```python
#Importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')
```

```python
#loading the dataset
df = pd.read_csv('usedCars.csv')
df.head()
```

```
       Id        Company               Model           Variant
FuelType  \
0  555675  MARUTI SUZUKI  CELERIO(2017-2019)     1.0 ZXI AMT O
PETROL
1  556383  MARUTI SUZUKI                ALTO               LXI
PETROL
2  556422        HYUNDAI           GRAND I10    1.2 KAPPA ASTA
PETROL
3  556771           TATA               NEXON           XT PLUS
PETROL
4  559619           FORD                FIGO  EXI DURATORQ 1.4
DIESEL

   Colour  Kilometer  BodyStyle TransmissionType ManufactureDate
ModelYear  \
0  Silver      33197  HATCHBACK              NaN      2018-02-01
2018
1     Red      10322  HATCHBACK           Manual      2021-03-01
2021
2    Grey      37889  HATCHBACK           Manual      2015-03-01
2015
3  A Blue      13106  HATCHBACK              NaN      2020-08-01
2020
4  Silver     104614  HATCHBACK           Manual      2010-11-01
2010

  CngKit       Price      Owner DealerState
DealerName  \
0    NaN  5.75 Lakhs  1st Owner   Karnataka                  Top Gear
Cars
1    NaN  4.35 Lakhs  1st Owner   Karnataka  Renew 4 u Automobiles PVT
Ltd
2    NaN   4.7 Lakhs  1st Owner   Karnataka        Anant Cars Auto
Pvt Ltd
3    NaN   9.9 Lakhs  1st Owner   Karnataka                   Adeep
Motors
4    NaN   2.7 Lakhs  2nd Owner   Karnataka                  Zippy
```

```
Automart
```

```
        City  Warranty  QualityScore
0  Bangalore         1           7.8
1  Bangalore         1           8.3
2  Bangalore         1           7.9
3  Bangalore         1           8.1
4  Bangalore         0           7.5
```

Some Numerical Information about the Data

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1064 entries, 0 to 1063
Data columns (total 19 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Id                1064 non-null   int64
 1   Company           1064 non-null   object
 2   Model             1064 non-null   object
 3   Variant           1064 non-null   object
 4   FuelType          1063 non-null   object
 5   Colour            1064 non-null   object
 6   Kilometer         1064 non-null   int64
 7   BodyStyle         1064 non-null   object
 8   TransmissionType  350 non-null    object
 9   ManufactureDate   1064 non-null   object
 10  ModelYear         1064 non-null   int64
 11  CngKit            22 non-null     object
 12  Price             1064 non-null   object
 13  Owner             1064 non-null   object
 14  DealerState       1064 non-null   object
 15  DealerName        1064 non-null   object
 16  City              1064 non-null   object
 17  Warranty          1064 non-null   int64
 18  QualityScore      1064 non-null   float64
dtypes: float64(1), int64(4), object(14)
memory usage: 158.1+ KB
```

```
df.nunique()
```

```
Id                  1064
Company               23
Model                218
Variant              575
FuelType               5
Colour                76
Kilometer           1006
BodyStyle             10
```

```
TransmissionType        9
ManufactureDate       162
ModelYear              17
CngKit                  2
Price                 367
Owner                   4
DealerState            10
DealerName             57
City                   11
Warranty                2
QualityScore           43
dtype: int64
```

```
df.isnull().sum()
```

```
Id                      0
Company                 0
Model                   0
Variant                 0
FuelType                1
Colour                  0
Kilometer               0
BodyStyle               0
TransmissionType      714
ManufactureDate         0
ModelYear               0
CngKit               1042
Price                   0
Owner                   0
DealerState             0
DealerName              0
City                    0
Warranty                0
QualityScore            0
dtype: int64
```

Data Preprocessing

```
# Define a function for convert price to float value
def convert_amount(amount_str):
    if "Lakhs" in amount_str:
        return float(amount_str.replace(' Lakhs', '').replace(',', 
'')) * 100000
    else:
        return float(amount_str.replace(',', ''))

df['Price'] = df['Price'].apply(convert_amount)

# Drop Unnecessary Columns
df = df.drop(['Id', 'CngKit', 'TransmissionType'], axis=1)
```

```python
# Apply fillna on FuelType column
df['FuelType'] = df['FuelType'].fillna('PETROL')

# Define a function for reduce unique values of categorical columns
def unique_reduce(x, dic):
    if x in dic.keys():
        return x
    else :
        return 'Others'

fuel_dic = dict(df['FuelType'].value_counts().head(2))
df['FuelType'] = df['FuelType'].apply(lambda x : unique_reduce(x,
fuel_dic))
df['FuelType'].value_counts()
```

```
FuelType
PETROL    671
DIESEL    365
Others     28
Name: count, dtype: int64
```

```python
company_dic = df['Company'].value_counts().head(7)
df['Company'] = df['Company'].apply(lambda x : unique_reduce(x,
company_dic))
df['Company'].value_counts()
```

```
Company
MARUTI SUZUKI    252
Others           219
HYUNDAI          199
HONDA            126
MAHINDRA          96
TATA              60
FORD              58
TOYOTA            54
Name: count, dtype: int64
```

```python
color_dic = df['Colour'].value_counts().head(5)
df['Colour'] = df['Colour'].apply(lambda x : unique_reduce(x,
color_dic))
df['Colour'].value_counts()
```

```
Colour
Others    341
White     289
Silver    134
Grey      127
Red       109
Black      64
Name: count, dtype: int64
```

```
body_dic = df['BodyStyle'].value_counts().head(3)
df['BodyStyle'] = df['BodyStyle'].apply(lambda x : unique_reduce(x, body_dic))
df['BodyStyle'].value_counts()
```

```
BodyStyle
HATCHBACK    423
SUV          304
SEDAN        262
Others        75
Name: count, dtype: int64
```

```
dealer_dic = df['DealerState'].value_counts().head(4)
df['DealerState'] = df['DealerState'].apply(lambda x : unique_reduce(x, dealer_dic))
df['DealerState'].value_counts()
```

```
DealerState
Others         355
Delhi          196
Maharashtra    194
Karnataka      165
Haryana        154
Name: count, dtype: int64
```

```
city_dic = df['City'].value_counts().head(6)
df['City'] = df['City'].apply(lambda x : unique_reduce(x, city_dic))
df['City'].value_counts()
```

```
City
Others       234
Delhi        196
Bangalore    165
Gurgaon      154
Pune         147
Noida         95
Kolkata       73
Name: count, dtype: int64
```

```
def dealer_category(x):
    if x in ['Car Estate', 'Carz Villa', 'SUSHIL CARS PVT. LTD', 'Taneja Fourwheels', 'Car Choice Exclusif', 'Fast Wheels Cars', 'K.S. Motors']:
        return 'Dealer Type1'
    elif x in ['Sai Motors', 'LUXMI CARS GURGAON', 'Guru Kripa Motors', 'Star Auto India']:
        return 'Dealer Type2'
    elif x in ['Shree Radha Krishna Motors', 'Shiv Auto Wings', 'Mahindra First Choice Wheels Ltd', 'Noida Car Point ll', 'Jeen Mata Motors', 'OM Motors', 'Sireesh Auto Pvt Ltd', 'Max Motors', 'Adeep Motors']:
```

```
        return 'Dealer Type3'
    elif x in ['Ikka Motors', 'Pitbox Motors', 'Noida Car Ghar',
'Cardiction', 'Car&Bike Superstore Pune', 'Zippy Automart', 'SK
Associates', 'Anant Cars Auto Pvt Ltd', 'DrivUS Motorcorp', 'Vinayak
Autolink Private Limited'] :
        return 'Dealer Type4'
    elif x in ['Prestige Autoworld Pvt Ltd', 'PROPEL MOTORS', 'Royal
Motors (Prop. Auto Carriage Pvt Ltd)', 'MM Motors', 'Sri Vaishnavi
Cars', 'Top Gear Cars', 'Renew 4 u Automobiles PVT Ltd'] :
        return 'Dealer Type5'
    else :
        return 'Other Dealers'

df['DealerName'] = df['DealerName'].apply(lambda x :
dealer_category(x))
df['DealerName'].value_counts()
```

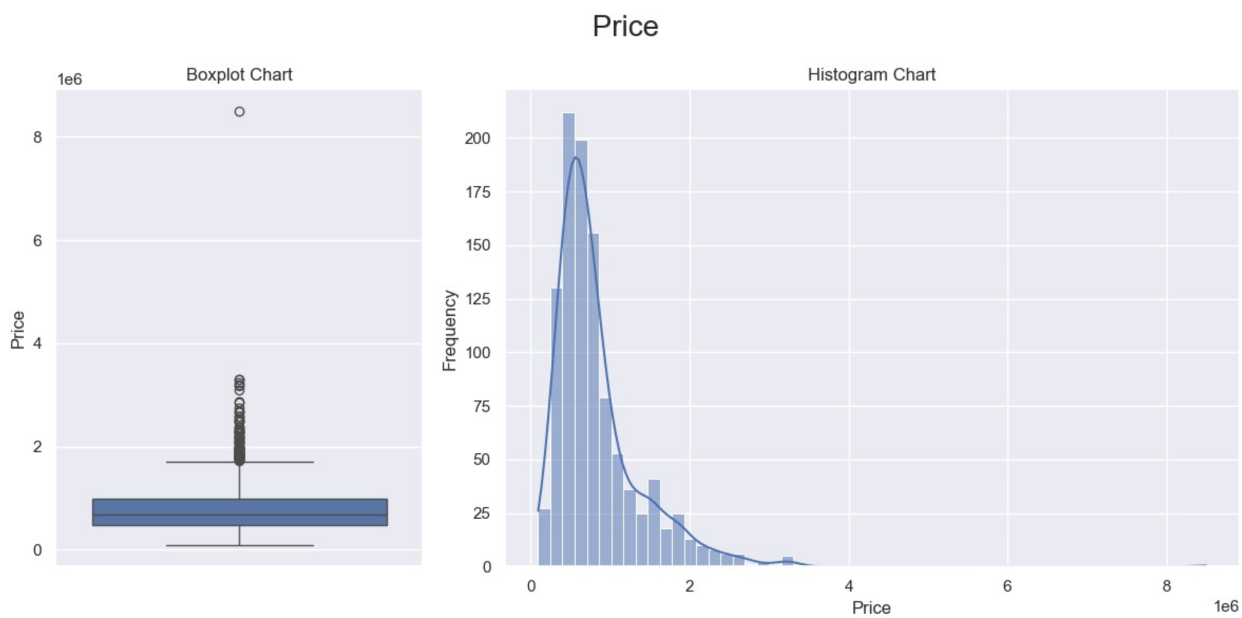
```
DealerName
Other Dealers    209
Dealer Type4     199
Dealer Type5     188
Dealer Type3     182
Dealer Type1     180
Dealer Type2     106
Name: count, dtype: int64
```

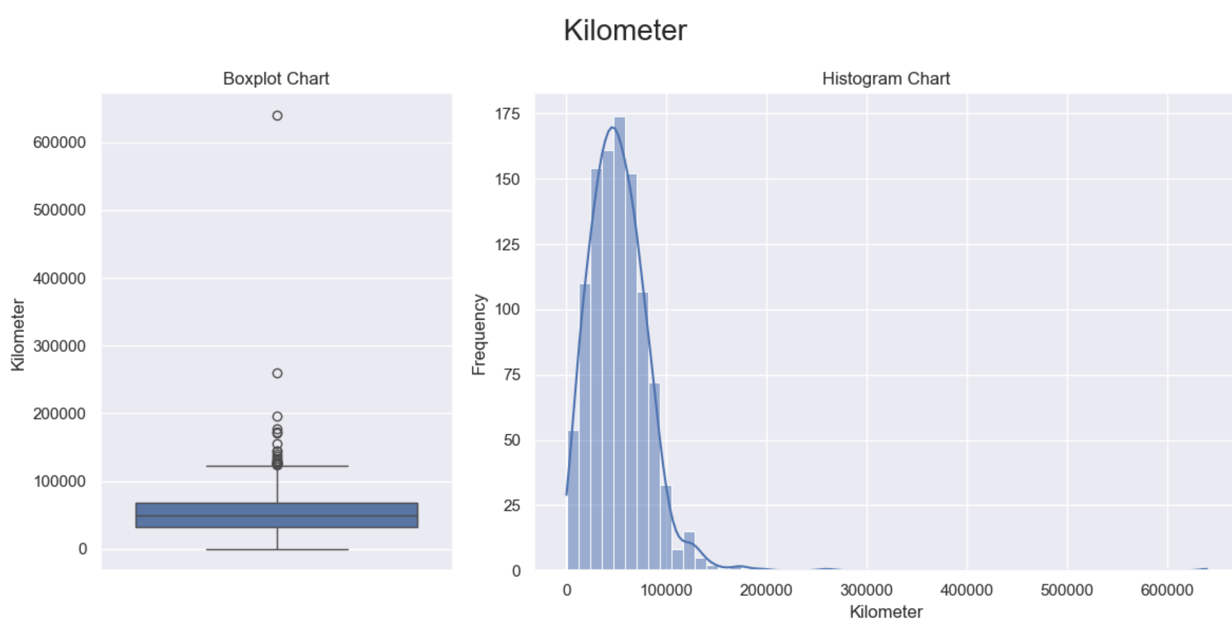
```
# change type of owner column to int and remove 3 and 4 values
df['Owner'] = df['Owner'].str[0]
df['Owner'] = df['Owner'].map(int)
df= df[df['Owner'] < 3 ]
```

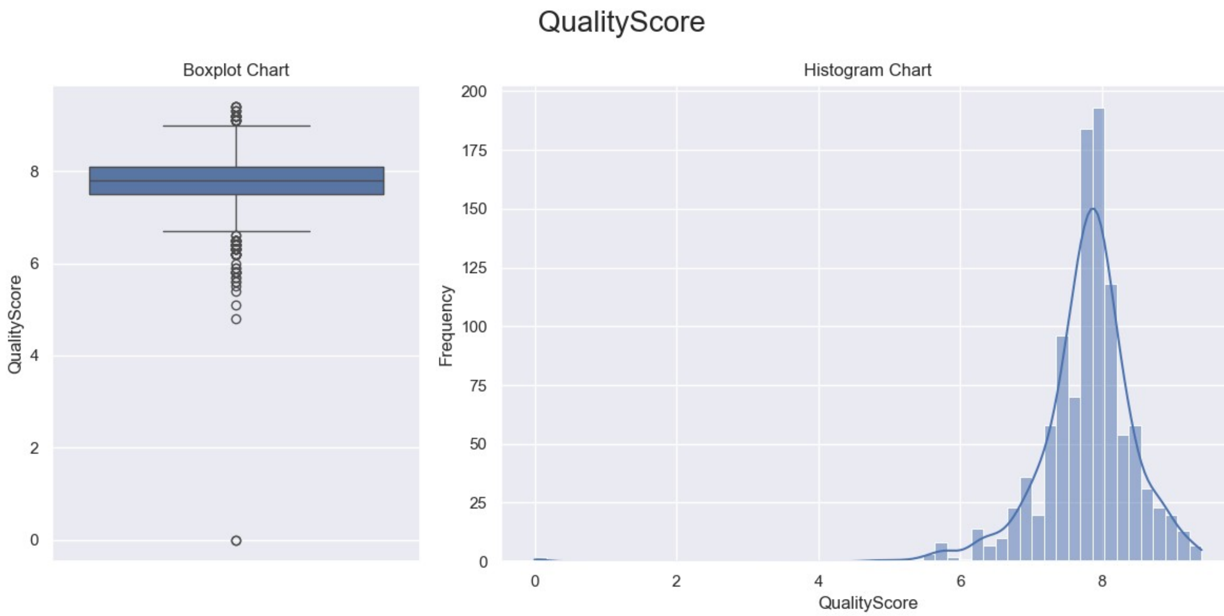
Data Visualization

```
# Define list of Continuous columns Names
continuous = ['Price', 'Kilometer', 'QualityScore']

# Distribution of Categorical Features
def plot_continious_distribution(df, column):

    width_ratios = [2, 4]
    gridspec_kw = {'width_ratios':width_ratios}
    fig, ax = plt.subplots(1, 2, figsize=(12, 6), gridspec_kw =
gridspec_kw)
    fig.suptitle(f' {column} ', fontsize=20)

    sns.boxplot(df[column], ax=ax[0])
    ax[0].set_title('Boxplot Chart')
    ax[0].set_ylabel(column)

    sns.histplot(x = df[column], kde=True, ax=ax[1], multiple =
```

```
'stack', bins=55)
    ax[1].set_title('Histogram Chart')
    ax[1].set_ylabel('Frequency')
    ax[1].set_xlabel(column)

    plt.tight_layout()
    plt.show()
for conti in continuous :
    plot_continious_distribution(df, conti)
```

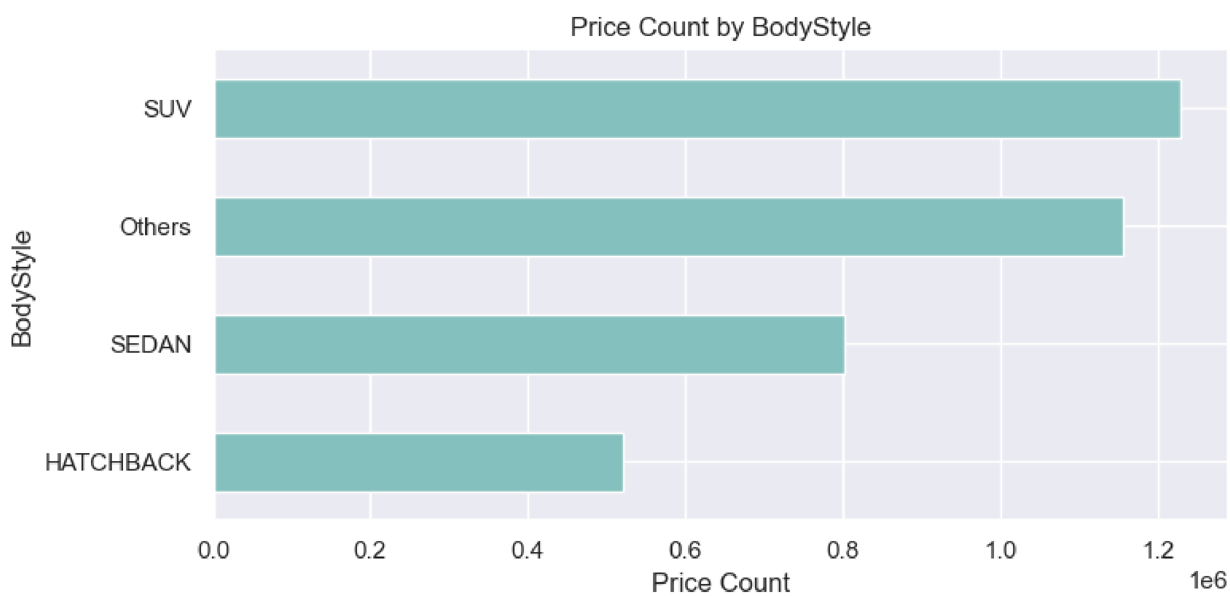


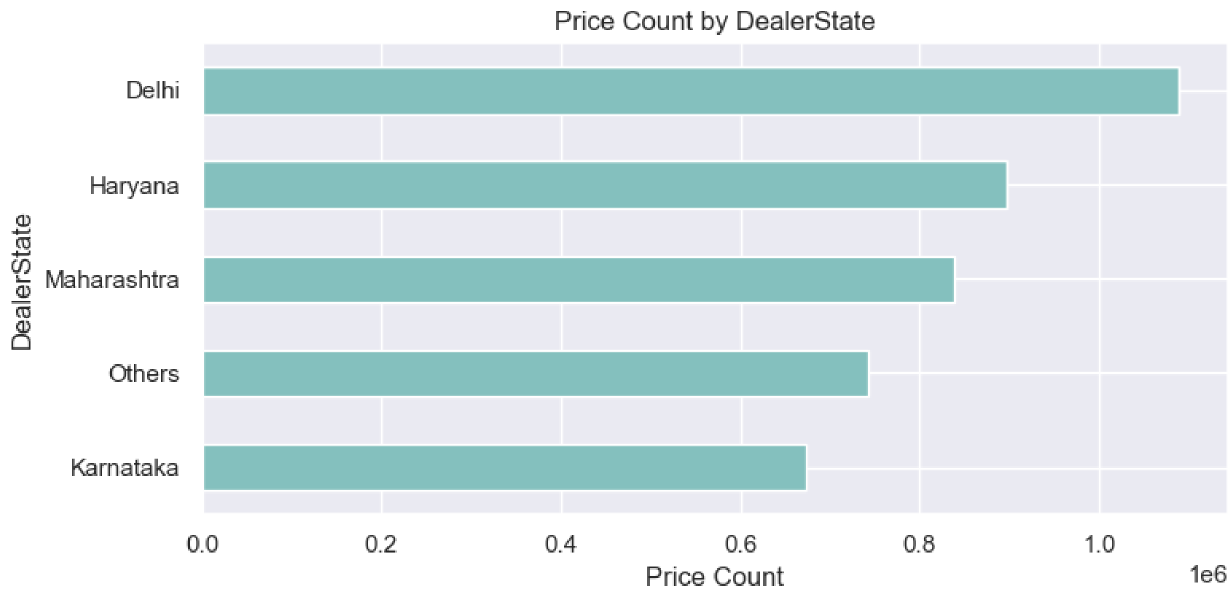


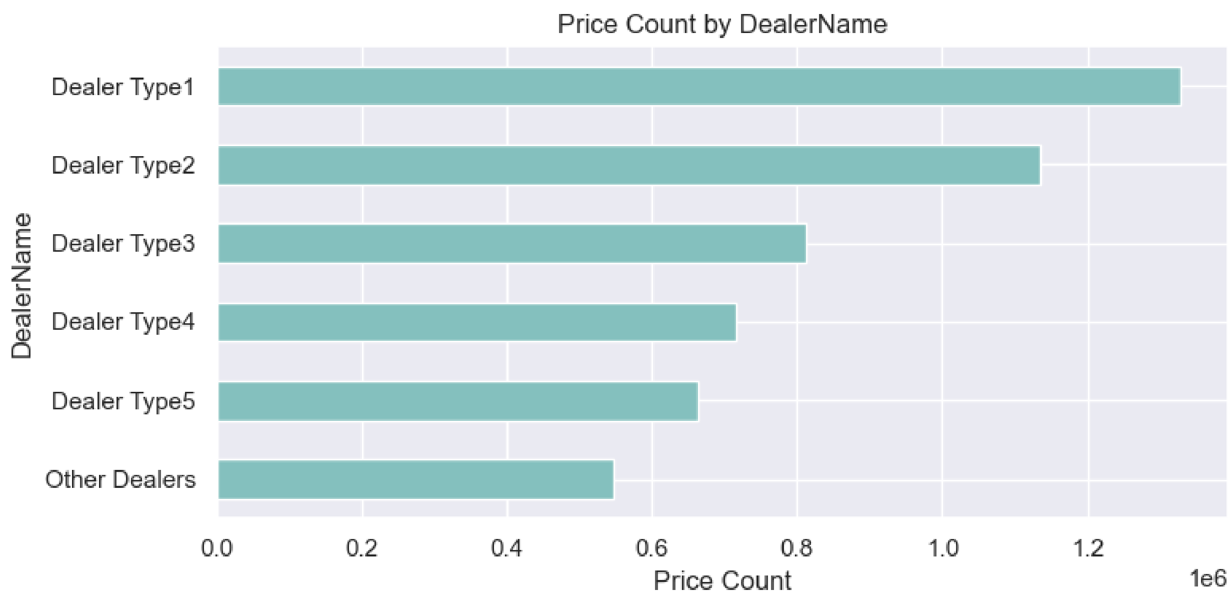


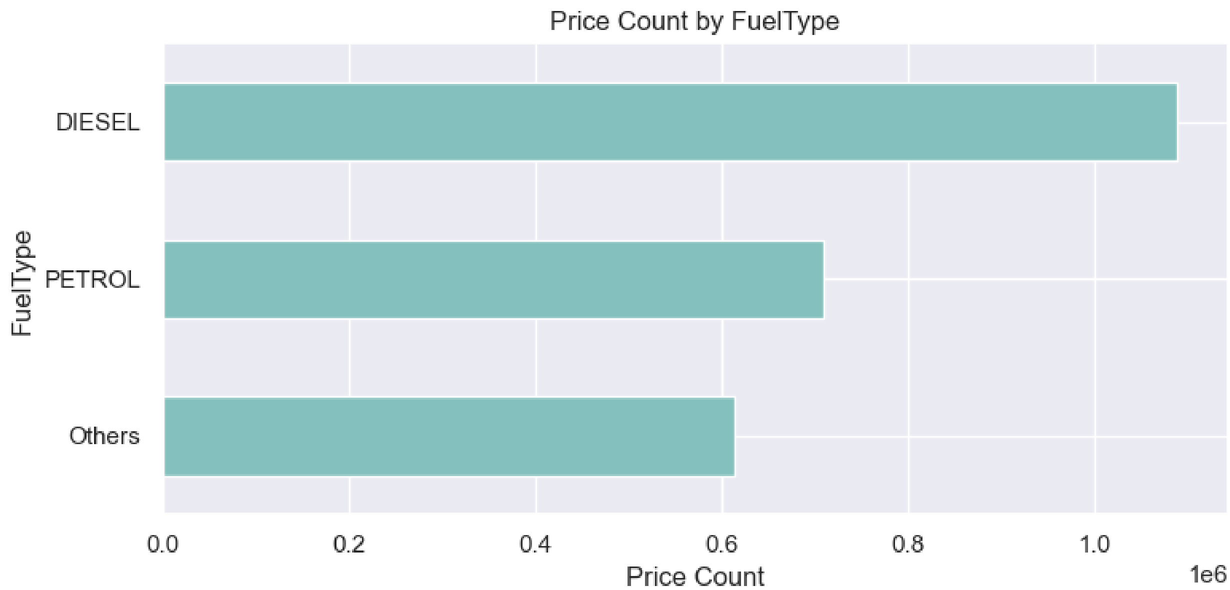

```
# Define a Function for Barh Plot
def bar_plot(x, y, df):
    barh = df.groupby([x])[y].mean()
    barh.sort_values(ascending=True, inplace=True)
    barh.plot(kind='barh',  color = '#84c0be', figsize=(8,4))
    plt.title(f'{y} Count by {x}')
    plt.xlabel(f'{y} Count')
    plt.ylabel(x)

    plt.tight_layout()
    plt.show()

bar_plot('Company', 'Price', df)
bar_plot('BodyStyle', 'Price', df)
bar_plot('DealerState', 'Price', df)
bar_plot('DealerName', 'Price', df)
bar_plot('FuelType', 'Price', df)
bar_plot('City', 'Price', df)
```


Price Count by Company
TOYOTA
Others
MAHINDRA
TATA
FORD
HYUNDAI
HONDA
MARUTI SUZUKI
Company
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Price Count
1e6


Price Count by BodyStyle
SUV
Others
SEDAN
HATCHBACK
BodyStyle
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Price Count
1e6


Price Count by DealerState
DealerState
Delhi
Haryana
Maharashtra
Others
Karnataka
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Price Count


Price Count by DealerName
DealerName
Dealer Type1
Dealer Type2
Dealer Type3
Dealer Type4
Dealer Type5
Other Dealers
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1e6
Price Count



Data Preprocessing

```
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Initialize StandardScaler
stc = StandardScaler()
# Initialize LabelEncoder
le = LabelEncoder()

stc_cols = ['Kilometer', 'Price', 'QualityScore']
dum_cols = ['Company', 'FuelType', 'Colour', 'BodyStyle',
'DealerState', 'DealerName', 'City']
```

```
# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])
# Apply Get Dummies to the selected columns
df = pd.get_dummies(df, columns=dum_cols)
```

Training and Evaluating Different Models

```
from sklearn.model_selection import train_test_split

x = df.drop(['Price', 'Model', 'Variant', 'ManufactureDate'], axis=1)
y = df['Price']

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

#Importing the Libraries
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import make_classification
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import VotingRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, r2_score

# List of Mdels to Try
models = [
    ('Linear Regression', LinearRegression()),
    ('Ridge Regression', Ridge()),
    ('Decision Tree', DecisionTreeRegressor()),
    ('Random Forest', RandomForestRegressor()),
    ('Gradient Boosting', GradientBoostingRegressor()),
    ('K-Nearest Neighbors', KNeighborsRegressor()),
    ('XGB Regressor', XGBRegressor())
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f'{name}: Mean Squared Error = {round(mse,3)}, R-squared =
{round(r2, 3)}')
```

```
Linear Regression: Mean Squared Error = 0.243, R-squared = 0.66
Ridge Regression: Mean Squared Error = 0.243, R-squared = 0.66
```

```
Decision Tree: Mean Squared Error = 0.51, R-squared = 0.286
Random Forest: Mean Squared Error = 0.184, R-squared = 0.742
Gradient Boosting: Mean Squared Error = 0.209, R-squared = 0.708
K-Nearest Neighbors: Mean Squared Error = 0.275, R-squared = 0.615
XGB Regressor: Mean Squared Error = 0.212, R-squared = 0.703
```

```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid to search
param_grid = {
    'n_estimators': [160, 150, 170],
    'max_depth': [None, 10, 20],
}

# Initialize the Random Forest Regressor
rf_model_tuned = RandomForestRegressor(random_state=42)

# Initialize GridSearchCV
grid_search = GridSearchCV(rf_model_tuned, param_grid, cv=3,
scoring='neg_mean_squared_error', n_jobs=-1, verbose=True)

# Fit the grid search to the data
grid_search.fit(x_train, y_train)

# Get the best parameters
rf_best_params = grid_search.best_params_

# Retrain the model with the best parameters
rf_model_best = RandomForestRegressor(**rf_best_params,
random_state=42)
rf_model_best.fit(x_train, y_train)

# Predict using the updated features
y_pred_best = rf_model_best.predict(x_test)
```

```
Fitting 3 folds for each of 9 candidates, totalling 27 fits
```

```
# Evaluate the tuned Random Forest model
mse_best = mean_squared_error(y_test, y_pred_best)
r2_best = r2_score(y_test, y_pred_best)

print(f'Best Parameters: {rf_best_params}')
print(f'Mean Squared Error (Tuned Random Forest): {round(mse_best,
3)}')
print(f'R-squared (Tuned Random Forest): {round(r2_best, 3)}')
```

```
Best Parameters: {'max_depth': 10, 'n_estimators': 150}
Mean Squared Error (Tuned Random Forest): 0.18
R-squared (Tuned Random Forest): 0.748
```

```
# Visualize the Predicted Prices Against the Actual Prices
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred_best)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
linestyle='--', color='black', label='Perfect Prediction')
plt.title('Actual Prices vs. Predicted Prices (Enseble Model)')
plt.ylabel('Predicted Prices')
plt.xlabel('Actual Prices')
plt.legend()
plt.show()
```

Summary and Conclusion

In this project, I focused on predicting the prices of used cars in India using various data preprocessing techniques and a machine learning model. The steps and methodologies employed are as follows:

1. Data Cleaning and Preprocessing:
   - String to Numeric Conversion: Converted values in the price column from strings to numeric format.

- Handling Missing Values: Removed columns with a high number of null values to ensure data quality and consistency.
- Categorical Simplification: Reduced the number of unique values in some categorical columns to simplify the model.

2. Data Visualization:
   - Created appropriate visualizations to explore and understand the data patterns and relationships, providing valuable insights into the dataset.
3. Data Standardization and Label Encoding:
   - Performed data standardization to normalize the features.
   - Applied label encoding to convert categorical variables into numerical format.
4. Model Training and Optimization:
   - Trained a Random Forest model on the processed dataset.
   - Optimized the model using Grid Search to improve accuracy.
5. Model Evaluation:
   - The final model achieved an accuracy of 74.8%. Given the complexity of the model and the variability of the data, this result is considered satisfactory.

These steps ensured a comprehensive analysis and model training process, leading to a reasonably accurate prediction model for used car prices in Indi

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