Fiat500_VehicleSelection

June 12, 2023

DATE:-6-6-2023 ____**FIAT500_VEHICLE SELECTION** USING **LINEAR , LASSO , RIDGE**

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing,svm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

[ ]:
```
df=pd.read_csv(r"/content/fiat500_VehicleSelection_Dataset (1).csv")
df
```

[ ]:
```
        ID   model  engine_power  age_in_days      km  previous_owners  \
0        1  lounge            51          882   25000                1
1        2     pop            51         1186   32500                1
2        3   sport            74         4658  142228                1
3        4  lounge            51         2739  160000                1
4        5     pop            73         3074  106880                1
…      …     …           …          …      …              …
1533  1534   sport            51         3712  115280                1
1534  1535  lounge            74         3835  112000                1
1535  1536     pop            51         2223   60457                1
1536  1537  lounge            51         2557   80750                1
1537  1538     pop            51         1766   54276                1

            lat        lon  price
0     44.907242   8.611560   8900
1     45.666359  12.241890   8800
2     45.503300  11.417840   4200
3     40.633171  17.634609   6000
4     41.903221  12.495650   5700
…         …         …    …
1533  45.069679   7.704920   5200
1534  45.845692   8.666870   4600
1535  45.481541   9.413480   7500
1536  45.000702   7.682270   5990
```

```
1537  40.323410  17.568270   7900

[1538 rows x 9 columns]
```

[ ]:
```
df.head()
```

[ ]:
```
   ID   model  engine_power  age_in_days      km  previous_owners        lat  \
0   1  lounge            51          882   25000                1  44.907242
1   2     pop            51         1186   32500                1  45.666359
2   3   sport            74         4658  142228                1  45.503300
3   4  lounge            51         2739  160000                1  40.633171
4   5     pop            73         3074  106880                1  41.903221

         lon  price
0   8.611560   8900
1  12.241890   8800
2  11.417840   4200
3  17.634609   6000
4  12.495650   5700
```

[ ]:
```
df.tail()
```

[ ]:
```
        ID   model  engine_power  age_in_days      km  previous_owners  \
1533  1534   sport            51         3712  115280                1
1534  1535  lounge            74         3835  112000                1
1535  1536     pop            51         2223   60457                1
1536  1537  lounge            51         2557   80750                1
1537  1538     pop            51         1766   54276                1

            lat       lon  price
1533  45.069679   7.70492   5200
1534  45.845692   8.66687   4600
1535  45.481541   9.41348   7500
1536  45.000702   7.68227   5990
1537  40.323410  17.56827   7900
```

[ ]:
```
df.shape
```

[ ]:
```
(1538, 9)
```

[ ]:
```
df.describe
```

[ ]:
```
<bound method NDFrame.describe of         ID   model  engine_power  age_in_days
km  previous_owners  \
0        1  lounge            51          882   25000                1
1        2     pop            51         1186   32500                1
2        3   sport            74         4658  142228                1
```

```
3        4  lounge            51          2739  160000                1
4        5     pop            73          3074  106880                1
…     …      …           …           …      …                 …
1533  1534   sport            51          3712  115280                1
1534  1535  lounge            74          3835  112000                1
1535  1536     pop            51          2223   60457                1
1536  1537  lounge            51          2557   80750                1
1537  1538     pop            51          1766   54276                1

            lat        lon  price
0     44.907242   8.611560   8900
1     45.666359  12.241890   8800
2     45.503300  11.417840   4200
3     40.633171  17.634609   6000
4     41.903221  12.495650   5700
…         …          …     …
1533  45.069679   7.704920   5200
1534  45.845692   8.666870   4600
1535  45.481541   9.413480   7500
1536  45.000702   7.682270   5990
1537  40.323410  17.568270   7900

[1538 rows x 9 columns]>
```

[ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1538 entries, 0 to 1537
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               1538 non-null   int64
 1   model            1538 non-null   object
 2   engine_power     1538 non-null   int64
 3   age_in_days      1538 non-null   int64
 4   km               1538 non-null   int64
 5   previous_owners  1538 non-null   int64
 6   lat              1538 non-null   float64
 7   lon              1538 non-null   float64
 8   price            1538 non-null   int64
dtypes: float64(2), int64(6), object(1)
memory usage: 108.3+ KB
```

[ ]:
```python
df.isna().any()
```

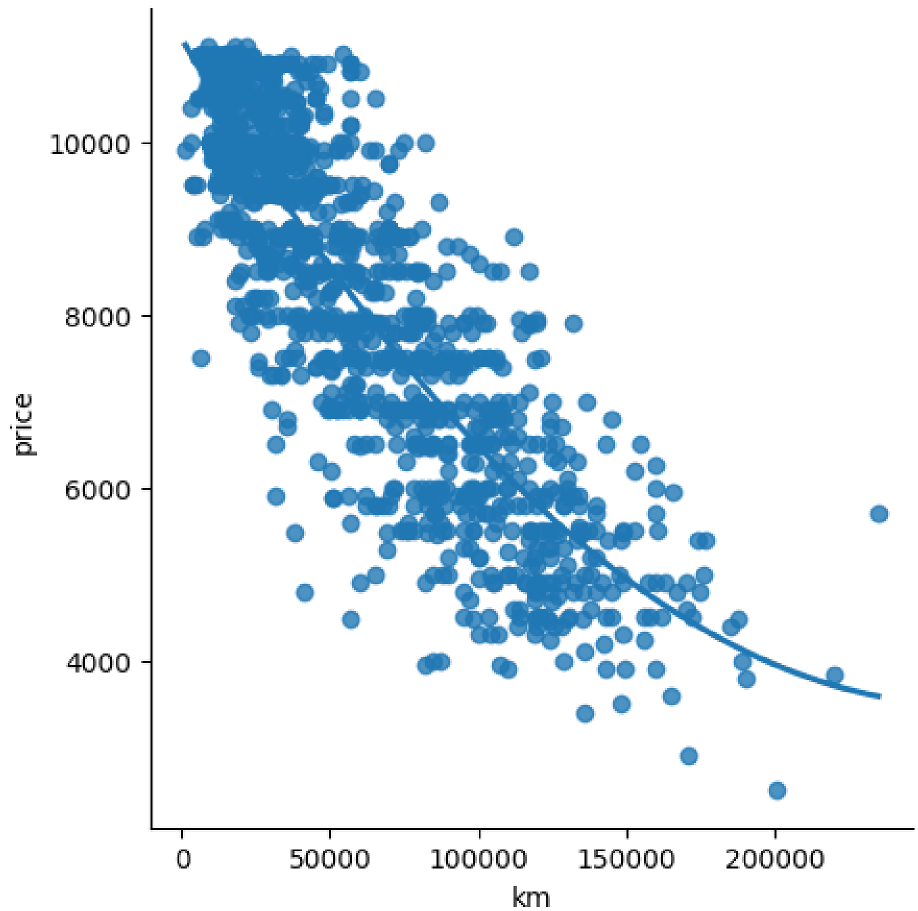
[ ]:
```
ID                   False
model                False
```

```
engine_power       False
age_in_days        False
km                 False
previous_owners    False
lat                False
lon                False
price              False
dtype: bool
```

[ ]:
```
df.isna().any()
```

[ ]:
```
ID                 False
model              False
engine_power       False
age_in_days        False
km                 False
previous_owners    False
lat                False
lon                False
price              False
dtype: bool
```

[ ]:
```
sns.lmplot(x='km',y='price',data=df,order=2,ci=None)
plt.show()
```



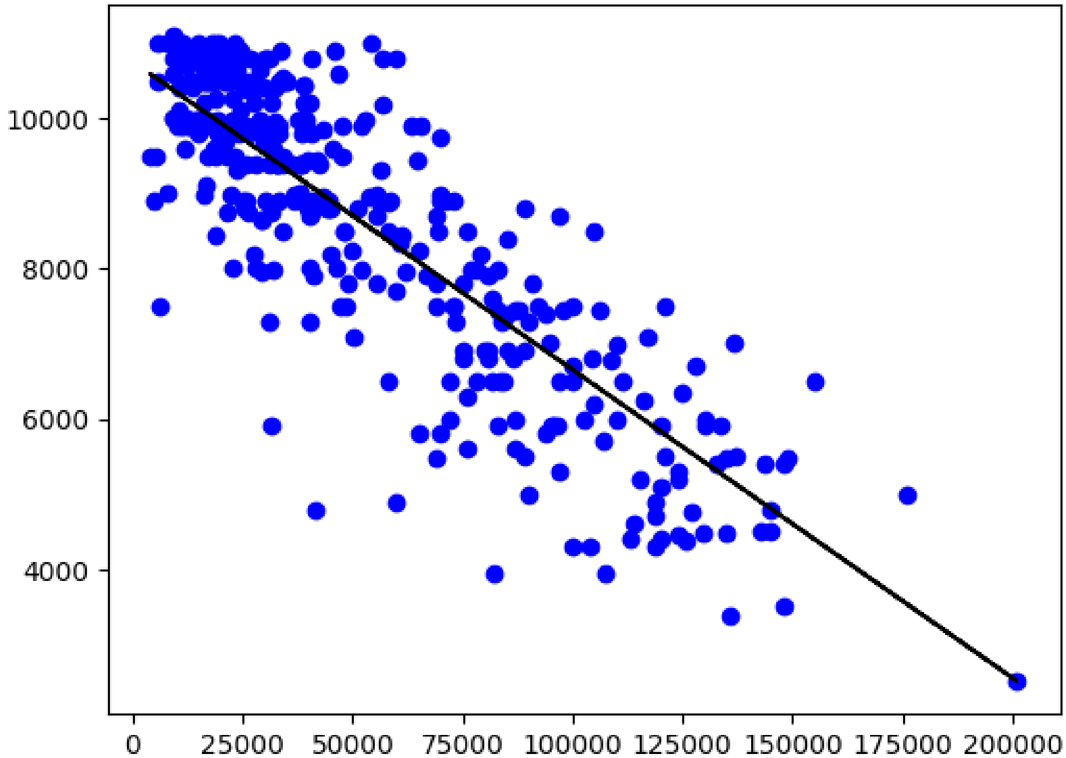
[ ]:
```
x=np.array(df['km']).reshape(-1,1)
y=np.array(df['price']).reshape(-1,1)
```

[ ]:
```
df.dropna(inplace=True)
```

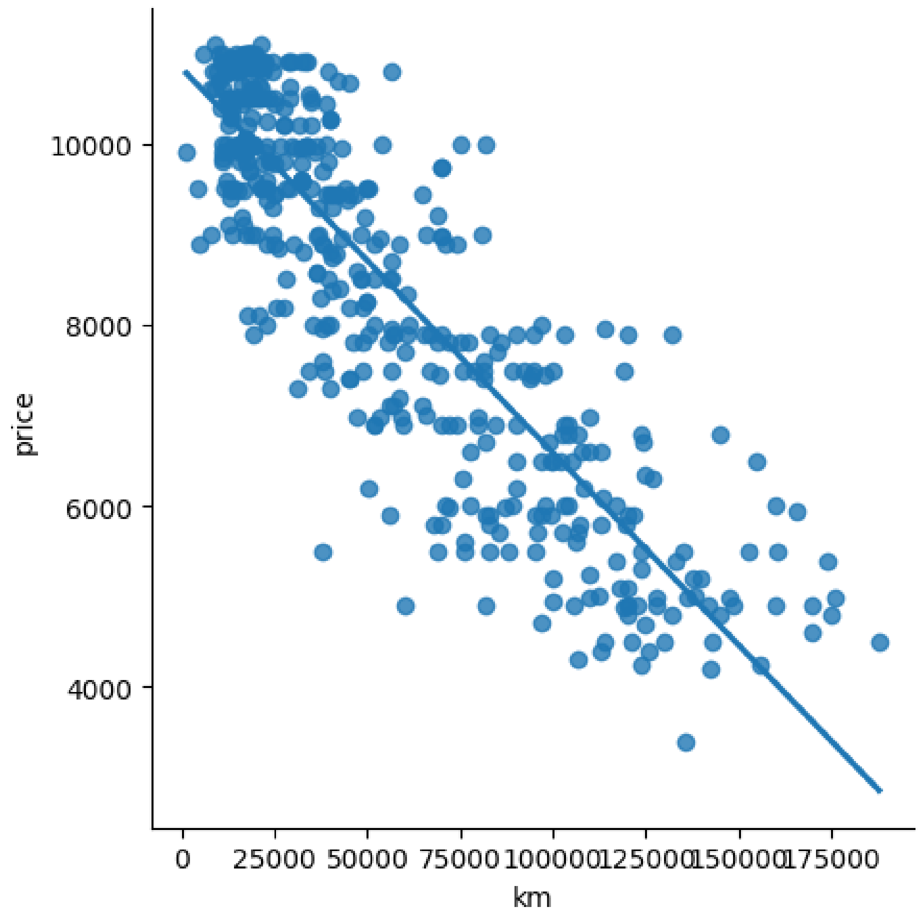
[ ]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
#splitting data into train and test
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score(x_test,y_test))
```

0.7415041964836075

[ ]:
```
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



[ ]:
```
df500=df[:][:500]
sns.lmplot(x="km",y="price",data=df500,order=1,ci=None)
plt.show()
```



[ ]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

[ ]:
```
#train model
model=LinearRegression()
model.fit(x_train,y_train)
#Evaluation the model on the test set
y_pred=model.predict(x_test)
r2=r2_score(y_test,y_pred)
print("R2 score:",r2)
```

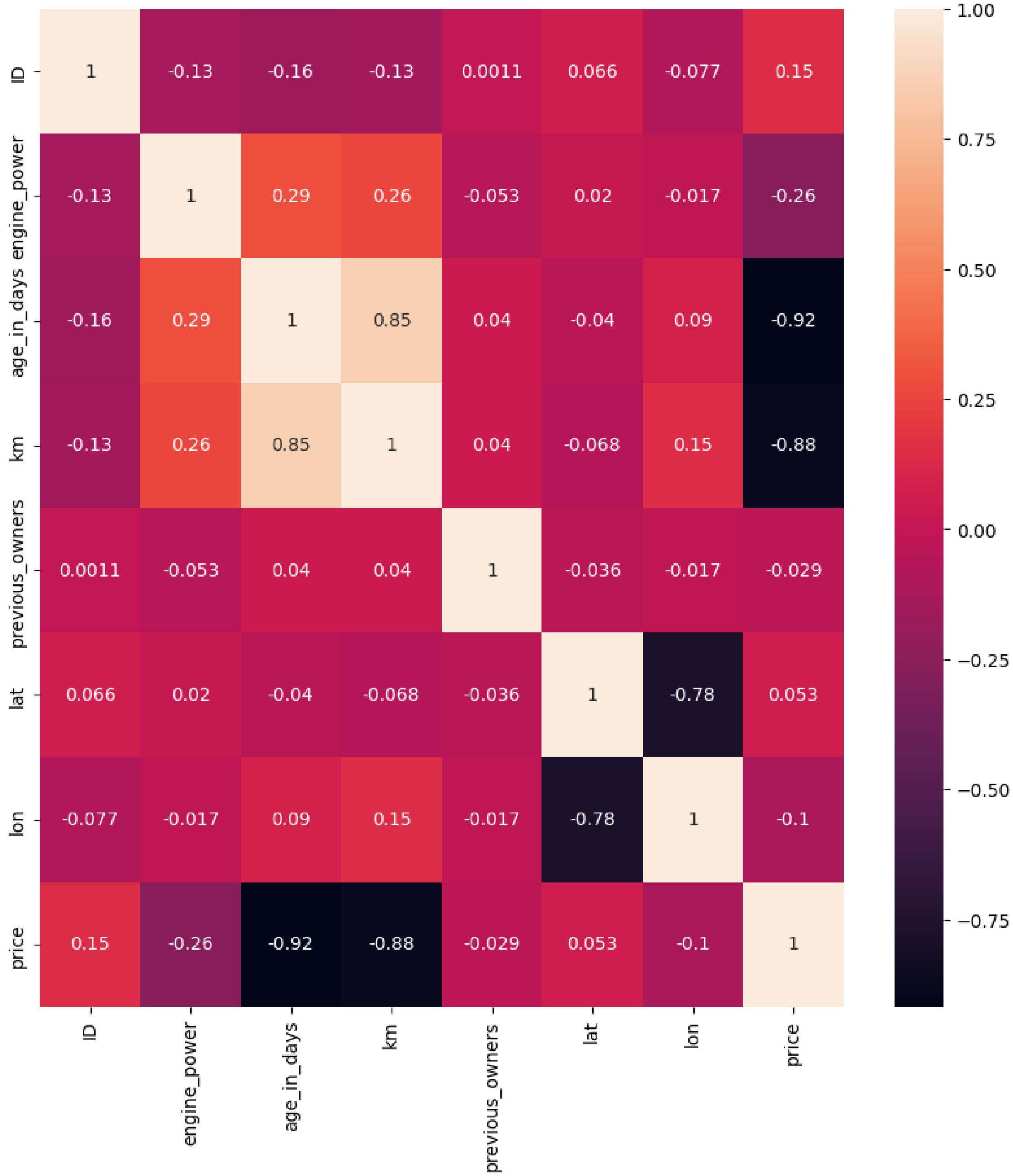
```
R2 score: 0.7415041964836075
```

[ ]:
```
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

[ ]:
```
plt.figure(figsize = (10, 10))
sns.heatmap(df500.corr(), annot = True)
```

```
plt.show()
```

```
<ipython-input-19-a0241e6b6c90>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df500.corr(), annot = True)
```



[ ]:
```
features=df.columns[0:1]
target=df.columns[-1]
```

[ ]:
```
X = df[features].values
y = df[target].values
#splot
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=17)
print("The dimension of X_train is {}".format(X_train.shape))
print("The dimension of X_test is {}".format(X_test.shape))
#Scale features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
The dimension of X_train is (1153, 1)
The dimension of X_test is (385, 1)
```

[ ]:
```
lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
actual = y_test
train_score_lr = lr.score(X_train, y_train)
test_score_lr = lr.score(X_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".format(train_score_lr))
print("The test score for lr model is {}".format(test_score_lr))
```

```

Linear Regression Model:

The train score for lr model is 0.0031028692647708
The test score for lr model is -0.008405634316406507
```

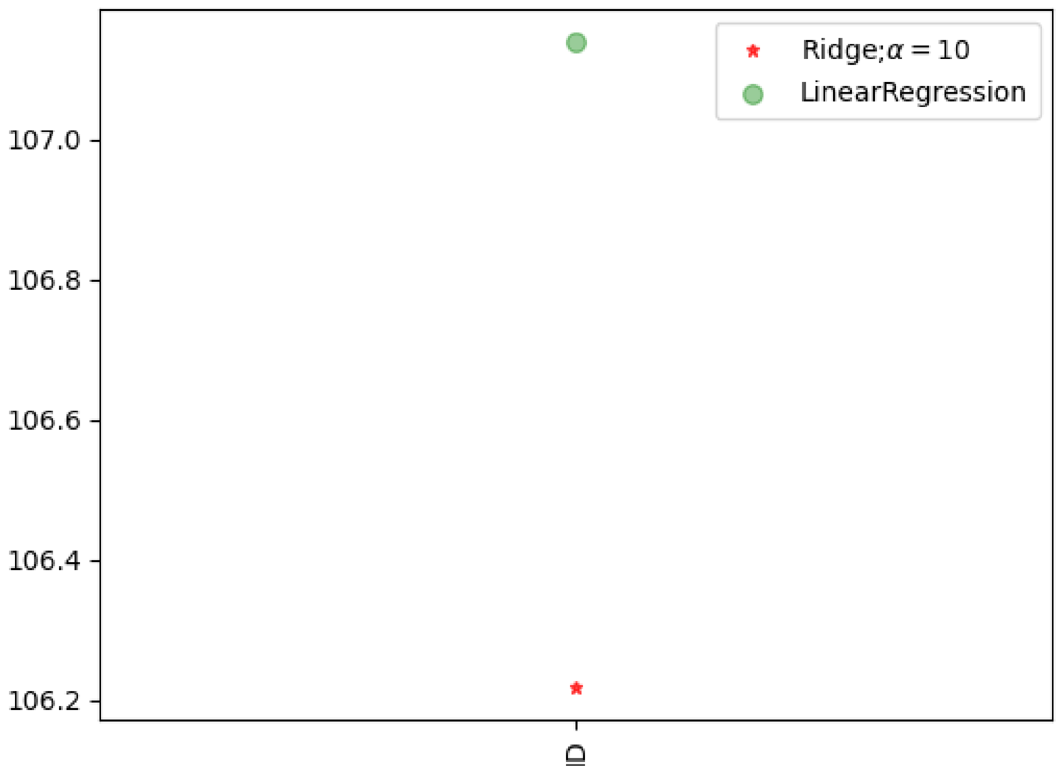
[ ]:
```
#Ridge Regression Model
ridgeReg = Ridge(alpha=10)
ridgeReg.fit(X_train,y_train)
#train and test scorefor ridge regression
train_score_ridge = ridgeReg.score(X_train, y_train)
test_score_ridge = ridgeReg.score(X_test, y_test)
print("\nRidge Model:\n")
print("The train score for ridge model is {}".format(train_score_ridge))
print("The test score for ridge model is {}".format(test_score_ridge))
```

```
Ridge Model:

The train score for ridge model is 0.0031026398591535997
The test score for ridge model is -0.008307809466001403
```

[ ]:
```python
plt.figure(figsize=(10,10))
```

[ ]:
```
<Figure size 1000x1000 with 0 Axes>

<Figure size 1000x1000 with 0 Axes>
```

[27]:
```python
plt.plot(features,ridgeReg.coef_,alpha=0.
↪7,linestyle='none',marker="*",markersize=5,color='red',label=r'Ridge;
↪$\alpha=10$',zorder=7)
plt.plot(features,lr.coef_,alpha=0.
↪4,linestyle='none',marker="o",markersize=7,color='green',label='LinearRegression')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



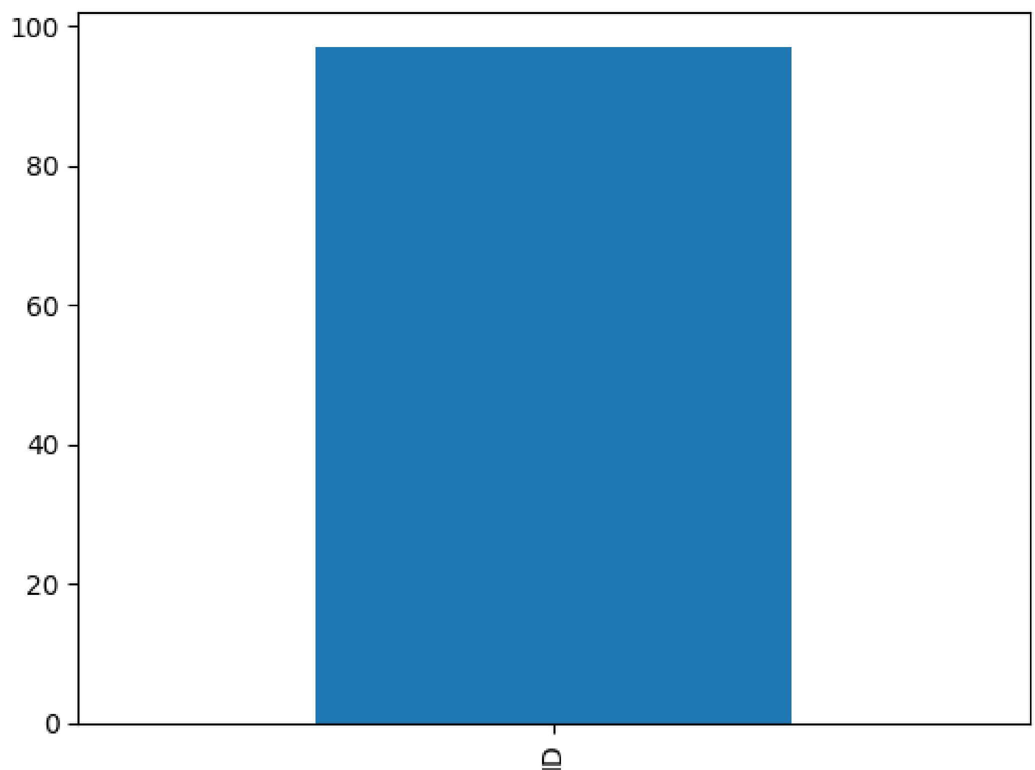
[31]:
```python
#Lasso regression model
print("\nLasso Model: \n")
```

```
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for ls model is 0.003075838461310987
The test score for ls model is -0.007367578602064606
```

[32]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind =␣
↪"bar")
```

[32]: <Axes: >

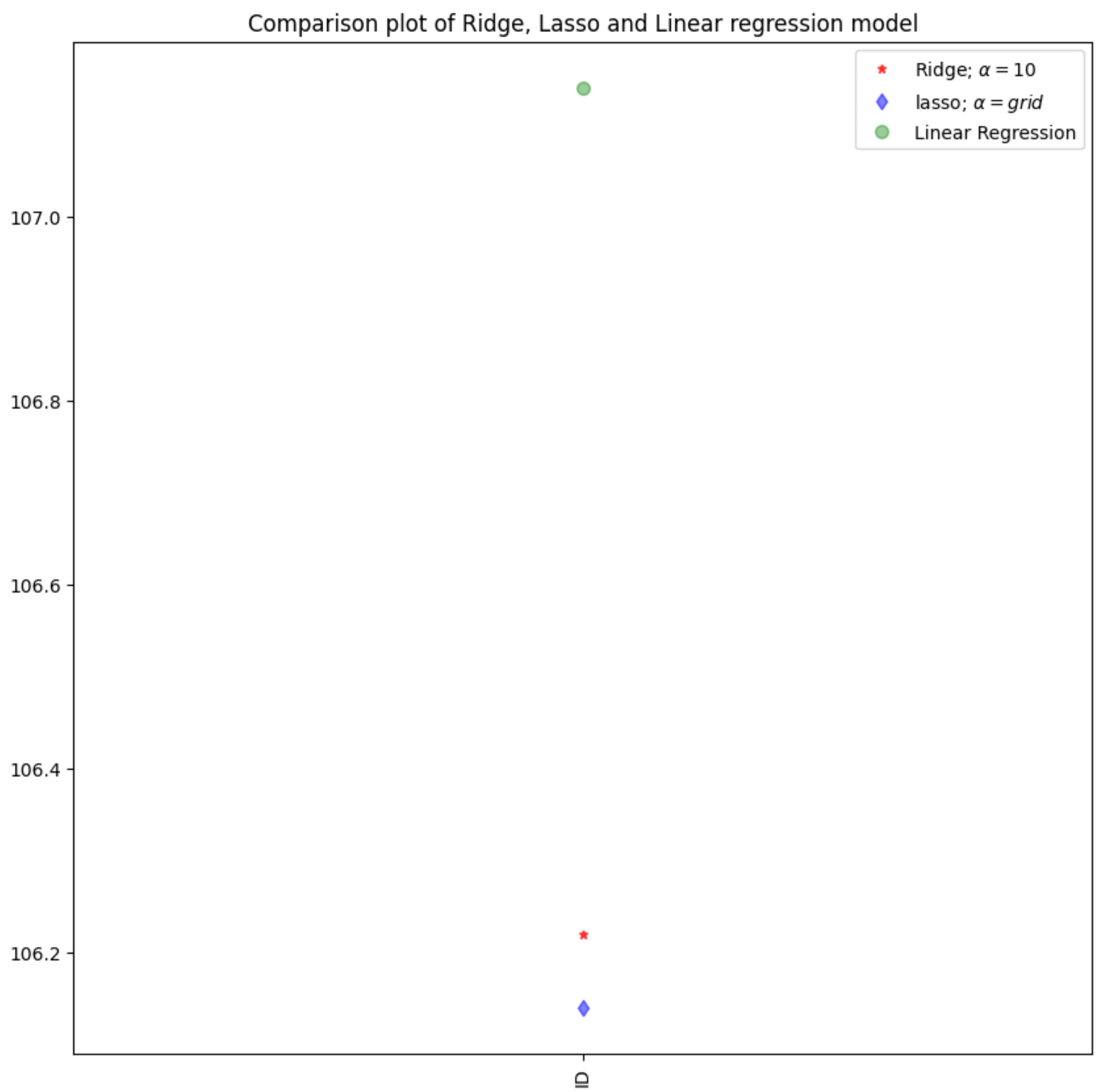


[33]:
```
#Using the linear CV model
from sklearn.linear_model import LassoCV
#Lasso Cross validation
```

```
lasso_cv = LassoCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10], random_state=0).
 ↪fit(X_train, y_train)
#score
print(lasso_cv.score(X_train, y_train))
print(lasso_cv.score(X_test, y_test))
```

```
0.0031025989567363688
-0.008299466692577973
```

[34]:
```
#plot size
plt.figure(figsize = (10, 10))
#add plot for ridge regression
plt.plot(features,ridgeReg.coef_,alpha=0.
 ↪7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;␣
 ↪$\alpha=10$',zorder=7)
#add plot for lasso regression
plt.plot(lasso_cv.coef_,alpha=0.
 ↪5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso;␣
 ↪$\alpha = grid$')
#add plot for linear model
plt.plot(features,lr.coef_,alpha=0.
 ↪4,linestyle='none',marker='o',markersize=7,color='green',label='Linear␣
 ↪Regression')
#rotate axis
plt.xticks(rotation = 90)
plt.legend()
plt.title("Comparison plot of Ridge, Lasso and Linear regression model")
plt.show()
```



[35]:
```
#Using the linear CV model
from sklearn.linear_model import RidgeCV
#Ridge Cross validation
ridge_cv = RidgeCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10]).fit(X_train,␣
  ↪y_train)
#score
print("The train score for ridge model is {}".format(ridge_cv.score(X_train,␣
  ↪y_train)))
print("The train score for ridge model is {}".format(ridge_cv.score(X_test,␣
  ↪y_test)))
```

```
The train score for ridge model is 0.0031026398591535997
The train score for ridge model is -0.008307809466002958
```

[36]:
```
from sklearn.linear_model import ElasticNet
regr=ElasticNet()
regr.fit(X,y)
print(regr.coef_)
print(regr.intercept_)
```

```
[0.12455754]
8480.156871173602
```

[39]:
```
y_pred_elastic=regr.predict(X_train)
```

[40]:
```
mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
print(mean_squared_error)
```

```
3708273.194830543
```