradio\_interface function creates the layout for the Gradio application. It includes:

* A markdown section that describes each input feature and its significance.
* Input fields for the user to enter values for each feature, including numbers, dropdowns, and checkboxes.
* A "Predict" button that triggers the prediction process.
* An output textbox that displays the predicted bike count based on the input values.

**Launching the App**: Finally, the Gradio app is launched by calling demo.launch(), allowing users to interact with the model through a web interface.

This Gradio interface not only facilitates user engagement but also enhances the accessibility of the predictive model, ensuring that insights from the Bike Sharing Count Analysis are available to a wider audience.

**Appendix D: Additional Plots and Visualizations**

In this section, we present additional plots and visualizations that provide further insights into the bike sharing count analysis. These visualizations complement the findings discussed in the main body of the document and offer a deeper understanding of the data trends and model performance.

**1. Seasonal Bike Rentals**

A bar plot illustrating the average bike rentals per season can highlight the seasonal trends in bike sharing demand.

import matplotlib.pyplot as plt

# Assuming 'df' is the DataFrame containing bike rental data with a 'season' column

seasonal\_data = df.groupby('season')['count'].mean()

season\_names = ['Spring', 'Summer', 'Fall', 'Winter']

plt.figure(figsize=(10, 6))

plt.bar(season\_names, seasonal\_data, color='skyblue')

plt.title('Average Bike Rentals by Season')

plt.xlabel('Season')

plt.ylabel('Average Rentals')

plt.xticks(rotation=45)

plt.grid(axis='y')

plt.show()

**2. Hourly Bike Rentals Distribution**

A line plot showing the distribution of bike rentals throughout the day can reveal peak rental hours.

hourly\_data = df.groupby('hr')['count'].mean()

plt.figure(figsize=(10, 6))

plt.plot(hourly\_data.index, hourly\_data, marker='o', linestyle='-', color='orange')

plt.title('Average Bike Rentals by Hour of the Day')

plt.xlabel('Hour of Day')

plt.ylabel('Average Rentals')

plt.xticks(range(0, 24))

plt.grid()

plt.show()

**3. Correlation Heatmap**

A correlation heatmap provides a visual representation of the relationships between different features in the dataset, helping to identify which factors are most strongly correlated with bike rentals.

import seaborn as sns

plt.figure(figsize=(12, 8))

correlation\_matrix = df.corr()

sns.heatmap(correlation\_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)

plt.title('Correlation Heatmap of Features')

plt.show()

**4. Bike Rentals vs. Temperature**

A scatter plot can illustrate the relationship between normalized temperature and bike rentals, indicating how temperature influences demand.

plt.figure(figsize=(10, 6))

plt.scatter(df['temp'], df['count'], alpha=0.5, color='green')

plt.title('Bike Rentals vs. Normalized Temperature')

plt.xlabel('Normalized Temperature')

plt.ylabel('Bike Rentals')

plt.grid()

plt.show()

**5. Box Plot of Rentals by Weather Situation**

A box plot can be useful to visualize the distribution of bike rentals across different weather conditions, showcasing how various situations affect rental counts.

plt.figure(figsize=(10, 6))

sns.boxplot(x='weathersit', y='count', data=df, palette='Set2')

plt.title('Bike Rentals Distribution by Weather Situation')

plt.xlabel('Weather Situation')

plt.ylabel('Bike Rentals')

plt.xticks(ticks=[0, 1, 2], labels=['Clear', 'Mist', 'Light Snow'])

plt.grid(axis='y')

plt.show()

These visualizations collectively provide a comprehensive overview of the bike sharing dynamics captured in the dataset. By examining these plots, stakeholders can gain valuable insights into rental patterns, which can guide decision-making in urban planning and bike-sharing operations.