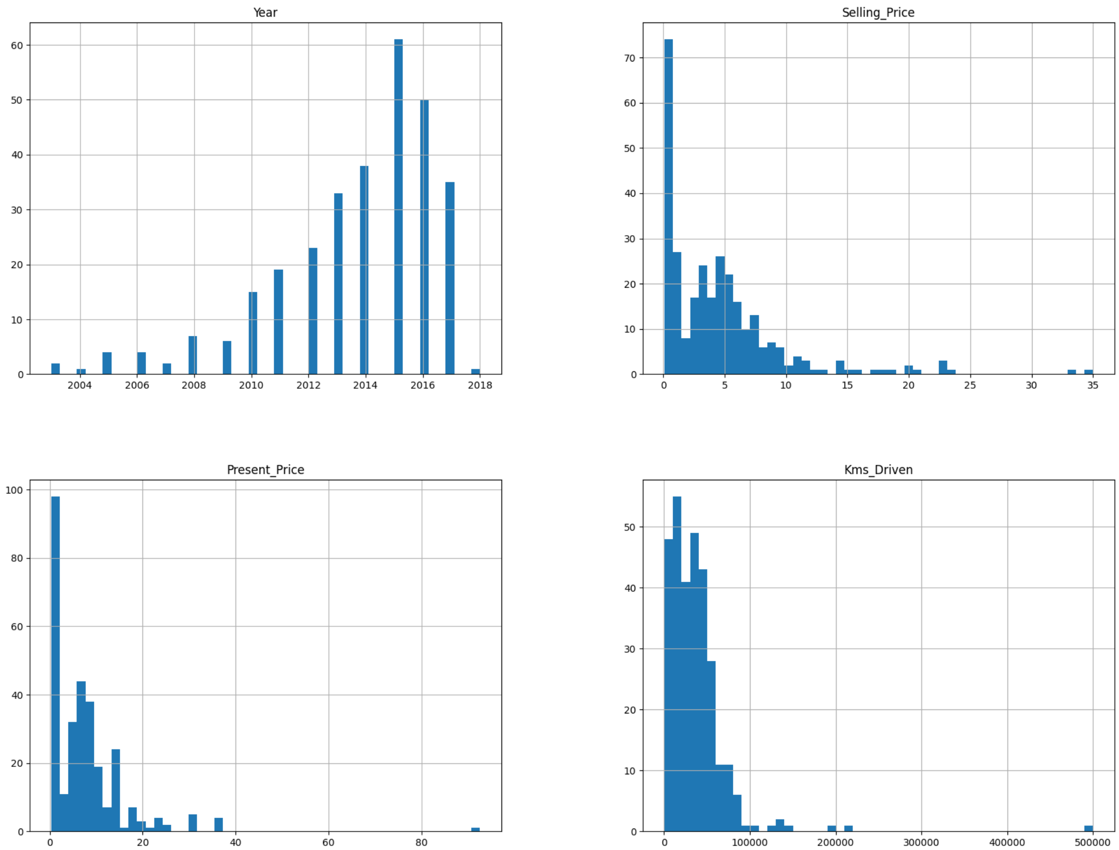
carpricingmodel

February 18, 2025

[79]:
```
from sklearn.model_selection import train_test_split
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import StratifiedShuffleSplit
```

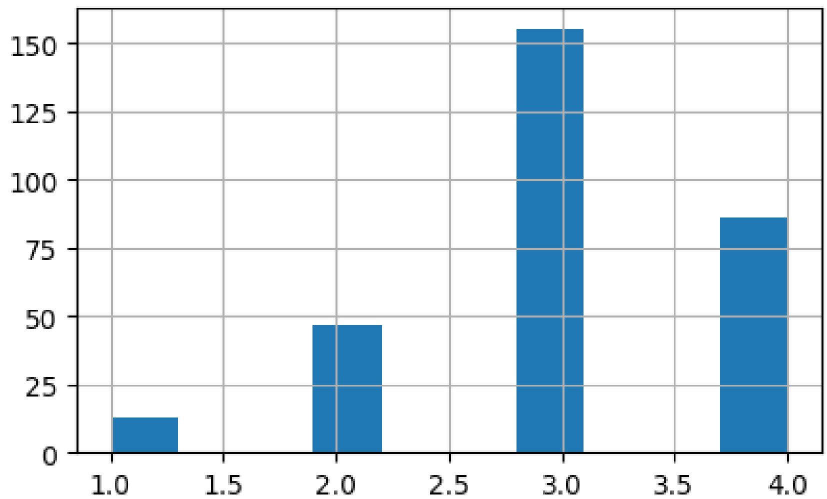
[80]:
```
cars = pd.read_csv("car-data.csv")
cars.info()
cars.hist(column=['Year', 'Selling_Price', 'Present_Price', 'Kms_Driven'],␣
 ↪bins=50, figsize=(20,15))
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Car_Name       301 non-null    object
 1   Year           301 non-null    int64
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Seller_Type    301 non-null    object
 7   Transmission   301 non-null    object
 8   Owner          301 non-null    int64
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```



[81]:
```python
np.random.seed(42)
strat_train_set, strat_test_set = train_test_split(cars, test_size=0.2,␣
↪random_state=42)
cars['Year_Cat'] = pd.cut(cars["Year"], bins=[2003, 2007, 2011, 2015, 2019, np.
↪inf], labels=[1, 2, 3, 4, 5], include_lowest=True)
cars['Year_Cat'].hist(figsize=(5,3))
```

[81]:
```
<Axes: >
```



[82]:
```
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(cars, cars['Year_Cat']):
    strat_train_set = cars.loc[train_index]
    strat_test_set = cars.loc[test_index]

strat_test_set['Year_Cat'].value_counts() / len(strat_test_set)
```

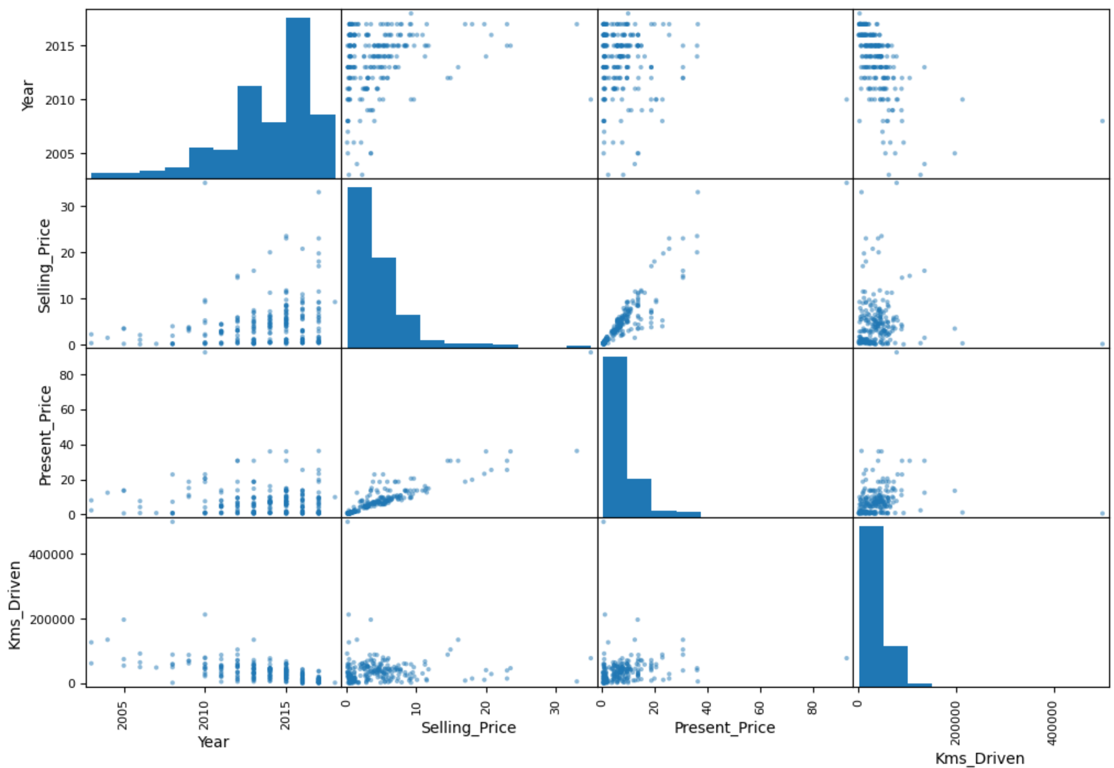
[82]:
```
Year_Cat
3    0.508197
4    0.278689
2    0.163934
1    0.049180
5    0.000000
Name: count, dtype: float64
```

[83]:
```
corr_matrix = strat_train_set.corr(numeric_only=True)
corr_matrix['Selling_Price'].sort_values(ascending=False)
```

[83]:
```
Selling_Price     1.000000
Present_Price     0.883762
Year              0.207411
Kms_Driven        0.025787
Owner            -0.075288
Name: Selling_Price, dtype: float64
```

[84]:
```
from pandas.plotting import scatter_matrix
attributes = ['Year', 'Selling_Price', 'Present_Price', 'Kms_Driven']
scatter_matrix(strat_train_set[attributes], figsize=(12,8))
```

[84]:
```
array([[<Axes: xlabel='Year', ylabel='Year'>,
        <Axes: xlabel='Selling_Price', ylabel='Year'>,
        <Axes: xlabel='Present_Price', ylabel='Year'>,
        <Axes: xlabel='Kms_Driven', ylabel='Year'>],
       [<Axes: xlabel='Year', ylabel='Selling_Price'>,
        <Axes: xlabel='Selling_Price', ylabel='Selling_Price'>,
        <Axes: xlabel='Present_Price', ylabel='Selling_Price'>,
        <Axes: xlabel='Kms_Driven', ylabel='Selling_Price'>],
       [<Axes: xlabel='Year', ylabel='Present_Price'>,
        <Axes: xlabel='Selling_Price', ylabel='Present_Price'>,
        <Axes: xlabel='Present_Price', ylabel='Present_Price'>,
        <Axes: xlabel='Kms_Driven', ylabel='Present_Price'>],
       [<Axes: xlabel='Year', ylabel='Kms_Driven'>,
        <Axes: xlabel='Selling_Price', ylabel='Kms_Driven'>,
        <Axes: xlabel='Present_Price', ylabel='Kms_Driven'>,
        <Axes: xlabel='Kms_Driven', ylabel='Kms_Driven'>]], dtype=object)
```



[85]:
```python
strat_train_set['Kms_Year'] = strat_train_set['Kms_Driven']/
    (2019-(strat_train_set['Year']))
corr_matrix = strat_train_set.corr(numeric_only=True)
corr_matrix['Selling_Price'].sort_values(ascending=False)
```

[85]:
```
Selling_Price    1.000000
Present_Price    0.883762
Kms_Year         0.233357
Year             0.207411
Kms_Driven       0.025787
Owner           -0.075288
Name: Selling_Price, dtype: float64
```

[86]:
```
strat_train_set['Owner']
cars_labels = strat_train_set['Selling_Price']
cars_inputs = strat_train_set.drop('Selling_Price', axis=1)
```

[87]:
```
from sklearn.preprocessing import OneHotEncoder
cats = cars_inputs[['Year_Cat']]
cat_encoder = OneHotEncoder()
cars_cat_1hot = cat_encoder.fit_transform(cats)
print(cars_cat_1hot)
```

```
<Compressed Sparse Row sparse matrix of dtype 'float64'
        with 240 stored elements and shape (240, 4)>
  Coords        Values
  (0, 2)        1.0
  (1, 2)        1.0
  (2, 3)        1.0
  (3, 3)        1.0
  (4, 3)        1.0
  (5, 2)        1.0
  (6, 3)        1.0
  (7, 3)        1.0
  (8, 2)        1.0
  (9, 2)        1.0
  (10, 3)       1.0
  (11, 0)       1.0
  (12, 2)       1.0
  (13, 2)       1.0
  (14, 2)       1.0
  (15, 3)       1.0
  (16, 1)       1.0
  (17, 1)       1.0
  (18, 3)       1.0
  (19, 2)       1.0
  (20, 1)       1.0
  (21, 2)       1.0
  (22, 2)       1.0
  (23, 3)       1.0
  (24, 2)       1.0
  :     :
  (215, 3)      1.0
```

```
  (216, 1)	1.0
  (217, 0)	1.0
  (218, 3)	1.0
  (219, 2)	1.0
  (220, 2)	1.0
  (221, 1)	1.0
  (222, 2)	1.0
  (223, 1)	1.0
  (224, 2)	1.0
  (225, 3)	1.0
  (226, 2)	1.0
  (227, 3)	1.0
  (228, 3)	1.0
  (229, 3)	1.0
  (230, 1)	1.0
  (231, 3)	1.0
  (232, 2)	1.0
  (233, 3)	1.0
  (234, 2)	1.0
  (235, 2)	1.0
  (236, 2)	1.0
  (237, 2)	1.0
  (238, 2)	1.0
  (239, 1)	1.0
```

[88]:

```
import numpy as np
from sklearn.base import BaseEstimator, TransformerMixin

kms_ix, years_ix = 4, 1

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_kms_per_year=True):

        self.add_kms_per_year = add_kms_per_year

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        if self.add_kms_per_year:
            kms_per_year = X[:, kms_ix] / X[:, years_ix]
            return np.c_[X, kms_per_year]
        return X

attr_adder = CombinedAttributesAdder(add_kms_per_year=True)
cars_extra_attribs = attr_adder.transform(cars.values)
print(cars_extra_attribs[1, :])
```

```
['sx4' 2013 4.75 9.54 43000 'Diesel' 'Dealer' 'Manual' 0 3
 21.361152508693493]
```

[89]:
```python
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='median')
print(cars.info())
cars_num = cars.drop(['Car_Name', 'Fuel_Type', 'Seller_Type', 'Transmission',␣
 ↪'Selling_Price'], axis=1)
imputer.fit(cars_num)
I = imputer.transform(cars_num)
cars_num_tr = pd.DataFrame(I, columns=cars_num.columns, index=cars_num.index)
imputer.statistics_
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Car_Name       301 non-null    object
 1   Year           301 non-null    int64
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Seller_Type    301 non-null    object
 7   Transmission   301 non-null    object
 8   Owner          301 non-null    int64
 9   Year_Cat       301 non-null    category
dtypes: category(1), float64(2), int64(3), object(4)
memory usage: 21.8+ KB
None
```

[89]:
```
array([2.014e+03, 6.400e+00, 3.200e+04, 0.000e+00, 3.000e+00])
```

[90]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer

num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler())
])

cars_num_tr = num_pipeline.fit_transform(cars_num)

num_attribs = list(cars_num)
cat_attribs = ['Car_Name', 'Fuel_Type', 'Seller_Type', 'Transmission']
```

```
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_attribs),
    ('cat', OneHotEncoder(), cat_attribs),
])

cars_prepared = full_pipeline.fit_transform(cars)
```

[91]:
```
from sklearn.linear_model import LinearRegression

cars_labels = cars['Selling_Price']
lin_reg = LinearRegression()
lin_reg.fit(cars_prepared, cars_labels)
```

[91]: LinearRegression()

[92]:
```
from sklearn.metrics import mean_squared_error

cars_predictions = lin_reg.predict(cars_prepared)
lin_mse = mean_squared_error(cars_labels, cars_predictions)
lin_rmse = np.sqrt(lin_mse)
print(float(lin_rmse))
```

1.0634629139767748

[93]:
```
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor()
tree_reg.fit(cars_prepared, cars_labels)
```

[93]: DecisionTreeRegressor()

[94]:
```
cars_predictions = tree_reg.predict(cars_prepared)
tree_mse = mean_squared_error(cars_labels, cars_predictions)
tree_rmse = np.sqrt(tree_mse)
print(float(tree_rmse))
```

6.196017278920048e-18

[95]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(tree_reg, cars_prepared, cars_labels,␣
 ↪scoring='neg_mean_squared_error', cv=10)
tree_rmse_scores = np.sqrt(-scores)

def display_scores(scores):
    print(f'Scores: {scores}')
    print(f'Mean: {scores.mean()}')
```

```
    print(f'Std: {scores.std()}')

display_scores(tree_rmse_scores)
```

```
Scores: [1.07117662 1.20692585 4.28891789 0.98736349 0.24344062 0.17700282
 0.52481743 1.71867779 0.86310872 1.50079646]
Mean: 1.2582227684234673
Std: 1.1162335779327988
```

[96]:
```
scores = cross_val_score(lin_reg, cars_prepared, cars_labels,␣
 ↪scoring='neg_mean_squared_error', cv=10)
lin_rmse_scores = np.sqrt(-scores)
display_scores(lin_rmse_scores)
```

```
Scores: [2.87838527 2.38005934 3.98754744 2.42208052 1.44508872 5.73709946
 5.30325862 1.07886731 0.72336354 0.8894474 ]
Mean: 2.6845197623973953
Std: 1.7104326681677304
```

[97]:
```
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor()
forest_scores = cross_val_score(forest_reg, cars_prepared, cars_labels,␣
 ↪scoring='neg_mean_squared_error', cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
display_scores(forest_rmse_scores)
```

```
Scores: [0.68271891 0.98526169 4.93226754 0.97031356 0.23006583 0.12468447
 0.41898564 0.85395612 0.70947582 0.90968391]
Mean: 1.081741349486706
Std: 1.3156033219617966
```

[98]:
```
forest_reg.fit(cars_prepared, cars_labels)
cars_predictions = forest_reg.predict(cars_prepared)
forest_mse = mean_squared_error(cars_labels, cars_predictions)
forest_rmse = np.sqrt(forest_mse)
print(float(forest_rmse))
```

```
0.5973745350695002
```

[99]:
```
from sklearn.model_selection import GridSearchCV

param_grid = [
    {'n_estimators': [6, 20, 50], 'max_features': [2, 4, 6, 8]},
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]}
]

forest_reg = RandomForestRegressor()
```

```python
grid_search = GridSearchCV(forest_reg, param_grid, cv=5,␣
↪scoring='neg_mean_squared_error', return_train_score=True)
grid_search.fit(cars_prepared, cars_labels)
```

[99]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [6, 20, 50]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             return_train_score=True, scoring='neg_mean_squared_error')
```

[100]:
```python
grid_search.best_params_
```

[100]:
```
{'max_features': 8, 'n_estimators': 6}
```

[101]:
```python
grid_search.best_estimator_.feature_importances_
feature_importances = grid_search.best_estimator_.feature_importances_
```

[102]:
```python
extra_attribs = ['kms_per_year']
cat_encoder = full_pipeline.named_transformers_['cat']
cat_one_hot_attribs = list(cat_encoder.categories_[0])
attributes = num_attribs + extra_attribs + cat_one_hot_attribs
sorted(zip(feature_importances, attributes), reverse=True)
```

[102]:
```
[(np.float64(0.19147916997818562), 'Present_Price'),
 (np.float64(0.1427537715826121), 'kms_per_year'),
 (np.float64(0.11858629801940197), 'fortuner'),
 (np.float64(0.09374510168414638), 'Kms_Driven'),
 (np.float64(0.06919484708435504), 'Year'),
 (np.float64(0.03775600600477059), 'innova'),
 (np.float64(0.019834980669262633), 'corolla altis'),
 (np.float64(0.01724904775701521), 'Year_Cat'),
 (np.float64(0.010019014313042822), 'city'),
 (np.float64(0.009940884980917716), 'creta'),
 (np.float64(0.008204007768785188), 'Owner'),
 (np.float64(0.006789504049951369), 'swift'),
 (np.float64(0.004702083776483866), 'elantra'),
 (np.float64(0.004360566949439956), 'eon'),
 (np.float64(0.003973509210570549), 'ciaz'),
 (np.float64(0.003439986135371672), 'verna'),
 (np.float64(0.0022369431089907877), 'sx4'),
 (np.float64(0.002088469571535239), 'Hero Passion X pro'),
 (np.float64(0.002053005933683601), 'grand i10'),
 (np.float64(0.0017896410630782093), 'ritz'),
 (np.float64(0.001370480875939674 6), 'i20'),
 (np.float64(0.00134068479625 2741), 'alto k10'),
 (np.float64(0.001103528580053006), 'alto 800'),
```

```
(np.float64(0.0008765971268103156), 'etios liva'),
(np.float64(0.0008728691631350443), 'i10'),
(np.float64(0.0008719323760699911), 'jazz'),
(np.float64(0.0007536203907288349), 'vitara brezza'),
(np.float64(0.0006233171605810042), 'omni'),
(np.float64(0.0005122507012307351), 's cross'),
(np.float64(0.0004038536578953734), '800'),
(np.float64(0.0003815055867974079), 'Yamaha FZ S V 2.0'),
(np.float64(0.0003620273841986335), 'wagon r'),
(np.float64(0.00035939074089613905), 'dzire'),
(np.float64(0.0003400229012375781), 'Honda CB Hornet 160R'),
(np.float64(0.0003127188680718657), 'xcent'),
(np.float64(0.0002888790445694 4213), 'brio'),
(np.float64(0.000260848187798816), 'ertiga'),
(np.float64(0.00024933245592037904), 'Bajaj Pulsar NS 200'),
(np.float64(0.0001696885127960594 2), 'etios gd'),
(np.float64(0.0001547654506342234), 'etios g'),
(np.float64(0.00013003266559364243), 'Yamaha FZ 16'),
(np.float64(0.00011225082513776494), 'Activa 3g'),
(np.float64(0.00010588174516671178), 'baleno'),
(np.float64(9.210184974526048e-05), 'etios cross'),
(np.float64(6.617850102064849e-05), 'amaze'),
(np.float64(4.9507940711910704e-05), 'KTM RC200'),
(np.float64(4.6215853926106404e-05), 'Bajaj Discover 125'),
(np.float64(4.510323461051944e-05), 'Hero  CBZ Xtreme'),
(np.float64(4.3489462838389254e-05), 'corolla'),
(np.float64(3.3275231689069455e-05), 'Royal Enfield Classic 350'),
(np.float64(2.8539330858100217e-05), 'Honda CB twister'),
(np.float64(2.363849450880111e-05), 'Suzuki Access 125'),
(np.float64(2.105586383355446e-05), 'Royal Enfield Thunder 350'),
(np.float64(1.8747028652513595e-05), 'Royal Enfield Classic 500'),
(np.float64(1.81706510649268e-05), 'UM Renegade Mojave'),
(np.float64(1.8166174902516737e-05), 'Bajaj Pulsar RS200'),
(np.float64(1.7511846087135102e-05), 'TVS Jupyter'),
(np.float64(1.7219572220782123e-05), 'Bajaj Avenger 220'),
(np.float64(1.19347981522004e-05), 'Hero Passion Pro'),
(np.float64(1.151487638770048e-05), 'Royal Enfield Bullet 350'),
(np.float64(1.1321044738912393e-05), 'Hero Hunk'),
(np.float64(1.108082872914254e-05), 'ignis'),
(np.float64(1.0765669443143758e-05), 'KTM 390 Duke '),
(np.float64(8.766994517921094e-06), 'Activa 4g'),
(np.float64(7.108788026480059e-06), 'Bajaj Pulsar 150'),
(np.float64(7.006037935809671e-06), 'Bajaj  ct 100'),
(np.float64(5.583527885358099e-06), 'Honda CBR 150'),
(np.float64(5.3256736495435446e-06), 'Hero Honda Passion Pro'),
(np.float64(2.9348438253248654e-06), 'KTM RC390'),
(np.float64(2.6315132437803757e-06), 'Bajaj Pulsar 135 LS'),
```

```
 (np.float64(2.401207310361192e-06), 'Honda Activa 4G'),
 (np.float64(2.2769080378261248e-06), 'Yamaha FZ S '),
 (np.float64(2.2349202217336457e-06), 'Yamaha Fazer '),
 (np.float64(2.2274383810202134e-06), 'Hero  Ignitor Disc'),
 (np.float64(2.2271594137267666e-06), 'TVS Apache RTR 160'),
 (np.float64(2.1950737580427665e-06), 'Hero Extreme'),
 (np.float64(1.8932619743610976e-06), 'Bajaj Pulsar 220 F'),
 (np.float64(1.5667810209161802e-06), 'Royal Enfield Thunder 500'),
 (np.float64(1.2105455236411757e-06), 'Hero Glamour'),
 (np.float64(1.1901705983339778e-06), 'Bajaj Pulsar  NS 200'),
 (np.float64(1.0932491178938084e-06), 'TVS Apache RTR 180'),
 (np.float64(1.0674314656374504e-06), 'Bajaj Avenger 150'),
 (np.float64(8.374288790015381e-07), 'Hyosung GT250R'),
 (np.float64(8.031297648346274e-07), 'Bajaj Dominar 400'),
 (np.float64(5.32711700690899e-07), 'Hero Honda CBZ extreme'),
 (np.float64(4.943353258185405e-07), 'Honda Karizma'),
 (np.float64(4.843582387460654e-07), 'Bajaj Avenger Street 220'),
 (np.float64(4.657700955179459e-07), 'Bajaj Discover 100'),
 (np.float64(3.0956229320459994e-07), 'Bajaj Avenger 220 dtsi'),
 (np.float64(2.835963921036255e-07), 'Honda CB Unicorn'),
 (np.float64(2.457181872683984e-07), 'Bajaj Avenger 150 street'),
 (np.float64(2.3639110938819172e-07), 'TVS Wego'),
 (np.float64(1.7569078936651373e-07), 'Yamaha FZ  v 2.0'),
 (np.float64(1.678796455813725e-07), 'Honda Dream Yuga '),
 (np.float64(1.3030159522800662e-07), 'Hero Splender Plus'),
 (np.float64(6.368878752696533e-08), 'Honda CB Shine'),
 (np.float64(4.7778536413299924e-08), 'Hero Super Splendor'),
 (np.float64(3.4599322358347355e-08), 'Hero Splender iSmart'),
 (np.float64(2.4017517246993284e-08), 'Mahindra Mojo XT300'),
 (np.float64(2.1993367700592956e-08), 'TVS Sport '),
 (np.float64(0.0), 'land cruiser'),
 (np.float64(0.0), 'camry'),
 (np.float64(0.0), 'Honda CB Trigger'),
 (np.float64(0.0), 'Honda Activa 125')]
```

[103]:
```
final_model = grid_search.best_estimator_
X_test = strat_test_set.drop('Selling_Price', axis=1)
y_test = strat_test_set['Selling_Price'].copy()

X_test_prepared = full_pipeline.transform(X_test)

final_predictions = final_model.predict(X_test_prepared)
final_mse = mean_squared_error(y_test, final_predictions)
final_rmse = np.sqrt(final_mse)

print(f'RMSE: {float(final_rmse)}')
```

```
RMSE: 0.9556866755678471
```

[104]:

```
from scipy import stats
from sklearn.metrics import r2_score

def sign(n):
    return n/abs(n)

confidence = 0.95
squared_errors = (final_predictions - y_test) ** 2
CI = list(stats.t.interval(confidence, len(squared_errors) - 1,
            loc=squared_errors.mean(),
            scale=stats.sem(squared_errors)))

signs = [sign(num) for num in CI]
CI = np.sqrt(np.abs(CI))
CI *= signs
print(f'CI: {CI}')
print(f'R^2: {r2_score(y_test, final_predictions)}')
```

```
CI: [-0.37595678  1.40286049]
R^2: 0.958186920128087
```