# Kode Random Forest VS Logistic Regression
## Veronica-Eliandani

[1]:
```python
import pandas as pd
import numpy as np

df_prt=pd.read_csv('DatasetUTS.csv')
df_prt.head(20)
```

[1]:

| | squaremeters | numberofrooms | hasyard | haspool | floors | citycode | \ |
|---|---|---|---|---|---|---|---|
| 0 | 75523 | 3 | no | yes | 63 | 9373 | |
| 1 | 55712 | 58 | no | yes | 19 | 34457 | |
| 2 | 86929 | 100 | yes | no | 11 | 98155 | |
| 3 | 51522 | 3 | no | no | 61 | 9047 | |
| 4 | 96470 | 74 | yes | no | 21 | 92029 | |
| 5 | 79770 | 3 | no | yes | 69 | 54812 | |
| 6 | 75985 | 60 | yes | no | 67 | 6517 | |
| 7 | 64169 | 88 | no | yes | 6 | 61711 | |
| 8 | 92383 | 12 | no | no | 78 | 71982 | |
| 9 | 95121 | 46 | no | yes | 3 | 9382 | |
| 10 | 76485 | 47 | yes | no | 9 | 90254 | |
| 11 | 87060 | 27 | no | yes | 91 | 51803 | |
| 12 | 66683 | 19 | yes | yes | 6 | 50801 | |
| 13 | 84559 | 29 | no | yes | 69 | 53057 | |
| 14 | 76091 | 38 | yes | no | 32 | 59451 | |
| 15 | 92696 | 49 | yes | no | 38 | 74381 | |
| 16 | 59800 | 47 | no | yes | 27 | 44815 | |
| 17 | 54836 | 25 | no | yes | 53 | 64601 | |
| 18 | 70021 | 52 | yes | no | 28 | 95678 | |
| 19 | 54368 | 11 | yes | yes | 20 | 55761 | |

| | citypartrange | numprevowners | made | isnewbuilt | hasstormprotector | basement | \ |
|---|---|---|---|---|---|---|---|
| 0 | 3 | 8 | 2005 | old | yes | 4313 | |
| 1 | 6 | 8 | 2021 | old | no | 2937 | |
| 2 | 3 | 4 | 2003 | new | no | 6326 | |
| 3 | 8 | 3 | 2012 | new | yes | 632 | |
| 4 | 4 | 2 | 2011 | new | yes | 5414 | |
| 5 | 10 | 5 | 2018 | old | yes | 8871 | |
| 6 | 6 | 9 | 2009 | new | yes | 4878 | |
| 7 | 3 | 9 | 2011 | new | yes | 3054 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 8 | 3 | 7 | 2000 | old | no | 7507 |
| 9 | 7 | 9 | 1994 | old | no | 615 |
| 10 | 2 | 9 | 2008 | new | no | 2860 |
| 11 | 8 | 10 | 2000 | old | no | 6629 |
| 12 | 6 | 2 | 2001 | old | no | 7473 |
| 13 | 7 | 7 | 2000 | new | no | 3573 |
| 14 | 5 | 8 | 2016 | new | no | 8150 |
| 15 | 9 | 2 | 2021 | old | no | 1559 |
| 16 | 6 | 9 | 2021 | old | no | 5075 |
| 17 | 10 | 5 | 2020 | new | no | 5278 |
| 18 | 4 | 6 | 1992 | old | yes | 4480 |
| 19 | 3 | 7 | 2021 | old | no | 231 |

| | attic | garage | hasstorageroom | hasguestroom | price | category |
|---|---|---|---|---|---|---|
| 0 | 9005 | 956 | no | 7 | 7559081.5 | Luxury |
| 1 | 8852 | 135 | yes | 9 | 5574642.1 | Middle |
| 2 | 4748 | 654 | no | 10 | 8696869.3 | Luxury |
| 3 | 5792 | 807 | yes | 5 | 5154055.2 | Middle |
| 4 | 1172 | 716 | yes | 9 | 9652258.1 | Luxury |
| 5 | 7117 | 240 | no | 7 | 7986665.8 | Luxury |
| 6 | 281 | 384 | yes | 5 | 7607322.9 | Luxury |
| 7 | 129 | 726 | no | 9 | 6420823.1 | Middle |
| 8 | 9056 | 892 | yes | 1 | 9244344.0 | Luxury |
| 9 | 1221 | 328 | no | 10 | 9515440.4 | Luxury |
| 10 | 3129 | 982 | no | 1 | 7653300.8 | Luxury |
| 11 | 435 | 512 | no | 7 | 8711426.0 | Luxury |
| 12 | 796 | 237 | yes | 3 | 6677649.1 | Middle |
| 13 | 9556 | 918 | yes | 8 | 8460604.0 | Luxury |
| 14 | 6037 | 930 | no | 7 | 7614076.6 | Luxury |
| 15 | 5111 | 957 | yes | 2 | 9272740.1 | Luxury |
| 16 | 3104 | 864 | no | 4 | 5984462.1 | Middle |
| 17 | 1059 | 313 | yes | 6 | 5492532.0 | Middle |
| 18 | 6919 | 680 | yes | 1 | 7005572.2 | Luxury |
| 19 | 1939 | 223 | no | 8 | 5446398.1 | Middle |

[2]:
```
df_prt2=df_prt.drop('price',axis=1)
df_prt2.head(20)
```

[2]:

| | squaremeters | numberofrooms | hasyard | haspool | floors | citycode | \ |
|---|---|---|---|---|---|---|---|
| 0 | 75523 | 3 | no | yes | 63 | 9373 | |
| 1 | 55712 | 58 | no | yes | 19 | 34457 | |
| 2 | 86929 | 100 | yes | no | 11 | 98155 | |
| 3 | 51522 | 3 | no | no | 61 | 9047 | |
| 4 | 96470 | 74 | yes | no | 21 | 92029 | |
| 5 | 79770 | 3 | no | yes | 69 | 54812 | |
| 6 | 75985 | 60 | yes | no | 67 | 6517 | |
| 7 | 64169 | 88 | no | yes | 6 | 61711 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 8 | 92383 | 12 | no | no | 78 | 71982 |
| 9 | 95121 | 46 | no | yes | 3 | 9382 |
| 10 | 76485 | 47 | yes | no | 9 | 90254 |
| 11 | 87060 | 27 | no | yes | 91 | 51803 |
| 12 | 66683 | 19 | yes | yes | 6 | 50801 |
| 13 | 84559 | 29 | no | yes | 69 | 53057 |
| 14 | 76091 | 38 | yes | no | 32 | 59451 |
| 15 | 92696 | 49 | yes | no | 38 | 74381 |
| 16 | 59800 | 47 | no | yes | 27 | 44815 |
| 17 | 54836 | 25 | no | yes | 53 | 64601 |
| 18 | 70021 | 52 | yes | no | 28 | 95678 |
| 19 | 54368 | 11 | yes | yes | 20 | 55761 |

| | citypartrange | numprevowners | made | isnewbuilt | hasstormprotector | basement \ |
|---|---|---|---|---|---|---|
| 0 | 3 | 8 | 2005 | old | yes | 4313 |
| 1 | 6 | 8 | 2021 | old | no | 2937 |
| 2 | 3 | 4 | 2003 | new | no | 6326 |
| 3 | 8 | 3 | 2012 | new | yes | 632 |
| 4 | 4 | 2 | 2011 | new | yes | 5414 |
| 5 | 10 | 5 | 2018 | old | yes | 8871 |
| 6 | 6 | 9 | 2009 | new | yes | 4878 |
| 7 | 3 | 9 | 2011 | new | yes | 3054 |
| 8 | 3 | 7 | 2000 | old | no | 7507 |
| 9 | 7 | 9 | 1994 | old | no | 615 |
| 10 | 2 | 9 | 2008 | new | no | 2860 |
| 11 | 8 | 10 | 2000 | old | no | 6629 |
| 12 | 6 | 2 | 2001 | old | no | 7473 |
| 13 | 7 | 7 | 2000 | new | no | 3573 |
| 14 | 5 | 8 | 2016 | new | no | 8150 |
| 15 | 9 | 2 | 2021 | old | no | 1559 |
| 16 | 6 | 9 | 2021 | old | no | 5075 |
| 17 | 10 | 5 | 2020 | new | no | 5278 |
| 18 | 4 | 6 | 1992 | old | yes | 4480 |
| 19 | 3 | 7 | 2021 | old | no | 231 |

| | attic | garage | hasstorageroom | hasguestroom | category |
|---|---|---|---|---|---|
| 0 | 9005 | 956 | no | 7 | Luxury |
| 1 | 8852 | 135 | yes | 9 | Middle |
| 2 | 4748 | 654 | no | 10 | Luxury |
| 3 | 5792 | 807 | yes | 5 | Middle |
| 4 | 1172 | 716 | yes | 9 | Luxury |
| 5 | 7117 | 240 | no | 7 | Luxury |
| 6 | 281 | 384 | yes | 5 | Luxury |
| 7 | 129 | 726 | no | 9 | Middle |
| 8 | 9056 | 892 | yes | 1 | Luxury |
| 9 | 1221 | 328 | no | 10 | Luxury |
| 10 | 3129 | 982 | no | 1 | Luxury |

```
11    435    512              no             7   Luxury
12    796    237             yes             3   Middle
13   9556    918             yes             8   Luxury
14   6037    930              no             7   Luxury
15   5111    957             yes             2   Luxury
16   3104    864              no             4   Middle
17   1059    313             yes             6   Middle
18   6919    680             yes             1   Luxury
19   1939    223              no             8   Middle
```

[3]:
```python
df_prt2['category'].value_counts()
```

[3]:
```
category
Basic      4344
Luxury     3065
Middle     2591
Name: count, dtype: int64
```

[4]:
```python
print("data null \n", df_prt2.isnull().sum())
print("\ndata kosong \n", df_prt2.empty)
print("\ndata nnan \n",df_prt2.isna().sum())
```

```
data null
 squaremeters          0
numberofrooms         0
hasyard               0
haspool               0
floors                0
citycode              0
citypartrange         0
numprevowners         0
made                  0
isnewbuilt            0
hasstormprotector     0
basement              0
attic                 0
garage                0
hasstorageroom        0
hasguestroom          0
category              0
dtype: int64

data kosong
 False

data nnan
 squaremeters          0
```

```
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
category             0
dtype: int64
```

[5]:
```python
print("Sebelum Pengecekan data duplikat,",df_prt2.shape)

df_prt3 = df_prt2.drop_duplicates(keep='last')
print("Setelah Pengecekan data duplikat,", df_prt2.shape)
```

```
Sebelum Pengecekan data duplikat, (10000, 17)
Setelah Pengecekan data duplikat, (10000, 17)
```

[6]:
```python
from sklearn.model_selection import train_test_split
x = df_prt3.drop(columns=['category'], axis=1)
y = df_prt3['category']

X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.25,␣
 ↪random_state=71)

print(X_train.shape)
print(X_test.shape)
```

```
(7500, 16)
(2500, 16)
```

[7]:
```python
import pandas as pd
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer


kolom_kategori = ['hasyard', 'haspool', 'isnewbuilt', 'hasstormprotector',␣
 ↪'hasstorageroom']
```

```
transform = make_column_transformer(
    (OneHotEncoder(), kolom_kategori),
    remainder='passthrough'
)

X_train_enc = transform.fit_transform(X_train)

X_test_enc = transform.transform(X_test)

df_train_enc = pd.DataFrame(X_train_enc, columns=transform.
 ↪get_feature_names_out())
df_test_enc = pd.DataFrame(X_test_enc, columns=transform.
 ↪get_feature_names_out())

print("Encoded Training Data:\n", df_train_enc.head(10))
print("Encoded Testing Data:\n", df_test_enc.head(10))
```

```
Encoded Training Data:
    onehotencoder__hasyard_no  onehotencoder__hasyard_yes  \
0                        0.0                         1.0
1                        0.0                         1.0
2                        0.0                         1.0
3                        0.0                         1.0
4                        1.0                         0.0
5                        0.0                         1.0
6                        0.0                         1.0
7                        0.0                         1.0
8                        0.0                         1.0
9                        0.0                         1.0

   onehotencoder__haspool_no  onehotencoder__haspool_yes  \
0                        1.0                         0.0
1                        1.0                         0.0
2                        0.0                         1.0
3                        1.0                         0.0
4                        0.0                         1.0
5                        1.0                         0.0
6                        0.0                         1.0
7                        1.0                         0.0
8                        1.0                         0.0
9                        0.0                         1.0

   onehotencoder__isnewbuilt_new  onehotencoder__isnewbuilt_old  \
0                            0.0                            1.0
1                            1.0                            0.0
2                            0.0                            1.0
3                            0.0                            1.0
```

```
4                         1.0                        0.0
5                         0.0                        1.0
6                         1.0                        0.0
7                         1.0                        0.0
8                         0.0                        1.0
9                         0.0                        1.0

   onehotencoder__hasstormprotector_no  onehotencoder__hasstormprotector_yes  \
0                                  1.0                                   0.0
1                                  0.0                                   1.0
2                                  1.0                                   0.0
3                                  0.0                                   1.0
4                                  1.0                                   0.0
5                                  0.0                                   1.0
6                                  0.0                                   1.0
7                                  1.0                                   0.0
8                                  0.0                                   1.0
9                                  1.0                                   0.0

   onehotencoder__hasstorageroom_no  onehotencoder__hasstorageroom_yes  …  \
0                               1.0                                0.0  …
1                               1.0                                0.0  …
2                               1.0                                0.0  …
3                               0.0                                1.0  …
4                               0.0                                1.0  …
5                               1.0                                0.0  …
6                               0.0                                1.0  …
7                               1.0                                0.0  …
8                               0.0                                1.0  …
9                               0.0                                1.0  …

   remainder__numberofrooms  remainder__floors  remainder__citycode  \
0                      93.0               98.0              68872.0
1                      97.0               20.0              93104.0
2                      86.0               27.0              61694.0
3                      10.0               94.0              15304.0
4                      98.0               63.0               1173.0
5                      46.0               19.0              14625.0
6                      47.0               23.0              80519.0
7                      82.0               21.0              62528.0
8                      92.0               73.0              39608.0
9                      55.0               76.0              67738.0

   remainder__citypartrange  remainder__numprevowners  remainder__made  \
0                       6.0                      10.0           2009.0
1                       9.0                       3.0           1993.0
2                      10.0                       9.0           1995.0
3                      10.0                       8.0           2005.0
```

```
4                        8.0                        8.0           2016.0
5                       10.0                        4.0           2021.0
6                        6.0                        2.0           2013.0
7                        7.0                        6.0           1995.0
8                        6.0                        7.0           2000.0
9                        3.0                        4.0           2011.0

   remainder__basement  remainder__attic  remainder__garage  \
0               1016.0            2441.0              792.0
1               6768.0            7803.0              901.0
2               1588.0            2201.0              789.0
3               4171.0            4794.0              574.0
4               2287.0            8181.0              426.0
5               9802.0            4844.0              984.0
6               2975.0            5534.0              900.0
7               5336.0            8216.0              634.0
8               4147.0            7554.0              606.0
9               5746.0            3337.0              220.0

   remainder__hasguestroom
0                      7.0
1                      2.0
2                      0.0
3                     10.0
4                      6.0
5                      9.0
6                      2.0
7                      0.0
8                      3.0
9                      8.0

[10 rows x 21 columns]
Encoded Testing Data:
    onehotencoder__hasyard_no  onehotencoder__hasyard_yes  \
0                         1.0                         0.0
1                         0.0                         1.0
2                         0.0                         1.0
3                         1.0                         0.0
4                         0.0                         1.0
5                         0.0                         1.0
6                         0.0                         1.0
7                         1.0                         0.0
8                         1.0                         0.0
9                         1.0                         0.0

   onehotencoder__haspool_no  onehotencoder__haspool_yes  \
0                        0.0                         1.0
1                        0.0                         1.0
```

```
2                      0.0                      1.0
3                      1.0                      0.0
4                      1.0                      0.0
5                      1.0                      0.0
6                      1.0                      0.0
7                      0.0                      1.0
8                      1.0                      0.0
9                      0.0                      1.0

   onehotencoder__isnewbuilt_new  onehotencoder__isnewbuilt_old  \
0                            0.0                            1.0
1                            0.0                            1.0
2                            0.0                            1.0
3                            0.0                            1.0
4                            1.0                            0.0
5                            1.0                            0.0
6                            0.0                            1.0
7                            1.0                            0.0
8                            1.0                            0.0
9                            1.0                            0.0

   onehotencoder__hasstormprotector_no  onehotencoder__hasstormprotector_yes  \
0                                  0.0                                   1.0
1                                  0.0                                   1.0
2                                  1.0                                   0.0
3                                  1.0                                   0.0
4                                  0.0                                   1.0
5                                  0.0                                   1.0
6                                  0.0                                   1.0
7                                  0.0                                   1.0
8                                  0.0                                   1.0
9                                  1.0                                   0.0

   onehotencoder__hasstorageroom_no  onehotencoder__hasstorageroom_yes  …  \
0                               0.0                                1.0  …
1                               0.0                                1.0  …
2                               0.0                                1.0  …
3                               1.0                                0.0  …
4                               0.0                                1.0  …
5                               0.0                                1.0  …
6                               1.0                                0.0  …
7                               0.0                                1.0  …
8                               0.0                                1.0  …
9                               1.0                                0.0  …

   remainder__numberofrooms  remainder__floors  remainder__citycode  \
0                      10.0               87.0              41867.0
1                      35.0                2.0              78416.0
```

```
2                     28.0                  20.0                  47125.0
3                     42.0                  65.0                  70699.0
4                     42.0                  76.0                  67080.0
5                     19.0                  97.0                  78485.0
6                      2.0                  11.0                   3545.0
7                      7.0                  24.0                  19018.0
8                     96.0                  41.0                   2434.0
9                     49.0                  66.0                  93489.0

   remainder__citypartrange  remainder__numprevowners  remainder__made  \
0                       6.0                      10.0           1997.0
1                       1.0                       6.0           2016.0
2                       1.0                       3.0           2015.0
3                       9.0                       2.0           2010.0
4                       8.0                       2.0           2015.0
5                      10.0                       6.0           2017.0
6                       2.0                       4.0           2020.0
7                       7.0                       2.0           1998.0
8                       5.0                       1.0           2007.0
9                       3.0                       8.0           2001.0

   remainder__basement  remainder__attic  remainder__garage  \
0               8945.0            1203.0              142.0
1               3311.0            1636.0              967.0
2               8462.0             890.0              523.0
3               2336.0            8483.0              319.0
4               5678.0            8046.0              135.0
5               6040.0            2747.0              150.0
6                339.0            1049.0              245.0
7                 21.0            9711.0              657.0
8               1816.0            4036.0              534.0
9               5294.0            9984.0              276.0

   remainder__hasguestroom
0                     10.0
1                      6.0
2                      7.0
3                      2.0
4                      4.0
5                      3.0
6                      1.0
7                      7.0
8                      1.0
9                      5.0

[10 rows x 21 columns]
```

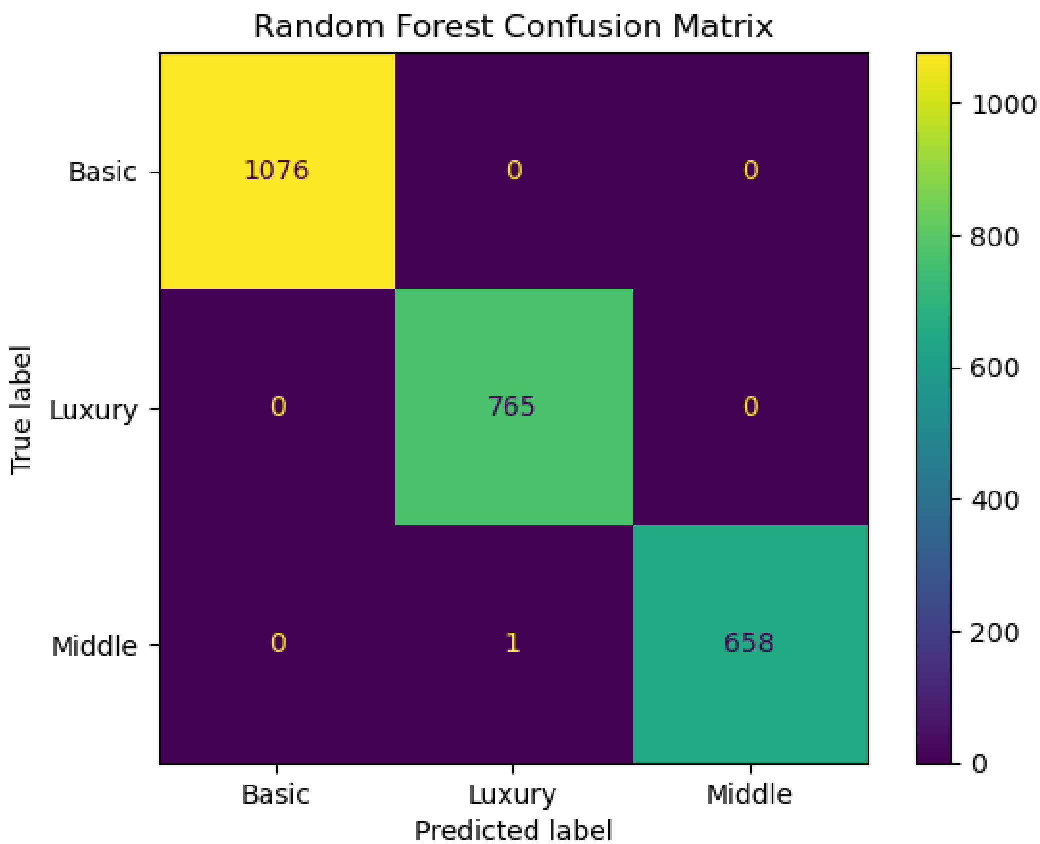
[8]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectPercentile, SelectKBest
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.metrics import␣
↪classification_report,confusion_matrix,ConfusionMatrixDisplay
import numpy as np

pipe_RF = Pipeline(steps=[
    ('data scaling', StandardScaler()),
    ('feature select', SelectKBest()),
    ('clf', RandomForestClassifier(random_state=71, class_weight='balanced'))
])

params_grid_RF = [
    {
        'data scaling': [StandardScaler()],
        'feature select__k': np.arange(2, 6),
        'clf__max_depth': np.arange(4, 5),
        'clf__n_estimators': [100, 150]
    },
    {
        'data scaling': [StandardScaler()],
        'feature select': [SelectPercentile()],
        'feature select__percentile': np.arange(20, 50),
        'clf__max_depth': np.arange(4, 5),
        'clf__n_estimators': [100, 150]
    },
    {
        'data scaling': [MinMaxScaler()],
        'feature select__k': np.arange(2, 6),
        'clf__max_depth': np.arange(4, 5),
        'clf__n_estimators': [100, 150]
    },
    {
        'data scaling': [MinMaxScaler()],
        'feature select': [SelectPercentile()],
        'feature select__percentile': np.arange(20, 50),
        'clf__max_depth': np.arange(4, 5),
        'clf__n_estimators': [100, 150]
    }
]

SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=71)

GSCV_RF = GridSearchCV(pipe_RF, params_grid_RF, cv=SKF)
```

```
GSCV_RF.fit(X_train_enc, y_train)

print("GSV Training Finished")
```

```
GSV Training Finished
```

[9]:
```
print("CV Score : {}".format(GSCV_RF.best_score_))
print("Test Score : {}".format(GSCV_RF.best_estimator_.score(X_test_enc,␣
 ↪y_test)))
print("Best Model: ", GSCV_RF.best_estimator_)
mask = GSCV_RF.best_estimator_.named_steps['feature select'].get_support()
print("Best Features:", df_train_enc.columns[mask])

RF_pred = GSCV_RF.predict(X_test_enc)

import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, RF_pred, labels=GSCV_RF.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=GSCV_RF.
 ↪classes_)
disp.plot()
plt.title("Random Forest Confusion Matrix")
plt.show()

print("classification report RF:\n", classification_report(y_test, RF_pred))
```

```
CV Score : 0.9994666666666667
Test Score : 0.9996
Best Model:  Pipeline(steps=[('data scaling', StandardScaler()),
                ('feature select', SelectPercentile(percentile=36)),
                ('clf',
                 RandomForestClassifier(class_weight='balanced', max_depth=4,
                                        n_estimators=150, random_state=71))])
Best Features: Index(['onehotencoder__hasyard_no', 'onehotencoder__hasyard_yes',
       'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
       'onehotencoder__isnewbuilt_new', 'onehotencoder__isnewbuilt_old',
       'remainder__squaremeters', 'remainder__garage'],
      dtype='object')
```




```
classification report RF:
              precision    recall  f1-score   support

       Basic       1.00      1.00      1.00      1076
      Luxury       1.00      1.00      1.00       765
      Middle       1.00      1.00      1.00       659

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```

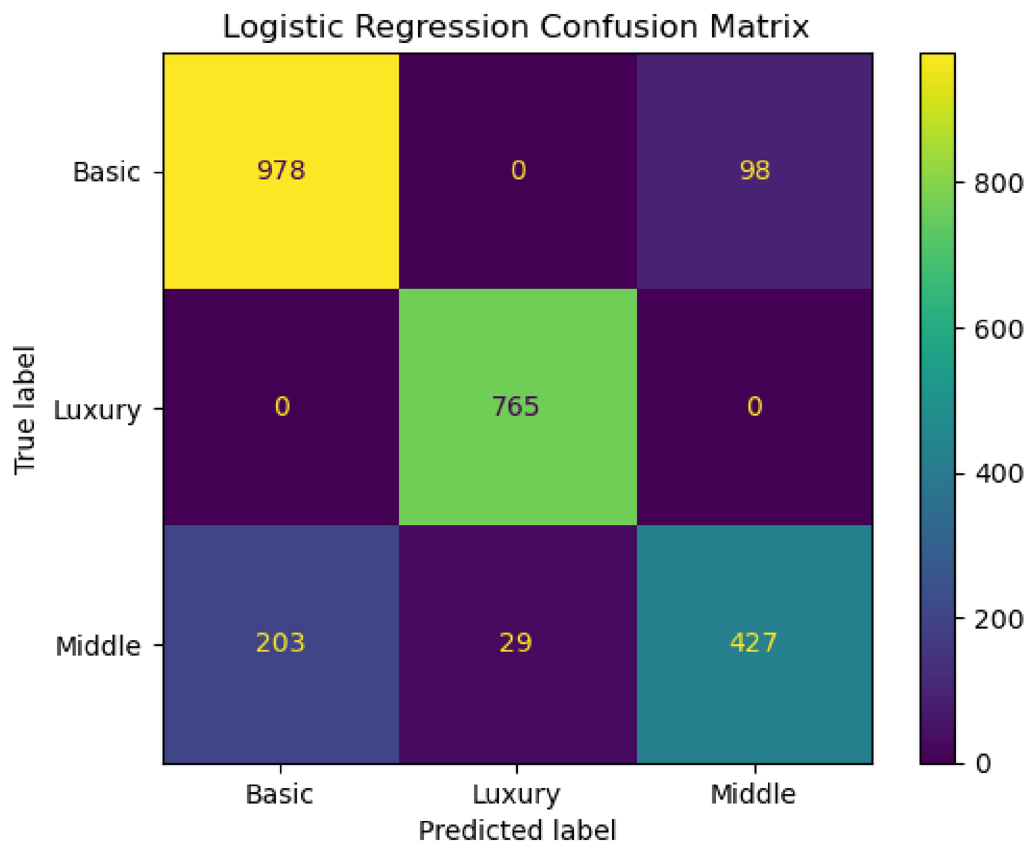
[10]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectPercentile, SelectKBest
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.metrics import
 ↪classification_report,confusion_matrix,ConfusionMatrixDisplay
import numpy as np
```

```python
pipe_logreg = Pipeline(steps=[
    ('scaler', StandardScaler()),
    ('feature_select', SelectKBest()),
    ('classifier', LogisticRegression(random_state=71, class_weight='balanced'))
])

params_grid_logreg = [
    {
        'scaler': [StandardScaler()],
        'feature_select__k': np.arange(2, 6),
        'classifier__penalty': ['l2'],
        'classifier__C': [0.1, 1, 10],
        'classifier__solver': ['liblinear']
    },
    {
        'scaler': [StandardScaler()],
        'feature_select': [SelectPercentile()],
        'feature_select__percentile': np.arange(20, 50),
        'classifier__penalty': ['l2'],
        'classifier__C': [0.1, 1, 10],
        'classifier__solver': ['liblinear']
    },
    {
        'scaler': [MinMaxScaler()],
        'feature_select__k': np.arange(2, 6),
        'classifier__penalty': ['l2'],
        'classifier__C': [0.1, 1, 10],
        'classifier__solver': ['liblinear']
    },
    {
        'scaler': [MinMaxScaler()],
        'feature_select': [SelectPercentile()],
        'feature_select__percentile': np.arange(20, 50),
        'classifier__penalty': ['l2'],
        'classifier__C': [0.1, 1, 10],
        'classifier__solver': ['liblinear']
    }
]

SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=71)

GSCV_logreg = GridSearchCV(pipe_logreg, params_grid_logreg, cv=SKF)
GSCV_logreg.fit(X_train_enc, y_train)

print("Logistic Regression Training Finished")
```

```
Logistic Regression Training Finished
```

[11]:
```python
print("CV Score: {}".format(GSCV_logreg.best_score_))
print("Test Score: {}".format(GSCV_logreg.best_estimator_.score(X_test_enc,␣
 ↪y_test)))
print("Best Model: ", GSCV_logreg.best_estimator_)

mask = GSCV_logreg.best_estimator_.named_steps['feature_select'].get_support()
print("Best Features:", df_train_enc.columns[mask])

logreg_pred = GSCV_logreg.predict(X_test_enc)

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
 ↪classification_report

cm = confusion_matrix(y_test, logreg_pred, labels=GSCV_logreg.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=GSCV_logreg.
 ↪classes_)
disp.plot()
plt.title("Logistic Regression Confusion Matrix")
plt.show()

print("Classification Report:\n", classification_report(y_test, logreg_pred))
```

```
CV Score: 0.8712
Test Score: 0.868
Best Model:  Pipeline(steps=[('scaler', StandardScaler()),
                ('feature_select', SelectPercentile(percentile=36)),
                ('classifier',
                 LogisticRegression(C=10, class_weight='balanced',
                                    random_state=71, solver='liblinear'))])
Best Features: Index(['onehotencoder__hasyard_no', 'onehotencoder__hasyard_yes',
       'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
       'onehotencoder__isnewbuilt_new', 'onehotencoder__isnewbuilt_old',
       'remainder__squaremeters', 'remainder__garage'],
      dtype='object')
```




```
Classification Report:
              precision    recall  f1-score   support

       Basic       0.83      0.91      0.87      1076
      Luxury       0.96      1.00      0.98       765
      Middle       0.81      0.65      0.72       659

    accuracy                           0.87      2500
   macro avg       0.87      0.85      0.86      2500
weighted avg       0.87      0.87      0.86      2500
```

[12]:

```
import pickle
with open('BestModel_RF_LR_Seaborn.pkl', 'wb') as r:
    pickle.dump((GSCV_RF),r)

print("Model RF Disimpan")
```

```
Model RF Disimpan
```

**Kode Gradient Boosting**
**Classifier VS Support Vector Machine**
**Szwagery**

[4]:
```
import pandas as pd
import numpy as np

df_prt = pd.read_csv('DatasetUTS.csv')
df_prt.head(20)
```

[4]:
```
    squaremeters  numberofrooms hasyard haspool  floors  citycode  \
0          75523              3      no     yes      63      9373
1          55712             58      no     yes      19     34457
2          86929            100     yes      no      11     98155
3          51522              3      no      no      61      9047
4          96470             74     yes      no      21     92029
5          79770              3      no     yes      69     54812
6          75985             60     yes      no      67      6517
7          64169             88      no     yes       6     61711
8          92383             12      no      no      78     71982
9          95121             46      no     yes       3      9382
10         76485             47     yes      no       9     90254
11         87060             27      no     yes      91     51803
12         66683             19     yes     yes       6     50801
13         84559             29      no     yes      69     53057
14         76091             38     yes      no      32     59451
15         92696             49     yes      no      38     74381
16         59800             47      no     yes      27     44815
17         54836             25      no     yes      53     64601
18         70021             52     yes      no      28     95678
19         54368             11     yes     yes      20     55761

    citypartrange  numprevowners  made isnewbuilt hasstormprotector  basement  \
0               3              8  2005        old               yes      4313
1               6              8  2021        old                no      2937
2               3              4  2003        new                no      6326
3               8              3  2012        new               yes       632
4               4              2  2011        new               yes      5414
5              10              5  2018        old               yes      8871
6               6              9  2009        new               yes      4878
7               3              9  2011        new               yes      3054
```

| | | | | | | |
|---|---|---|---|---|---|---|
| 8 | 3 | 7 | 2000 | old | no | 7507 |
| 9 | 7 | 9 | 1994 | old | no | 615 |
| 10 | 2 | 9 | 2008 | new | no | 2860 |
| 11 | 8 | 10 | 2000 | old | no | 6629 |
| 12 | 6 | 2 | 2001 | old | no | 7473 |
| 13 | 7 | 7 | 2000 | new | no | 3573 |
| 14 | 5 | 8 | 2016 | new | no | 8150 |
| 15 | 9 | 2 | 2021 | old | no | 1559 |
| 16 | 6 | 9 | 2021 | old | no | 5075 |
| 17 | 10 | 5 | 2020 | new | no | 5278 |
| 18 | 4 | 6 | 1992 | old | yes | 4480 |
| 19 | 3 | 7 | 2021 | old | no | 231 |

| | attic | garage | hasstorageroom | hasguestroom | price | category |
|---|---|---|---|---|---|---|
| 0 | 9005 | 956 | no | 7 | 7559081.5 | Luxury |
| 1 | 8852 | 135 | yes | 9 | 5574642.1 | Middle |
| 2 | 4748 | 654 | no | 10 | 8696869.3 | Luxury |
| 3 | 5792 | 807 | yes | 5 | 5154055.2 | Middle |
| 4 | 1172 | 716 | yes | 9 | 9652258.1 | Luxury |
| 5 | 7117 | 240 | no | 7 | 7986665.8 | Luxury |
| 6 | 281 | 384 | yes | 5 | 7607322.9 | Luxury |
| 7 | 129 | 726 | no | 9 | 6420823.1 | Middle |
| 8 | 9056 | 892 | yes | 1 | 9244344.0 | Luxury |
| 9 | 1221 | 328 | no | 10 | 9515440.4 | Luxury |
| 10 | 3129 | 982 | no | 1 | 7653300.8 | Luxury |
| 11 | 435 | 512 | no | 7 | 8711426.0 | Luxury |
| 12 | 796 | 237 | yes | 3 | 6677649.1 | Middle |
| 13 | 9556 | 918 | yes | 8 | 8460604.0 | Luxury |
| 14 | 6037 | 930 | no | 7 | 7614076.6 | Luxury |
| 15 | 5111 | 957 | yes | 2 | 9272740.1 | Luxury |
| 16 | 3104 | 864 | no | 4 | 5984462.1 | Middle |
| 17 | 1059 | 313 | yes | 6 | 5492532.0 | Middle |
| 18 | 6919 | 680 | yes | 1 | 7005572.2 | Luxury |
| 19 | 1939 | 223 | no | 8 | 5446398.1 | Middle |

[5]:
```
df_prt2 = df_prt.drop('price' ,axis=1)
df_prt2.head(50)
```

[5]:

| | squaremeters | numberofrooms | hasyard | haspool | floors | citycode | \ |
|---|---|---|---|---|---|---|---|
| 0 | 75523 | 3 | no | yes | 63 | 9373 | |
| 1 | 55712 | 58 | no | yes | 19 | 34457 | |
| 2 | 86929 | 100 | yes | no | 11 | 98155 | |
| 3 | 51522 | 3 | no | no | 61 | 9047 | |
| 4 | 96470 | 74 | yes | no | 21 | 92029 | |
| 5 | 79770 | 3 | no | yes | 69 | 54812 | |
| 6 | 75985 | 60 | yes | no | 67 | 6517 | |
| 7 | 64169 | 88 | no | yes | 6 | 61711 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 8 | 92383 | 12 | no | no | 78 | 71982 |
| 9 | 95121 | 46 | no | yes | 3 | 9382 |
| 10 | 76485 | 47 | yes | no | 9 | 90254 |
| 11 | 87060 | 27 | no | yes | 91 | 51803 |
| 12 | 66683 | 19 | yes | yes | 6 | 50801 |
| 13 | 84559 | 29 | no | yes | 69 | 53057 |
| 14 | 76091 | 38 | yes | no | 32 | 59451 |
| 15 | 92696 | 49 | yes | no | 38 | 74381 |
| 16 | 59800 | 47 | no | yes | 27 | 44815 |
| 17 | 54836 | 25 | no | yes | 53 | 64601 |
| 18 | 70021 | 52 | yes | no | 28 | 95678 |
| 19 | 54368 | 11 | yes | yes | 20 | 55761 |
| 20 | 63053 | 6 | yes | yes | 28 | 45312 |
| 21 | 64393 | 8 | no | no | 51 | 95335 |
| 22 | 93876 | 60 | no | yes | 70 | 5484 |
| 23 | 84016 | 15 | yes | no | 55 | 63595 |
| 24 | 89768 | 48 | yes | yes | 17 | 71000 |
| 25 | 58478 | 5 | no | yes | 35 | 5898 |
| 26 | 66621 | 48 | no | no | 89 | 52165 |
| 27 | 73314 | 43 | no | yes | 38 | 49895 |
| 28 | 59972 | 28 | no | yes | 18 | 32083 |
| 29 | 71591 | 20 | yes | no | 58 | 46834 |
| 30 | 67311 | 67 | no | no | 10 | 45626 |
| 31 | 61534 | 73 | yes | no | 97 | 22943 |
| 32 | 84091 | 50 | no | yes | 72 | 22718 |
| 33 | 51434 | 64 | no | no | 23 | 79754 |
| 34 | 78960 | 55 | no | yes | 76 | 23408 |
| 35 | 81870 | 60 | no | yes | 100 | 58048 |
| 36 | 91559 | 36 | no | yes | 21 | 82521 |
| 37 | 72098 | 9 | no | yes | 67 | 91168 |
| 38 | 55232 | 23 | no | no | 8 | 849 |
| 39 | 53735 | 49 | no | yes | 92 | 2423 |
| 40 | 71397 | 71 | no | no | 93 | 68199 |
| 41 | 65151 | 81 | yes | yes | 3 | 66191 |
| 42 | 61484 | 91 | yes | no | 94 | 87015 |
| 43 | 57160 | 15 | yes | yes | 43 | 40786 |
| 44 | 55933 | 15 | no | no | 97 | 5800 |
| 45 | 81936 | 68 | no | no | 92 | 6143 |
| 46 | 99683 | 12 | yes | no | 77 | 18300 |
| 47 | 62887 | 45 | no | yes | 7 | 91125 |
| 48 | 73062 | 34 | yes | yes | 38 | 44770 |
| 49 | 84284 | 76 | no | no | 39 | 55723 |

| | citypartrange | numprevowners | made | isnewbuilt | hasstormprotector | basement | \ |
|---|---|---|---|---|---|---|---|
| 0 | 3 | 8 | 2005 | old | yes | 4313 | |
| 1 | 6 | 8 | 2021 | old | no | 2937 | |
| 2 | 3 | 4 | 2003 | new | no | 6326 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | 8 | 3 | 2012 | new | yes | 632 |
| 4 | 4 | 2 | 2011 | new | yes | 5414 |
| 5 | 10 | 5 | 2018 | old | yes | 8871 |
| 6 | 6 | 9 | 2009 | new | yes | 4878 |
| 7 | 3 | 9 | 2011 | new | yes | 3054 |
| 8 | 3 | 7 | 2000 | old | no | 7507 |
| 9 | 7 | 9 | 1994 | old | no | 615 |
| 10 | 2 | 9 | 2008 | new | no | 2860 |
| 11 | 8 | 10 | 2000 | old | no | 6629 |
| 12 | 6 | 2 | 2001 | old | no | 7473 |
| 13 | 7 | 7 | 2000 | new | no | 3573 |
| 14 | 5 | 8 | 2016 | new | no | 8150 |
| 15 | 9 | 2 | 2021 | old | no | 1559 |
| 16 | 6 | 9 | 2021 | old | no | 5075 |
| 17 | 10 | 5 | 2020 | new | no | 5278 |
| 18 | 4 | 6 | 1992 | old | yes | 4480 |
| 19 | 3 | 7 | 2021 | old | no | 231 |
| 20 | 3 | 1 | 1997 | old | yes | 8414 |
| 21 | 4 | 1 | 1990 | new | no | 3835 |
| 22 | 2 | 1 | 1999 | new | yes | 4086 |
| 23 | 1 | 7 | 2016 | new | no | 3284 |
| 24 | 6 | 9 | 1993 | old | yes | 2485 |
| 25 | 6 | 10 | 2016 | old | no | 8366 |
| 26 | 10 | 1 | 1995 | new | yes | 5024 |
| 27 | 10 | 1 | 2018 | old | yes | 3281 |
| 28 | 9 | 8 | 2021 | new | yes | 8384 |
| 29 | 7 | 4 | 1998 | old | no | 6486 |
| 30 | 3 | 3 | 1990 | new | yes | 6928 |
| 31 | 9 | 5 | 2001 | old | no | 9265 |
| 32 | 7 | 5 | 1993 | old | no | 2668 |
| 33 | 10 | 2 | 2012 | new | yes | 2080 |
| 34 | 8 | 4 | 2015 | new | yes | 7126 |
| 35 | 3 | 8 | 2020 | old | no | 3632 |
| 36 | 6 | 2 | 2007 | old | yes | 788 |
| 37 | 2 | 3 | 2014 | new | no | 9080 |
| 38 | 8 | 3 | 1991 | old | no | 1492 |
| 39 | 4 | 7 | 2006 | old | no | 8654 |
| 40 | 3 | 10 | 1995 | new | yes | 3477 |
| 41 | 7 | 9 | 1991 | old | no | 3218 |
| 42 | 8 | 8 | 2013 | new | no | 5486 |
| 43 | 8 | 8 | 2002 | old | no | 4018 |
| 44 | 9 | 8 | 2001 | new | yes | 7369 |
| 45 | 3 | 1 | 2011 | new | no | 6393 |
| 46 | 5 | 8 | 2002 | old | yes | 4034 |
| 47 | 4 | 3 | 1993 | new | no | 292 |
| 48 | 4 | 8 | 2016 | old | no | 9823 |
| 49 | 5 | 1 | 1998 | old | no | 4500 |

| | attic | garage | hasstorageroom | hasguestroom | category |
|---|---|---|---|---|---|
| 0 | 9005 | 956 | no | 7 | Luxury |
| 1 | 8852 | 135 | yes | 9 | Middle |
| 2 | 4748 | 654 | no | 10 | Luxury |
| 3 | 5792 | 807 | yes | 5 | Middle |
| 4 | 1172 | 716 | yes | 9 | Luxury |
| 5 | 7117 | 240 | no | 7 | Luxury |
| 6 | 281 | 384 | yes | 5 | Luxury |
| 7 | 129 | 726 | no | 9 | Middle |
| 8 | 9056 | 892 | yes | 1 | Luxury |
| 9 | 1221 | 328 | no | 10 | Luxury |
| 10 | 3129 | 982 | no | 1 | Luxury |
| 11 | 435 | 512 | no | 7 | Luxury |
| 12 | 796 | 237 | yes | 3 | Middle |
| 13 | 9556 | 918 | yes | 8 | Luxury |
| 14 | 6037 | 930 | no | 7 | Luxury |
| 15 | 5111 | 957 | yes | 2 | Luxury |
| 16 | 3104 | 864 | no | 4 | Middle |
| 17 | 1059 | 313 | yes | 6 | Middle |
| 18 | 6919 | 680 | yes | 1 | Luxury |
| 19 | 1939 | 223 | no | 8 | Middle |
| 20 | 6270 | 939 | yes | 8 | Middle |
| 21 | 2403 | 559 | no | 6 | Middle |
| 22 | 5991 | 494 | yes | 8 | Luxury |
| 23 | 9879 | 641 | no | 2 | Luxury |
| 24 | 108 | 864 | no | 7 | Luxury |
| 25 | 4799 | 979 | yes | 7 | Middle |
| 26 | 8103 | 388 | yes | 4 | Middle |
| 27 | 5020 | 968 | no | 8 | Luxury |
| 28 | 7226 | 226 | yes | 4 | Middle |
| 29 | 3310 | 366 | no | 0 | Luxury |
| 30 | 7808 | 774 | yes | 5 | Middle |
| 31 | 8974 | 755 | yes | 6 | Middle |
| 32 | 4669 | 766 | no | 8 | Luxury |
| 33 | 9575 | 753 | no | 7 | Middle |
| 34 | 5012 | 974 | yes | 0 | Luxury |
| 35 | 5960 | 723 | yes | 3 | Luxury |
| 36 | 4788 | 132 | yes | 8 | Luxury |
| 37 | 9356 | 740 | yes | 9 | Luxury |
| 38 | 5697 | 625 | no | 6 | Middle |
| 39 | 9588 | 290 | yes | 8 | Middle |
| 40 | 5530 | 342 | no | 2 | Luxury |
| 41 | 9119 | 849 | no | 4 | Middle |
| 42 | 3641 | 766 | no | 3 | Middle |
| 43 | 4871 | 836 | yes | 2 | Middle |
| 44 | 6739 | 686 | yes | 6 | Middle |

```
45    9082      734             no              0    Luxury
46    2877      787            yes              6    Luxury
47     744      675             no              4    Middle
48    7174      728            yes              0    Luxury
49    4877      480             no              6    Luxury
```

[6]:
```
df_prt2['category'].value_counts()
```

[6]:
```
category
Basic     4344
Luxury    3065
Middle    2591
Name: count, dtype: int64
```

[7]:
```
print("data null\n", df_prt2.isnull().sum())
print("\ndata kosong\n", df_prt2.empty)
print("\ndata nan\n", df_prt2.isna().sum)
```

```
data null
 squaremeters         0
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
category             0
dtype: int64

data kosong
 False

data nan
 <bound method DataFrame.sum of       squaremeters  numberofrooms  hasyard
haspool  floors  citycode  \
0            False          False    False    False   False     False
1            False          False    False    False   False     False
2            False          False    False    False   False     False
```

```
3             False           False    False    False    False      False
4             False           False    False    False    False      False
…             …            …      …      …      …      …
9995          False           False    False    False    False      False
9996          False           False    False    False    False      False
9997          False           False    False    False    False      False
9998          False           False    False    False    False      False
9999          False           False    False    False    False      False

      citypartrange  numprevowners   made  isnewbuilt  hasstormprotector  \
0             False           False  False       False              False
1             False           False  False       False              False
2             False           False  False       False              False
3             False           False  False       False              False
4             False           False  False       False              False
…             …            …    …        …                …
9995          False           False  False       False              False
9996          False           False  False       False              False
9997          False           False  False       False              False
9998          False           False  False       False              False
9999          False           False  False       False              False

      basement  attic  garage  hasstorageroom  hasguestroom  category
0        False  False   False           False         False     False
1        False  False   False           False         False     False
2        False  False   False           False         False     False
3        False  False   False           False         False     False
4        False  False   False           False         False     False
…        …    …     …             …            …         …
9995     False  False   False           False         False     False
9996     False  False   False           False         False     False
9997     False  False   False           False         False     False
9998     False  False   False           False         False     False
9999     False  False   False           False         False     False

[10000 rows x 17 columns]>
```

[8]:

```
print("Sebelum Pengecekan data duplikat, ", df_prt2.shape)
df_prt3 = df_prt2.drop_duplicates(keep='last')
print("Sebelum Pengecekan data duplikat, ", df_prt3.shape)
```

```
Sebelum Pengecekan data duplikat,  (10000, 17)
Sebelum Pengecekan data duplikat,  (10000, 17)
```

[9]:

```
from sklearn.model_selection import train_test_split
x = df_prt3.drop(columns=['category'],axis=1)
y = y=df_prt3['category']
```

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.
 ↪25,random_state=71)

print(x_train.shape)
print(x_test.shape)
```

```
(7500, 16)
(2500, 16)
```

[10]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer

kolom_kategori=['hasyard','haspool','isnewbuilt','hasstormprotector','hasstorageroom']


transform = make_column_transformer(
    (OneHotEncoder(),kolom_kategori),remainder='passthrough'
)

x_train_enc=transform.fit_transform(x_train)

x_test_enc=transform.fit_transform(x_test)

df_train_enc=pd.DataFrame(x_train_enc,columns=transform.get_feature_names_out())
df_test_enc=pd.DataFrame(x_test_enc,columns=transform.get_feature_names_out())

df_train_enc.head(20)
df_train_enc.head(20)
```

[10]:
```
    onehotencoder__hasyard_no  onehotencoder__hasyard_yes  \
0                         0.0                         1.0
1                         0.0                         1.0
2                         0.0                         1.0
3                         0.0                         1.0
4                         1.0                         0.0
5                         0.0                         1.0
6                         0.0                         1.0
7                         0.0                         1.0
8                         0.0                         1.0
9                         0.0                         1.0
10                        1.0                         0.0
11                        1.0                         0.0
12                        0.0                         1.0
13                        1.0                         0.0
14                        0.0                         1.0
15                        1.0                         0.0
```

```
16                      1.0                        0.0
17                      1.0                        0.0
18                      0.0                        1.0
19                      0.0                        1.0

    onehotencoder__haspool_no  onehotencoder__haspool_yes  \
0                         1.0                         0.0
1                         1.0                         0.0
2                         0.0                         1.0
3                         1.0                         0.0
4                         0.0                         1.0
5                         1.0                         0.0
6                         0.0                         1.0
7                         1.0                         0.0
8                         1.0                         0.0
9                         0.0                         1.0
10                        0.0                         1.0
11                        1.0                         0.0
12                        0.0                         1.0
13                        1.0                         0.0
14                        0.0                         1.0
15                        0.0                         1.0
16                        1.0                         0.0
17                        0.0                         1.0
18                        1.0                         0.0
19                        0.0                         1.0

    onehotencoder__isnewbuilt_new  onehotencoder__isnewbuilt_old  \
0                             0.0                            1.0
1                             1.0                            0.0
2                             0.0                            1.0
3                             0.0                            1.0
4                             1.0                            0.0
5                             0.0                            1.0
6                             1.0                            0.0
7                             1.0                            0.0
8                             0.0                            1.0
9                             0.0                            1.0
10                            0.0                            1.0
11                            0.0                            1.0
12                            1.0                            0.0
13                            0.0                            1.0
14                            0.0                            1.0
15                            1.0                            0.0
16                            1.0                            0.0
17                            1.0                            0.0
18                            0.0                            1.0
```

```
19                           1.0                           0.0

    onehotencoder__hasstormprotector_no  onehotencoder__hasstormprotector_yes  \
0                                   1.0                                   0.0
1                                   0.0                                   1.0
2                                   1.0                                   0.0
3                                   0.0                                   1.0
4                                   1.0                                   0.0
5                                   0.0                                   1.0
6                                   0.0                                   1.0
7                                   1.0                                   0.0
8                                   0.0                                   1.0
9                                   1.0                                   0.0
10                                  0.0                                   1.0
11                                  1.0                                   0.0
12                                  1.0                                   0.0
13                                  1.0                                   0.0
14                                  1.0                                   0.0
15                                  0.0                                   1.0
16                                  1.0                                   0.0
17                                  0.0                                   1.0
18                                  0.0                                   1.0
19                                  0.0                                   1.0

    onehotencoder__hasstorageroom_no  onehotencoder__hasstorageroom_yes  …  \
0                                1.0                                0.0  …
1                                1.0                                0.0  …
2                                1.0                                0.0  …
3                                0.0                                1.0  …
4                                0.0                                1.0  …
5                                1.0                                0.0  …
6                                0.0                                1.0  …
7                                1.0                                0.0  …
8                                0.0                                1.0  …
9                                0.0                                1.0  …
10                               1.0                                0.0  …
11                               0.0                                1.0  …
12                               1.0                                0.0  …
13                               0.0                                1.0  …
14                               0.0                                1.0  …
15                               1.0                                0.0  …
16                               0.0                                1.0  …
17                               0.0                                1.0  …
18                               1.0                                0.0  …
19                               1.0                                0.0  …

    remainder__numberofrooms  remainder__floors  remainder__citycode  \
```

```
0                        93.0                 98.0                 68872.0
1                        97.0                 20.0                 93104.0
2                        86.0                 27.0                 61694.0
3                        10.0                 94.0                 15304.0
4                        98.0                 63.0                  1173.0
5                        46.0                 19.0                 14625.0
6                        47.0                 23.0                 80519.0
7                        82.0                 21.0                 62528.0
8                        92.0                 73.0                 39608.0
9                        55.0                 76.0                 67738.0
10                       40.0                 24.0                 31204.0
11                       87.0                 32.0                 99233.0
12                        5.0                 35.0                 18130.0
13                       56.0                100.0                 93052.0
14                       91.0                 12.0                 93863.0
15                       11.0                 83.0                 37564.0
16                       89.0                 21.0                  2882.0
17                        4.0                  7.0                 36027.0
18                       41.0                  1.0                 85611.0
19                       44.0                 89.0                  2587.0

    remainder__citypartrange  remainder__numprevowners  remainder__made  \
0                        6.0                      10.0           2009.0
1                        9.0                       3.0           1993.0
2                       10.0                       9.0           1995.0
3                       10.0                       8.0           2005.0
4                        8.0                       8.0           2016.0
5                       10.0                       4.0           2021.0
6                        6.0                       2.0           2013.0
7                        7.0                       6.0           1995.0
8                        6.0                       7.0           2000.0
9                        3.0                       4.0           2011.0
10                       3.0                       4.0           2004.0
11                       2.0                       6.0           2013.0
12                       1.0                       3.0           1990.0
13                       3.0                       4.0           2012.0
14                       6.0                       4.0           2015.0
15                       1.0                       9.0           1998.0
16                       3.0                       7.0           2012.0
17                      10.0                       7.0           1991.0
18                       4.0                       6.0           1994.0
19                       5.0                       3.0           2021.0

    remainder__basement  remainder__attic  remainder__garage  \
0                1016.0            2441.0              792.0
1                6768.0            7803.0              901.0
2                1588.0            2201.0              789.0
```

```
3            4171.0         4794.0          574.0
4            2287.0         8181.0          426.0
5            9802.0         4844.0          984.0
6            2975.0         5534.0          900.0
7            5336.0         8216.0          634.0
8            4147.0         7554.0          606.0
9            5746.0         3337.0          220.0
10           3190.0         4409.0          337.0
11           3694.0         7923.0          317.0
12            999.0         2259.0          974.0
13           6358.0         7861.0          304.0
14           6751.0         7894.0          158.0
15           6004.0         4723.0          803.0
16           1540.0         5378.0          318.0
17           5623.0         2451.0          394.0
18           7386.0         7266.0          805.0
19           5328.0         7061.0          826.0

    remainder__hasguestroom
0                       7.0
1                       2.0
2                       0.0
3                      10.0
4                       6.0
5                       9.0
6                       2.0
7                       0.0
8                       3.0
9                       8.0
10                      4.0
11                      1.0
12                      0.0
13                      3.0
14                      4.0
15                      5.0
16                      5.0
17                      0.0
18                      9.0
19                      2.0

[20 rows x 21 columns]
```

[11]:

```python
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectPercentile, SelectKBest
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.pipeline import Pipeline
```

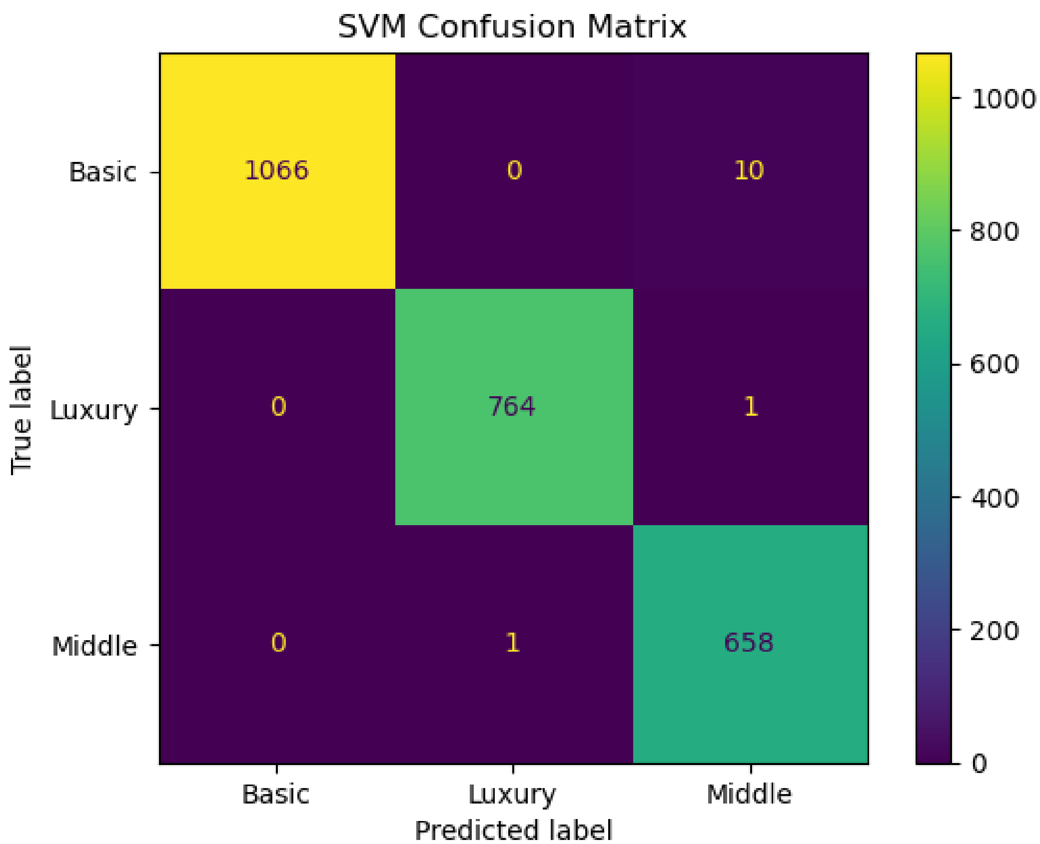
```python
from sklearn.metrics import classification_report, confusion_matrix,␣
↪ConfusionMatrixDisplay

pipe_svm = Pipeline(steps=[
    ('scale', MinMaxScaler()),
    ('feat_select', SelectKBest()),
    ('clf', SVC(class_weight='balanced')),
])

params_grid_svm = [
    {
    'scale': [MinMaxScaler()],
    'feat_select__k':np.arange(2,6),
    'clf__kernel': ['poly','rbf'],
    'clf__C':[0.1, 1],
    'clf__gamma':[0.1, 1]

    },
    {
        'scale': [MinMaxScaler()],
        'feat_select':[SelectPercentile()],
        'feat_select__percentile':np.arange(20,50),
        'clf__kernel':['poly','rbf'],
         'clf__C':[0.1, 1],
    'clf__gamma':[0.1, 1]
    },
    {
    'scale': [StandardScaler()],
    'feat_select__k':np.arange(2,6),
    'clf__kernel':['poly','rbf'],
     'clf__C':[0.1, 1],
    'clf__gamma':[0.1, 1]
    },
    {
        'scale': [StandardScaler()],
        'feat_select':[SelectPercentile()],
        'feat_select__percentile':np.arange(20,50),
        'clf__kernel':['poly','rbf'],
         'clf__C':[0.1, 1],
    'clf__gamma':[0.1, 1]
    }
]

estimator_svm = Pipeline(pipe_svm)

SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=71)
```

```
GSCV_SVM = GridSearchCV(pipe_svm, params_grid_svm, cv=SKF)

GSCV_SVM.fit(x_train_enc, y_train)
print("GSCV training finished")
```

```
GSCV training finished
```

[12]:
```
print("CV Score : {}".format(GSCV_SVM.best_score_))

print("Test Score: {}".format(GSCV_SVM.best_estimator_.
 ↪score(x_test_enc,y_test)))

print("Best Model: {}", GSCV_SVM.best_estimator_)
mask = GSCV_SVM.best_estimator_.named_steps['feat_select'].get_support()
print("Best features:", df_train_enc.columns[mask])

SVM_pred = GSCV_SVM.predict(x_test_enc)

import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, SVM_pred, labels=GSCV_SVM.classes_)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=GSCV_SVM.
 ↪classes_)
disp.plot()
plt.title("SVM Confusion Matrix")
plt.show()

print("Classification report SVM: \n", classification_report(y_test, SVM_pred))
```

```
CV Score : 0.9942666666666666
Test Score: 0.9952
Best Model: {} Pipeline(steps=[('scale', StandardScaler()),
                ('feat_select', SelectPercentile(percentile=31)),
                ('clf',
                 SVC(C=1, class_weight='balanced', gamma=1, kernel='poly'))])
Best features: Index(['onehotencoder__hasyard_no', 'onehotencoder__hasyard_yes',
       'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
       'onehotencoder__isnewbuilt_new', 'onehotencoder__isnewbuilt_old',
       'remainder__squaremeters'],
      dtype='object')
```




```
Classification report SVM:
              precision    recall  f1-score   support

       Basic       1.00      0.99      1.00      1076
      Luxury       1.00      1.00      1.00       765
      Middle       0.98      1.00      0.99       659

    accuracy                           1.00      2500
   macro avg       0.99      1.00      0.99      2500
weighted avg       1.00      1.00      1.00      2500
```

[13]:

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.tree import DecisionTreeClassifier

pipe_GBT= Pipeline(steps = [
         ('feat_select', SelectKBest()),
         ('clf', GradientBoostingClassifier(random_state=71))])
```

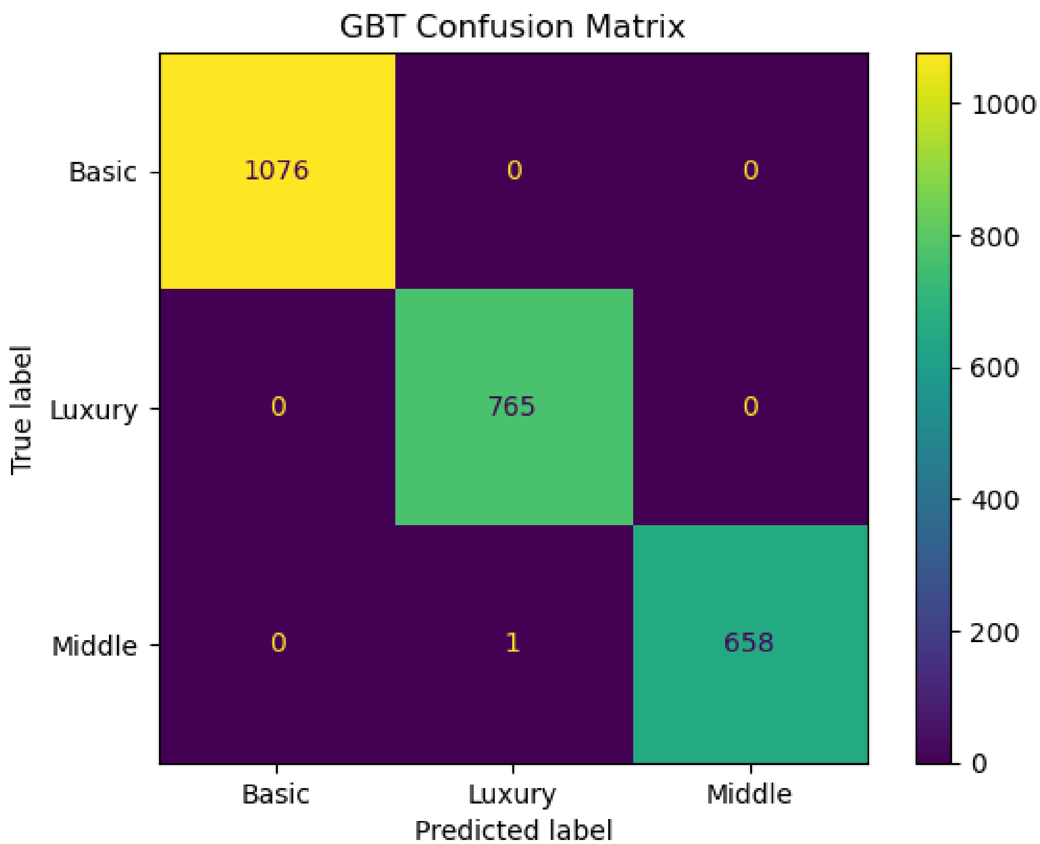
```
params_grid_GBT = [
    {
        'feat_select__k': np.arange(2,6),
     'clf__max_depth': [*np.arange(4, 5)],
     'clf__n_estimators': [100, 150],
     'clf__learning_rate': [0.01,0.1,1]
    },
    {
        'feat_select': [SelectPercentile()],
        'feat_select__percentile': np.arange(20, 50),
         'clf__max_depth': [*np.arange(4, 5)],
         'clf__n_estimators': [100, 150],
        'clf__learning_rate': [0.01,0.1,1]

    },
    {
        'feat_select__k': np.arange(2,6),
     'clf__max_depth': [*np.arange(4, 5)],
     'clf__n_estimators': [100, 150],
     'clf__learning_rate': [0.01,0.1,1]
    },
    {
        'feat_select': [SelectPercentile()],
        'feat_select__percentile': np.arange(20, 50),
         'clf__max_depth': [*np.arange(4, 5)],
         'clf__n_estimators': [100, 150],
        'clf__learning_rate': [0.01,0.1,1]
    }
]

GSCV_GBT = GridSearchCV(pipe_GBT,␣
 ↪params_grid_GBT,cv=StratifiedKFold(n_splits=5))
GSCV_GBT.fit(x_train_enc, y_train)
print("GSCV training finished")
```

```
GSCV training finished
```

[14]:
```
print("CV Score : {}".format(GSCV_GBT.best_score_))

print("Test Score: {}".format(GSCV_GBT.best_estimator_.
 ↪score(x_test_enc,y_test)))

print("Best Model: {}", GSCV_GBT.best_estimator_)

mask = GSCV_SVM.best_estimator_.named_steps['feat_select'].get_support()
print("Best features:", df_train_enc.columns[mask])
```

```
GBT_pred = GSCV_GBT.predict(x_test_enc)

import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, GBT_pred, labels=GSCV_GBT.classes_)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=GSCV_GBT.
 ↪classes_)
disp.plot()

plt.title("GBT Confusion Matrix")
plt.show()

print("Classification report GBT: \n", classification_report(y_test, GBT_pred))
```

```
CV Score : 0.9989333333333335
Test Score: 0.9996
Best Model: {} Pipeline(steps=[('feat_select', SelectPercentile(percentile=31)),
                ('clf',
                 GradientBoostingClassifier(learning_rate=0.01, max_depth=4,
                                            random_state=71))])
Best features: Index(['onehotencoder__hasyard_no', 'onehotencoder__hasyard_yes',
       'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
       'onehotencoder__isnewbuilt_new', 'onehotencoder__isnewbuilt_old',
       'remainder__squaremeters'],
      dtype='object')
```




```
Classification report GBT:
              precision    recall  f1-score   support

       Basic       1.00      1.00      1.00      1076
      Luxury       1.00      1.00      1.00       765
      Middle       1.00      1.00      1.00       659

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```

[15]:

```
import pickle
with open('klasifikasi_model.pkl', 'wb') as r:
    pickle.dump((GSCV_GBT),r)

print("Model GBT Disimpan")
```

```
Model GBT Disimpan
```

**Kode Ridge Regression VS Support Vector Regressor**
**I Made Ivan**

[84]:
```
import pandas as  pd
import numpy as np

df_prt=pd.read_csv(r'D:\SEMESTER 5\Machine Learning\TESTUTS\Dataset UTS_Gasal␣
↪2425.csv')
df_prt.head()
```

[84]:
```
   squaremeters  numberofrooms hasyard haspool  floors  citycode  \
0         75523              3      no     yes      63      9373
1         55712             58      no     yes      19     34457
2         86929            100     yes      no      11     98155
3         51522              3      no      no      61      9047
4         96470             74     yes      no      21     92029

   citypartrange  numprevowners  made isnewbuilt hasstormprotector  basement  \
0              3              8  2005        old               yes      4313
1              6              8  2021        old                no      2937
2              3              4  2003        new                no      6326
3              8              3  2012        new               yes       632
4              4              2  2011        new               yes      5414

   attic  garage hasstorageroom  hasguestroom      price category
0   9005     956             no             7  7559081.5   Luxury
1   8852     135            yes             9  5574642.1   Middle
2   4748     654             no            10  8696869.3   Luxury
3   5792     807            yes             5  5154055.2   Middle
4   1172     716            yes             9  9652258.1   Luxury
```

[85]:
```
df_prt2=df_prt.drop(['category'],axis=1)
df_prt2.head()
```

[85]:
```
   squaremeters  numberofrooms hasyard haspool  floors  citycode  \
0         75523              3      no     yes      63      9373
1         55712             58      no     yes      19     34457
2         86929            100     yes      no      11     98155
3         51522              3      no      no      61      9047
4         96470             74     yes      no      21     92029
```

```
   citypartrange  numprevowners  made isnewbuilt hasstormprotector  basement  \
0              3              8  2005        old               yes      4313
1              6              8  2021        old                no      2937
2              3              4  2003        new                no      6326
3              8              3  2012        new               yes       632
4              4              2  2011        new               yes      5414

   attic  garage hasstorageroom  hasguestroom      price
0   9005     956             no             7  7559081.5
1   8852     135            yes             9  5574642.1
2   4748     654             no            10  8696869.3
3   5792     807            yes             5  5154055.2
4   1172     716            yes             9  9652258.1
```

[86]:
```
df_prt2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   squaremeters       10000 non-null  int64
 1   numberofrooms      10000 non-null  int64
 2   hasyard            10000 non-null  object
 3   haspool            10000 non-null  object
 4   floors             10000 non-null  int64
 5   citycode           10000 non-null  int64
 6   citypartrange      10000 non-null  int64
 7   numprevowners      10000 non-null  int64
 8   made               10000 non-null  int64
 9   isnewbuilt         10000 non-null  object
 10  hasstormprotector  10000 non-null  object
 11  basement           10000 non-null  int64
 12  attic              10000 non-null  int64
 13  garage             10000 non-null  int64
 14  hasstorageroom     10000 non-null  object
 15  hasguestroom       10000 non-null  int64
 16  price              10000 non-null  float64
dtypes: float64(1), int64(11), object(5)
memory usage: 1.3+ MB
```

[87]:
```
df_prt.describe()
```

[87]:
```
        squaremeters  numberofrooms        floors      citycode  citypartrange  \
count    10000.00000   10000.000000  10000.000000  10000.000000   10000.000000
mean     49870.13120      50.358400     50.276300  50225.486100       5.510100
```

```
std     28774.37535      28.816696      28.889171  29006.675799        2.872024
min        89.00000       1.000000       1.000000      3.000000        1.000000
25%     25098.50000      25.000000      25.000000  24693.750000        3.000000
50%     50105.50000      50.000000      50.000000  50693.000000        5.000000
75%     74609.75000      75.000000      76.000000  75683.250000        8.000000
max     99999.00000     100.000000     100.000000  99953.000000       10.000000

       numprevowners          made      basement         attic       garage  \
count   10000.000000   10000.00000  10000.000000   10000.00000  10000.00000
mean        5.521700    2005.48850   5033.103900    5028.01060    553.12120
std         2.856667       9.30809   2876.729545    2894.33221    262.05017
min         1.000000    1990.00000      0.000000       1.00000    100.00000
25%         3.000000    1997.00000   2559.750000    2512.00000    327.75000
50%         5.000000    2005.50000   5092.500000    5045.00000    554.00000
75%         8.000000    2014.00000   7511.250000    7540.50000    777.25000
max        10.000000    2021.00000  10000.000000   10000.00000   1000.00000

       hasguestroom         price
count   10000.00000  1.000000e+04
mean        4.99460  4.993448e+06
std         3.17641  2.877424e+06
min         0.00000  1.031350e+04
25%         2.00000  2.516402e+06
50%         5.00000  5.016180e+06
75%         8.00000  7.469092e+06
max        10.00000  1.000677e+07
```

[88]:

```python
print(df_prt2['price'].value_counts())
```

```
price
7559081.5    1
2600292.1    1
3804577.4    1
3658559.7    1
2316639.4    1
            ..
5555606.6    1
5501007.5    1
9986201.2    1
9104801.8    1
146708.4     1
Name: count, Length: 10000, dtype: int64
```

[89]:

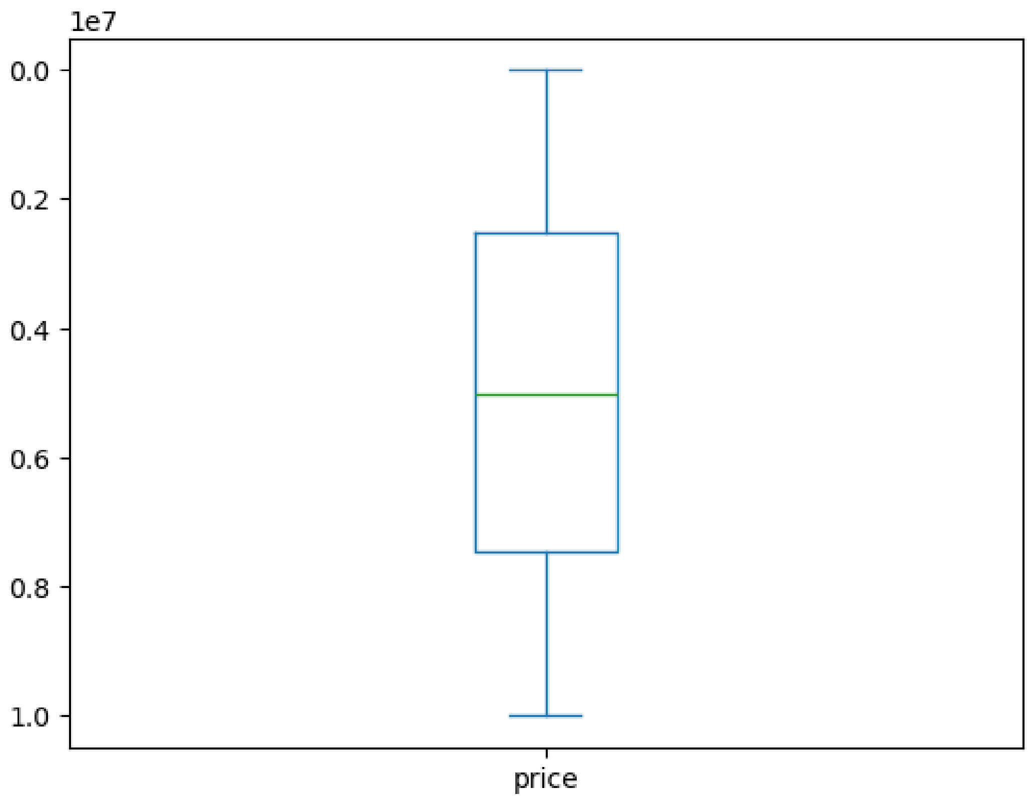
```python
print("data null \n", df_prt2.isnull().sum())
print("data kosong \n", df_prt2.empty)
print("data nan \n",df_prt2.isna().sum())
```

```
data null
```

```
 squaremeters         0
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
price                0
dtype: int64
data kosong
 False
data nan
 squaremeters         0
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
price                0
dtype: int64
```

[90]:
```
import matplotlib.pyplot as plt
df_prt2.price.plot(kind='box')
plt.gca().invert_yaxis()
plt.show
```

[90]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



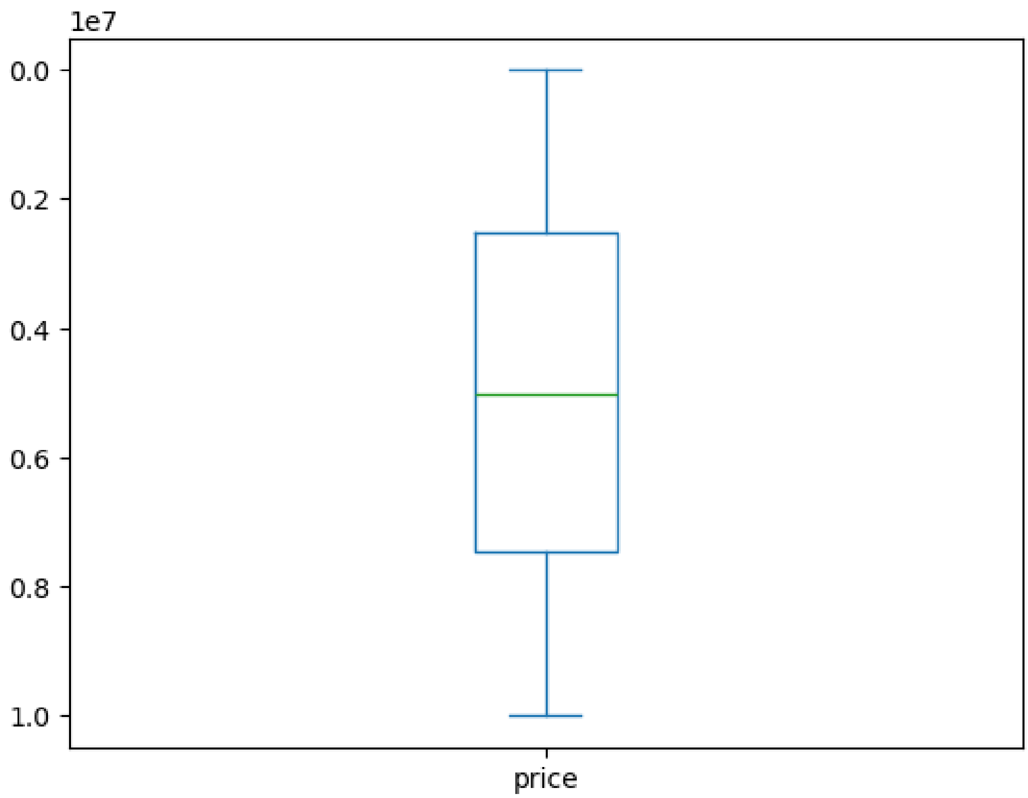

[91]:
```
print("Sebelum Pengecekan data duplikat, ",df_prt2.shape)
df_prt3=df_prt2.drop_duplicates(keep='last')
print("Setelah pengecekan data duplikat, ",df_prt3.shape)
```

```
Sebelum Pengecekan data duplikat,  (10000, 17)
Setelah pengecekan data duplikat,  (10000, 17)
```

[92]:
```
from pandas.api.types import is_numeric_dtype
def remove_outlier(df_in):
    for col_name in list(df_in.columns):
        if is_numeric_dtype(df_in[col_name]):
            q1 = df_in[col_name].quantile(0.25)
            q3 = df_in[col_name].quantile(0.75)

            iqr = q3-q1
            batas_atas = q3+(1.5*iqr)
            batas_bawah = q1-(1.5*iqr)

            df_out= df_in.loc[(df_in[col_name]>=batas_bawah)&(df_in[col_name]<=␣
 ↪batas_atas)]
    return df_out
```

```
df_prt_clean= remove_outlier(df_prt3)
print("Jumlah baris DataFrame sebelum dibuang outlier", df_prt3.shape[0])
print("jumlah baris DataFrame sesudah dibuang outlier", df_prt_clean.shape[0])
df_prt_clean.price.plot(kind='box', vert=True)

plt.gca().invert_yaxis()
plt.show()
```

```
Jumlah baris DataFrame sebelum dibuang outlier 10000
jumlah baris DataFrame sesudah dibuang outlier 10000
```




[93]:
```
from sklearn.model_selection import train_test_split
x=df_prt_clean.drop('price', axis =1)
y=y=df_prt_clean['price']
x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.30,␣
↪random_state=71)
print(x_train.shape)
print(x_test.shape)
```

```
(7000, 16)
(3000, 16)
```

[94]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer

kolom_kategori=['hasyard','haspool','isnewbuilt','hasstormprotector','hasstorageroom']


transform = make_column_transformer(
    (OneHotEncoder(),kolom_kategori),remainder='passthrough'
)

x_train_enc=transform.fit_transform(x_train)

x_test_enc=transform.fit_transform(x_test)

df_train_enc=pd.DataFrame(x_train_enc,columns=transform.get_feature_names_out())
df_test_enc=pd.DataFrame(x_test_enc,columns=transform.get_feature_names_out())

df_train_enc.head()
df_test_enc.head()
```

[94]:
```
   onehotencoder__hasyard_no  onehotencoder__hasyard_yes  \
0                        1.0                         0.0
1                        0.0                         1.0
2                        0.0                         1.0
3                        1.0                         0.0
4                        0.0                         1.0

   onehotencoder__haspool_no  onehotencoder__haspool_yes  \
0                        0.0                         1.0
1                        0.0                         1.0
2                        0.0                         1.0
3                        1.0                         0.0
4                        1.0                         0.0

   onehotencoder__isnewbuilt_new  onehotencoder__isnewbuilt_old  \
0                            0.0                            1.0
1                            0.0                            1.0
2                            0.0                            1.0
3                            0.0                            1.0
4                            1.0                            0.0

   onehotencoder__hasstormprotector_no  onehotencoder__hasstormprotector_yes  \
0                                  0.0                                   1.0
1                                  0.0                                   1.0
2                                  1.0                                   0.0
3                                  1.0                                   0.0
4                                  0.0                                   1.0
```

```
   onehotencoder__hasstorageroom_no  onehotencoder__hasstorageroom_yes  …  \
0                               0.0                                1.0  …
1                               0.0                                1.0  …
2                               0.0                                1.0  …
3                               1.0                                0.0  …
4                               0.0                                1.0  …

   remainder__numberofrooms  remainder__floors  remainder__citycode  \
0                      10.0               87.0              41867.0
1                      35.0                2.0              78416.0
2                      28.0               20.0              47125.0
3                      42.0               65.0              70699.0
4                      42.0               76.0              67080.0

   remainder__citypartrange  remainder__numprevowners  remainder__made  \
0                       6.0                      10.0           1997.0
1                       1.0                       6.0           2016.0
2                       1.0                       3.0           2015.0
3                       9.0                       2.0           2010.0
4                       8.0                       2.0           2015.0

   remainder__basement  remainder__attic  remainder__garage  \
0               8945.0            1203.0              142.0
1               3311.0            1636.0              967.0
2               8462.0             890.0              523.0
3               2336.0            8483.0              319.0
4               5678.0            8046.0              135.0

   remainder__hasguestroom
0                     10.0
1                      6.0
2                      7.0
3                      2.0
4                      4.0

[5 rows x 21 columns]
```

[121]:
```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_Ridge = Pipeline(steps= [
```

```
    ('scale', StandardScaler ()),
    ( 'feature_selection' , SelectKBest(score_func=f_regression)),
    ('reg', Ridge())
    ])

param_grid_Ridge = {
    'reg__alpha': [0.01,0.1,1,10, 100],
    'feature_selection__k': np.arange(1,20)
}

GSCV_RR = GridSearchCV(pipe_Ridge, param_grid_Ridge, cv=5,
                        scoring='neg_mean_squared_error', error_score='raise')
GSCV_RR.fit(x_train_enc, y_train)

print("Best model:{}".format(GSCV_RR. best_estimator_))
print("Ridge best parameters:{}".format(GSCV_RR.best_params_))
print("Koefisien/bobot:{}".format(GSCV_RR.best_estimator_.named_steps['reg'].
 ↪coef_))
print("Intercept/bias:{}".format(GSCV_RR.best_estimator_.named_steps['reg'].
 ↪intercept_))

Ridge_predict = GSCV_RR.predict (x_test_enc)
mse_Ridge = mean_squared_error(y_test, Ridge_predict)
mae_Ridge = mean_absolute_error (y_test, Ridge_predict)

print("Ridge Mean Squared Error (MSE): {}".format(mse_Ridge))
print("Ridge Mean Absolute Error (MAE): {}".format(mae_Ridge))
print("Ridge Root Mean Squared Eror: {}".format(np.sqrt(mse_Ridge)))
```

```
Best model:Pipeline(steps=[('scale', StandardScaler()),
                ('feature_selection',
                 SelectKBest(k=15,
                             score_func=<function f_regression at
0x000001D0D3870A40>)),
                ('reg', Ridge(alpha=0.01))])
Ridge best parameters:{'feature_selection__k': 15, 'reg__alpha': 0.01}
Koefisien/bobot:[-7.47070712e+02  7.47070712e+02 -7.44570858e+02  7.44570880e+02
  3.96052910e+01 -3.96053005e+01 -2.43537338e+01  2.43537202e+01
  2.88294485e+06  1.83512203e+01  1.38622056e+02 -1.81546415e+01
 -6.55762786e+00  4.83577972e+01 -5.44061594e+01]
Intercept/bias:4985857.002414286
Ridge Mean Squared Error (MSE): 6160574.544214095
Ridge Mean Absolute Error (MAE): 1980.657218509307
Ridge Root Mean Squared Eror: 2482.0504717297945
```

[122]:
```
df_results= pd.DataFrame(y_test, columns=['price'])
df_results=pd.DataFrame(y_test)
```

```
df_results['Ridge Prediction']=Ridge_predict

df_results['Selisih_price_RR']=df_results['Ridge Prediction']-␣
↪df_results['price']
df_results.head()
```

[122]:

| | price | Ridge Prediction | Selisih_price_RR |
|---|---|---|---|
| 312 | 7694726.7 | 7.696913e+06 | 2185.822744 |
| 7926 | 1611775.6 | 1.610822e+06 | -953.474572 |
| 5782 | 3253846.5 | 3.254829e+06 | 982.001773 |
| 8188 | 2359701.0 | 2.359300e+06 | -401.472867 |
| 795 | 8007425.5 | 8.006832e+06 | -593.390352 |

[123]:
```
df_results.describe()
```

[123]:

| | price | Ridge Prediction | Selisih_price_RR |
|---|---|---|---|
| count | 3.000000e+03 | 3.000000e+03 | 3000.000000 |
| mean | 5.011159e+06 | 5.011128e+06 | -30.666039 |
| std | 2.864485e+06 | 2.864492e+06 | 2482.274770 |
| min | 1.679920e+04 | 1.831542e+04 | -9598.444902 |
| 25% | 2.526030e+06 | 2.526748e+06 | -1537.662663 |
| 50% | 5.077257e+06 | 5.077359e+06 | 434.464843 |
| 75% | 7.480795e+06 | 7.482453e+06 | 1861.156444 |
| max | 1.000294e+07 | 1.000077e+07 | 6464.129853 |

[98]:
```
from sklearn.svm import SVR
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_SVR= Pipeline(steps=[
            ('scale', StandardScaler()),
            ('feature_selection', SelectKBest(score_func=f_regression)),
            ('reg', SVR(kernel= 'linear'))
            ])

param_grid_SVR={
    'reg__C':[0.01, 0.1, 1, 10, 100],
    'reg__epsilon': [0.1,0.2,0.5,1],
    'feature_selection__k':np.arange(1,20)
}
GSCV_SVR= GridSearchCV(pipe_SVR, param_grid_SVR, cv=5,␣
↪scoring='neg_mean_squared_error')
GSCV_SVR.fit(x_train_enc, y_train)
```

```
print("Best model:{}".format(GSCV_SVR.best_estimator_))
print("SVR best parrameter:{}".format(GSCV_SVR.best_params_))
print("koefisien/bobot: {}".format(GSCV_SVR.best_estimator_.named_steps['reg'].
 ↪coef_))
print("Intercept/bias: {}".format(GSCV_SVR.best_estimator_.named_steps['reg'].
 ↪intercept_))
SVR_predict = GSCV_SVR.predict(x_test_enc)
mse_SVR= mean_squared_error(y_test, SVR_predict)
mae_SVR = mean_absolute_error(y_test, SVR_predict)

print("SVR Mean Squared Error (MSE): {}".format(mse_SVR))
print("SVR Mean Absolute Error (MAE): {}".format(mae_SVR))
print("SVR Root Mean Squared Error: {}".format(np.sqrt(mse_SVR)))
```

```
Best model:Pipeline(steps=[('scale', StandardScaler()),
                ('feature_selection',
                 SelectKBest(score_func=<function f_regression at
0x000001D0D3870A40>)),
                ('reg', SVR(C=100, epsilon=1, kernel='linear'))])
SVR best parrameter:{'feature_selection__k': 10, 'reg__C': 100, 'reg__epsilon':
1}
koefisien/bobot: [[  6400.01671843  -6400.01671843 -10200.00041633
10200.00041633
   -4000.14694687   4000.14694687 605098.56123321  15049.56098259
   -4828.01628375  -9910.67321994]]
Intercept/bias: [4973262.08457655]
SVR Mean Squared Error (MSE): 5124644869912.438
SVR Mean Absolute Error (MAE): 1954758.342532865
SVR Root Mean Squared Error: 2263767.848060494
```

[99]:
```
df_results['SVR Prediction']= SVR_predict

df_results=pd.DataFrame(y_test)
df_results['SVR Prediction']=SVR_predict

df_results['Selisih_price_SVR']= df_results['SVR␣
 ↪Prediction']-df_results['price']
df_results.head()
```

[99]:

| | price | SVR Prediction | Selisih_price_SVR |
|---|---|---|---|
| 312 | 7694726.7 | 5.603579e+06 | -2.091148e+06 |
| 7926 | 1611775.6 | 4.272577e+06 | 2.660802e+06 |
| 5782 | 3253846.5 | 4.603777e+06 | 1.349931e+06 |
| 8188 | 2359701.0 | 4.432184e+06 | 2.072483e+06 |
| 795 | 8007425.5 | 5.599749e+06 | -2.407677e+06 |

[100]:
```
df_results.describe()
```

[100]:
```
              price  SVR Prediction  Selisih_price_SVR
count  3.000000e+03    3.000000e+03       3.000000e+03
mean   5.011159e+06    4.979057e+06      -3.210212e+04
std    2.864485e+06    6.016515e+05       2.263918e+06
min    1.679920e+04    3.863237e+06      -4.007492e+06
25%    2.526030e+06    4.455131e+06      -1.977637e+06
50%    5.077257e+06    4.996517e+06      -9.487858e+04
75%    7.480795e+06    5.487022e+06       1.937160e+06
max    1.000294e+07    6.069531e+06       3.958099e+06
```

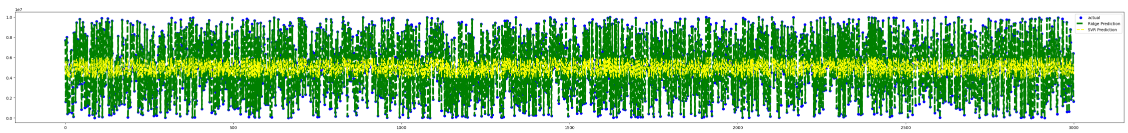
[124]:
```
df_results = pd.DataFrame({'price': y_test})

df_results['Ridge Prediction']=Ridge_predict

df_results['Selisih_IPK_RR'] = df_results['price']-df_results['Ridge␣
↪Prediction']

df_results['SVR Prediction']= SVR_predict
df_results['Selisih_IPK_SVR']= df_results['price']- df_results['SVR Prediction']


df_results.head()
```

[124]:
```
          price  Ridge Prediction  Selisih_IPK_RR  SVR Prediction  \
312   7694726.7      7.696913e+06    -2185.822744    5.603579e+06
7926  1611775.6      1.610822e+06      953.474572    4.272577e+06
5782  3253846.5      3.254829e+06     -982.001773    4.603777e+06
8188  2359701.0      2.359300e+06      401.472867    4.432184e+06
795   8007425.5      8.006832e+06      593.390352    5.599749e+06

      Selisih_IPK_SVR
312      2.091148e+06
7926    -2.660802e+06
5782    -1.349931e+06
8188    -2.072483e+06
795      2.407677e+06
```

[126]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(50,5))

data_len= range(len(y_test))

plt.scatter(data_len, df_results.price, label="actual", color="blue")
```

```
plt.plot(data_len, df_results['Ridge Prediction'], label ="Ridge Prediction",␣
 ↪color="green", linewidth=4,linestyle="dashed")
plt.plot(data_len, df_results['SVR Prediction'], label ="SVR Prediction",␣
 ↪color="yellow", linewidth=2,linestyle="--")

plt.legend()
plt.show
```

[126]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



[129]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np


mae_ridge= mean_absolute_error(df_results['price'], df_results['Ridge␣
 ↪Prediction'])
rmse_ridge= np.sqrt(mean_squared_error(df_results['price'], df_results['Ridge␣
 ↪Prediction']))
ridge_feature_count= GSCV_RR.best_params_['feature_selection__k']


mae_SVR= mean_absolute_error(df_results['price'], df_results['SVR Prediction'])
rmse_SVR= np.sqrt(mean_squared_error(df_results['price'], df_results['SVR␣
 ↪Prediction']))
svr_feature_count= GSCV_SVR.best_params_['feature_selection__k']


print(f"Ridge MAE:{mae_ridge}, Ridge RMSE: {rmse_ridge},Ridge Feature Count :
 ↪{ridge_feature_count}")
print(f"SVR MAE:{mae_SVR}, SVR RMSE: {rmse_SVR}, SVR Feature Count :
 ↪{svr_feature_count}")
```

```
Ridge MAE:1980.657218509307, Ridge RMSE: 2482.0504717297945,Ridge Feature Count
:15
SVR MAE:1954758.342532865, SVR RMSE: 2263767.848060494, SVR Feature Count :10
```

[1]:
```
import pickle
best_model = GSCV_SVR.best_estimator_

with open('BestModel_REG_SVR_Seaborn.pkl','wb') as f:
```

```
    pickle.dump(best_model, f)


print("Model terbaik berhasil disimpan ke 'BestModel_REG_SVR_Seaborn.pkl'")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 2
      1 import pickle
----> 2 best_model = GSCV_SVR.best_estimator_
      4 with open('BestModel_REG_SVR_Seaborn.pkl','wb') as f:
      5     pickle.dump(best_model, f)

NameError: name 'GSCV_SVR' is not defined
```

**Kode Lasso Regression VS Random Forest Regressor**
**Josua**

[31]:
```
import pandas as  pd
import numpy as np

df_prt=pd.read_csv(r'C:\Users\Lenovo\Documents\Kuliah - UAJY\Semester V -␣
 ↪2024-2025\Pembelajaran mesin dan Pembelajaran Mendalam - A\Projek UTS Gasal␣
 ↪20242025-20241018\Dataset UTS_Gasal 2425.csv')
df_prt.head()
```

[31]:
```
   squaremeters  numberofrooms hasyard haspool  floors  citycode  \
0         75523              3      no     yes      63      9373
1         55712             58      no     yes      19     34457
2         86929            100     yes      no      11     98155
3         51522              3      no      no      61      9047
4         96470             74     yes      no      21     92029

   citypartrange  numprevowners  made isnewbuilt hasstormprotector  basement  \
0              3              8  2005        old               yes      4313
1              6              8  2021        old                no      2937
2              3              4  2003        new                no      6326
3              8              3  2012        new               yes       632
4              4              2  2011        new               yes      5414

   attic  garage hasstorageroom  hasguestroom      price category
0   9005     956             no             7  7559081.5   Luxury
1   8852     135            yes             9  5574642.1   Middle
2   4748     654             no            10  8696869.3   Luxury
3   5792     807            yes             5  5154055.2   Middle
4   1172     716            yes             9  9652258.1   Luxury
```

[32]:
```
df_prt2=df_prt.drop(['category'],axis=1)
df_prt2.head()
```

[32]:
```
   squaremeters  numberofrooms hasyard haspool  floors  citycode  \
0         75523              3      no     yes      63      9373
1         55712             58      no     yes      19     34457
2         86929            100     yes      no      11     98155
3         51522              3      no      no      61      9047
```

```
4         96470            74     yes      no       21      92029

   citypartrange  numprevowners  made isnewbuilt hasstormprotector  basement  \
0              3              8  2005        old               yes      4313
1              6              8  2021        old                no      2937
2              3              4  2003        new                no      6326
3              8              3  2012        new               yes       632
4              4              2  2011        new               yes      5414

   attic  garage hasstorageroom  hasguestroom      price
0   9005     956             no             7  7559081.5
1   8852     135            yes             9  5574642.1
2   4748     654             no            10  8696869.3
3   5792     807            yes             5  5154055.2
4   1172     716            yes             9  9652258.1
```

[33]:
```
df_prt2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   squaremeters       10000 non-null  int64
 1   numberofrooms      10000 non-null  int64
 2   hasyard            10000 non-null  object
 3   haspool            10000 non-null  object
 4   floors             10000 non-null  int64
 5   citycode           10000 non-null  int64
 6   citypartrange      10000 non-null  int64
 7   numprevowners      10000 non-null  int64
 8   made               10000 non-null  int64
 9   isnewbuilt         10000 non-null  object
 10  hasstormprotector  10000 non-null  object
 11  basement           10000 non-null  int64
 12  attic              10000 non-null  int64
 13  garage             10000 non-null  int64
 14  hasstorageroom     10000 non-null  object
 15  hasguestroom       10000 non-null  int64
 16  price              10000 non-null  float64
dtypes: float64(1), int64(11), object(5)
memory usage: 1.3+ MB
```

[34]:
```
df_prt.describe()
```

[34]:
```
       squaremeters  numberofrooms        floors      citycode  citypartrange  \
count   10000.00000   10000.000000  10000.000000  10000.000000   10000.000000
```

```
mean    49870.13120     50.358400     50.276300  50225.486100      5.510100
std     28774.37535     28.816696     28.889171  29006.675799      2.872024
min        89.00000      1.000000      1.000000      3.000000      1.000000
25%     25098.50000     25.000000     25.000000  24693.750000      3.000000
50%     50105.50000     50.000000     50.000000  50693.000000      5.000000
75%     74609.75000     75.000000     76.000000  75683.250000      8.000000
max     99999.00000    100.000000    100.000000  99953.000000     10.000000

       numprevowners         made      basement        attic       garage  \
count   10000.000000  10000.00000  10000.000000  10000.00000  10000.00000
mean        5.521700   2005.48850   5033.103900   5028.01060    553.12120
std         2.856667      9.30809   2876.729545   2894.33221    262.05017
min         1.000000   1990.00000      0.000000      1.00000    100.00000
25%         3.000000   1997.00000   2559.750000   2512.00000    327.75000
50%         5.000000   2005.50000   5092.500000   5045.00000    554.00000
75%         8.000000   2014.00000   7511.250000   7540.50000    777.25000
max        10.000000   2021.00000  10000.000000  10000.00000   1000.00000

       hasguestroom         price
count   10000.00000  1.000000e+04
mean        4.99460  4.993448e+06
std         3.17641  2.877424e+06
min         0.00000  1.031350e+04
25%         2.00000  2.516402e+06
50%         5.00000  5.016180e+06
75%         8.00000  7.469092e+06
max        10.00000  1.000677e+07
```

[35]:
```python
print(df_prt2['price'].value_counts())
```

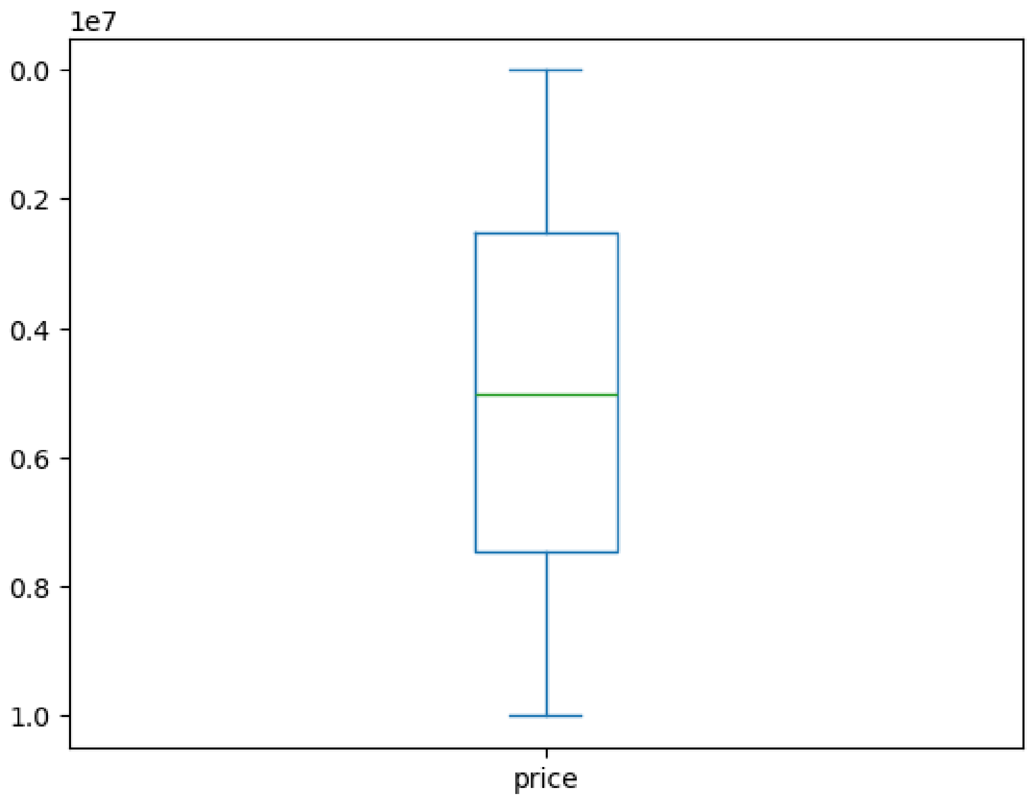
```
price
7559081.5    1
2600292.1    1
3804577.4    1
3658559.7    1
2316639.4    1
            ..
5555606.6    1
5501007.5    1
9986201.2    1
9104801.8    1
146708.4     1
Name: count, Length: 10000, dtype: int64
```

[36]:
```python
print("data null \n", df_prt2.isnull().sum())
print("data kosong \n", df_prt2.empty)
print("data nan \n",df_prt2.isna().sum())
```

```
data null
 squaremeters         0
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
price                0
dtype: int64
data kosong
 False
data nan
 squaremeters         0
numberofrooms        0
hasyard              0
haspool              0
floors               0
citycode             0
citypartrange        0
numprevowners        0
made                 0
isnewbuilt           0
hasstormprotector    0
basement             0
attic                0
garage               0
hasstorageroom       0
hasguestroom         0
price                0
dtype: int64
```

[37]:
```
import matplotlib.pyplot as plt
df_prt2.price.plot(kind='box')
plt.gca().invert_yaxis()
plt.show
```

[37]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



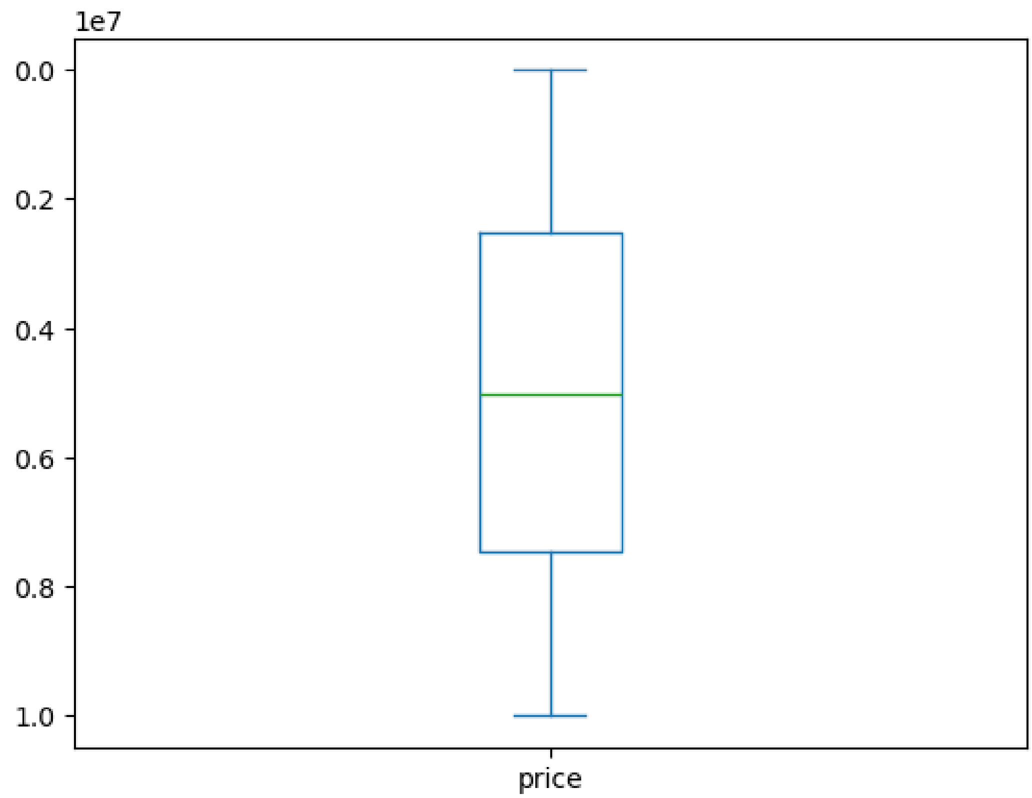

[38]:
```
print("Sebelum Pengecekan data duplikat, ",df_prt2.shape)
df_prt3=df_prt2.drop_duplicates(keep='last')
print("Setelah pengecekan data duplikat, ",df_prt3.shape)
```

```
Sebelum Pengecekan data duplikat,  (10000, 17)
Setelah pengecekan data duplikat,  (10000, 17)
```

[39]:
```
from pandas.api.types import is_numeric_dtype
def remove_outlier(df_in):
    for col_name in list(df_in.columns):
        if is_numeric_dtype(df_in[col_name]):
            q1 = df_in[col_name].quantile(0.25)
            q3 = df_in[col_name].quantile(0.75)

            iqr = q3-q1
            batas_atas = q3+(1.5*iqr)
            batas_bawah = q1-(1.5*iqr)

            df_out= df_in.loc[(df_in[col_name]>=batas_bawah)&(df_in[col_name]<=
 ↪batas_atas)]
    return df_out
```

```
df_prt_clean= remove_outlier(df_prt3)
print("Jumlah baris DataFrame sebelum dibuang outlier", df_prt3.shape[0])
print("jumlah baris DataFrame sesudah dibuang outlier", df_prt_clean.shape[0])
df_prt_clean.price.plot(kind='box', vert=True)

plt.gca().invert_yaxis()
plt.show()
```

```
Jumlah baris DataFrame sebelum dibuang outlier 10000
jumlah baris DataFrame sesudah dibuang outlier 10000
```




[40]:
```
from sklearn.model_selection import train_test_split

x=df_prt_clean.drop('price', axis =1)
y=y=df_prt_clean['price']

x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.30,␣
 ↪random_state=71)
print(x_train.shape)
print(x_test.shape)
```

```
(7000, 16)
```

(3000, 16)

[41]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer

kolom_kategori=['hasyard','haspool','isnewbuilt','hasstormprotector','hasstorageroom']


transform = make_column_transformer(
    (OneHotEncoder(),kolom_kategori),remainder='passthrough'
)

x_train_enc=transform.fit_transform(x_train)

x_test_enc=transform.fit_transform(x_test)

df_train_enc=pd.DataFrame(x_train_enc,columns=transform.get_feature_names_out())
df_test_enc=pd.DataFrame(x_test_enc,columns=transform.get_feature_names_out())

df_train_enc.head()
df_test_enc.head()
```

[41]:
```
   onehotencoder__hasyard_no  onehotencoder__hasyard_yes  \
0                        1.0                         0.0
1                        0.0                         1.0
2                        0.0                         1.0
3                        1.0                         0.0
4                        0.0                         1.0

   onehotencoder__haspool_no  onehotencoder__haspool_yes  \
0                        0.0                         1.0
1                        0.0                         1.0
2                        0.0                         1.0
3                        1.0                         0.0
4                        1.0                         0.0

   onehotencoder__isnewbuilt_new  onehotencoder__isnewbuilt_old  \
0                            0.0                            1.0
1                            0.0                            1.0
2                            0.0                            1.0
3                            0.0                            1.0
4                            1.0                            0.0

   onehotencoder__hasstormprotector_no  onehotencoder__hasstormprotector_yes  \
0                                  0.0                                   1.0
1                                  0.0                                   1.0
2                                  1.0                                   0.0
```

```
3                              1.0                                      0.0
4                              0.0                                      1.0

   onehotencoder__hasstorageroom_no  onehotencoder__hasstorageroom_yes  …  \
0                               0.0                                1.0  …
1                               0.0                                1.0  …
2                               0.0                                1.0  …
3                               1.0                                0.0  …
4                               0.0                                1.0  …

   remainder__numberofrooms  remainder__floors  remainder__citycode  \
0                      10.0               87.0              41867.0
1                      35.0                2.0              78416.0
2                      28.0               20.0              47125.0
3                      42.0               65.0              70699.0
4                      42.0               76.0              67080.0

   remainder__citypartrange  remainder__numprevowners  remainder__made  \
0                       6.0                      10.0           1997.0
1                       1.0                       6.0           2016.0
2                       1.0                       3.0           2015.0
3                       9.0                       2.0           2010.0
4                       8.0                       2.0           2015.0

   remainder__basement  remainder__attic  remainder__garage  \
0               8945.0            1203.0              142.0
1               3311.0            1636.0              967.0
2               8462.0             890.0              523.0
3               2336.0            8483.0              319.0
4               5678.0            8046.0              135.0

   remainder__hasguestroom
0                     10.0
1                      6.0
2                      7.0
3                      2.0
4                      4.0

[5 rows x 21 columns]
```

[42]:

```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

```python
pipe_Lasso = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectKBest(score_func=f_regression)),
    ('reg', Lasso(max_iter=1000))
])

param_grid_Lasso = {
    'reg__alpha': [0.01, 0.1, 1.0, 10, 100],
    'feature_selection__k': np.arange(1, x_train_enc.shape[1] + 1)
}

GSCV_Lasso = GridSearchCV(pipe_Lasso, param_grid_Lasso, cv=5,
                          scoring='neg_mean_squared_error')

GSCV_Lasso.fit(x_train_enc, y_train)

print("Best model: {}".format(GSCV_Lasso.best_estimator_))
print("Lasso best parameters: {}".format(GSCV_Lasso.best_params_))

print("Koefisien/bobot: {}".format(GSCV_Lasso.best_estimator_.
 ↪named_steps['reg'].coef_))
print("Intercept/bias: {}".format(GSCV_Lasso.best_estimator_.named_steps['reg'].
 ↪intercept_))

Lasso_predict = GSCV_Lasso.predict(x_test_enc)

mse_Lasso = mean_squared_error(y_test, Lasso_predict)
mae_Lasso = mean_absolute_error(y_test, Lasso_predict)

print("Lasso Mean Squared Error (MSE): {}".format(mse_Lasso))
print("Lasso Mean Absolute Error (MAE): {}".format(mae_Lasso))
print("Lasso Root Mean Squared Error : {}".format(np.sqrt(mse_Lasso)))
```

```
Best model: Pipeline(steps=[('scale', StandardScaler()),
                ('feature_selection',
                 SelectKBest(k=21,
                             score_func=<function f_regression at
0x00000199BAD5CC20>)),
                ('reg', Lasso(alpha=10))])
Lasso best parameters: {'feature_selection__k': 21, 'reg__alpha': 10}
Koefisien/bobot: [-1.47311841e+03  1.10178787e-13 -1.47477770e+03
2.07884503e-15
  6.01957021e+01 -0.00000000e+00 -6.09633387e+01  2.07884503e-14
 -7.50646917e+00  5.82076609e-14  2.88293144e+06 -0.00000000e+00
  1.56711009e+03 -0.00000000e+00  1.25698947e+02 -0.00000000e+00
 -0.00000000e+00 -0.00000000e+00 -0.00000000e+00  1.84582788e+01
 -4.57599517e+00]
```

```
Intercept/bias: 4985857.002414286
Lasso Mean Squared Error (MSE): 3684095.8047116166
Lasso Mean Absolute Error (MAE): 1500.9684308209926
Lasso Root Mean Squared Error : 1919.3998553484412
```

[43]:
```
df_results= pd.DataFrame(y_test, columns=['price'])
df_results=pd.DataFrame(y_test)
df_results['Lasso Prediction']=Lasso_predict

df_results['Selisih_price_RR']=df_results['Lasso Prediction']-
 ↪df_results['price']
df_results.head()
```

[43]:

| | price | Lasso Prediction | Selisih_price_RR |
|---|---|---|---|
| 312 | 7694726.7 | 7.699083e+06 | 4356.273967 |
| 7926 | 1611775.6 | 1.608193e+06 | -3582.826481 |
| 5782 | 3253846.5 | 3.253207e+06 | -639.321545 |
| 8188 | 2359701.0 | 2.360080e+06 | 379.126360 |
| 795 | 8007425.5 | 8.008200e+06 | 774.391222 |

[44]:
```
df_results.describe()
```

[44]:

| | price | Lasso Prediction | Selisih_price_RR |
|---|---|---|---|
| count | 3.000000e+03 | 3.000000e+03 | 3000.000000 |
| mean | 5.011159e+06 | 5.011127e+06 | -31.388900 |
| std | 2.864485e+06 | 2.864471e+06 | 1919.463116 |
| min | 1.679920e+04 | 1.632142e+04 | -6989.863933 |
| 25% | 2.526030e+06 | 2.525897e+06 | -1298.239677 |
| 50% | 5.077257e+06 | 5.075742e+06 | 3.999044 |
| 75% | 7.480795e+06 | 7.482028e+06 | 1195.909671 |
| max | 1.000294e+07 | 1.000120e+07 | 6914.646163 |

[45]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_rf = Pipeline(steps=[
            ('scale', StandardScaler()),
            ('feature_selection', SelectKBest(score_func=f_regression)),
            ('reg', RandomForestRegressor(random_state=0))
            ])

param_grid_rf = {
    'scale': [StandardScaler(), MinMaxScaler()],
```

```python
    'feature_selection__k': np.arange(5, 20),
    'reg__max_depth': np.arange(4, 6),
    'reg__n_estimators': [100, 150]
}

GSCV_rf = GridSearchCV(pipe_rf, param_grid_rf, cv=5,
                       scoring='neg_mean_squared_error')

GSCV_rf.fit(x_train_enc, y_train)

print("Best model: {}".format(GSCV_rf.best_estimator_))
print("Random Forest best parameters: {}".format(GSCV_rf.best_params_))

rf_predict = GSCV_rf.predict(x_test_enc)

mse_rf = mean_squared_error(y_test, rf_predict)
mae_rf = mean_absolute_error(y_test, rf_predict)

print("RF Mean Squared Error (MSE): {}".format(mse_rf))
print("RF Mean Absolute Error (MAE): {}".format(mae_rf))
print("RF Root Mean Squared Error : {}".format(np.sqrt(mse_rf)))
```

```
Best model: Pipeline(steps=[('scale', MinMaxScaler()),
                ('feature_selection',
                 SelectKBest(k=17,
                             score_func=<function f_regression at
0x00000199BAD5CC20>)),
                ('reg', RandomForestRegressor(max_depth=5, random_state=0))])
Random Forest best parameters: {'feature_selection__k': 17, 'reg__max_depth': 5,
'reg__n_estimators': 100, 'scale': MinMaxScaler()}
RF Mean Squared Error (MSE): 4025392643.7151427
RF Mean Absolute Error (MAE): 55679.41427729769
RF Root Mean Squared Error : 63445.982092762526
```

[46]:
```python
df_results['RF Prediction'] = rf_predict
df_results = pd.DataFrame(y_test)
df_results['RF Prediction'] = rf_predict

df_results['Selisih_price_RF'] = df_results['RF Prediction'] -␣
 ↪df_results['price']

df_results.head()
```

[46]:

| | price | RF Prediction | Selisih_price_RF |
|---|---|---|---|
| 312 | 7694726.7 | 7.662325e+06 | -32401.618400 |
| 7926 | 1611775.6 | 1.714107e+06 | 102331.032568 |
| 5782 | 3253846.5 | 3.260558e+06 | 6711.562914 |

```
8188  2359701.0   2.340957e+06     -18743.632949
795   8007425.5   7.961173e+06     -46252.005161
```

[47]:
```python
df_results.describe()
```

[47]:
```
              price  RF Prediction  Selisih_price_RF
count  3.000000e+03   3.000000e+03       3000.000000
mean   5.011159e+06   5.012454e+06       1295.560606
std    2.864485e+06   2.860337e+06      63443.327874
min    1.679920e+04   1.623675e+05    -145931.208126
25%    2.526030e+06   2.619698e+06     -55080.791351
50%    5.077257e+06   5.150637e+06        213.473997
75%    7.480795e+06   7.429236e+06      58800.239989
max    1.000294e+07   9.857014e+06     145568.337350
```

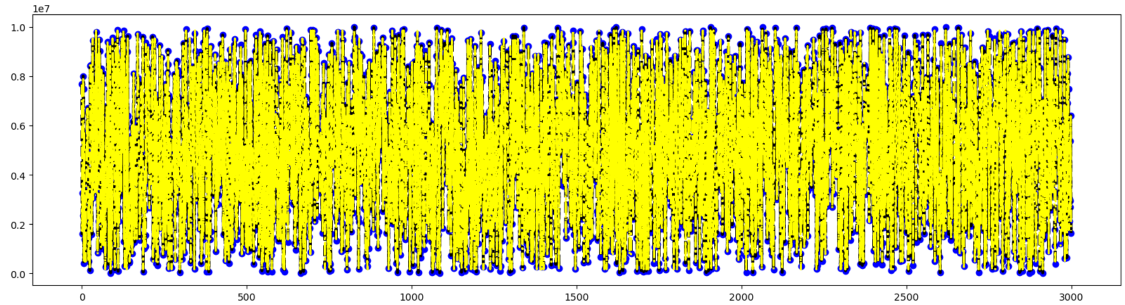
[49]:
```python
df_results = pd.DataFrame({'price': y_test})

df_results['Lasso Prediction'] = Lasso_predict
df_results['Selisih_price_LR'] = df_results['price'] - df_results['Lasso␣
↪Prediction']

df_results['RF Prediction'] = rf_predict
df_results['Selisih_price_RF'] = df_results['price'] - df_results['RF␣
↪Prediction']

df_results.head()
```

[49]:
```
          price  Lasso Prediction  Selisih_price_LR  RF Prediction  \
312   7694726.7      7.699083e+06      -4356.273967   7.662325e+06
7926  1611775.6      1.608193e+06       3582.826481   1.714107e+06
5782  3253846.5      3.253207e+06        639.321545   3.260558e+06
8188  2359701.0      2.360080e+06       -379.126360   2.340957e+06
795   8007425.5      8.008200e+06       -774.391222   7.961173e+06

      Selisih_price_RF
312       32401.618400
7926    -102331.032568
5782      -6711.562914
8188      18743.632949
795       46252.005161
```

[50]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(20,5))
data_len = range(len(y_test))
plt.scatter(data_len, df_results.price, label='actual', color="blue")
```

```
plt.plot(data_len, df_results['Lasso Prediction'], label='Lasso Prediction',␣
↪color="black", linewidth=3, linestyle="--")
plt.plot(data_len, df_results['RF Prediction'], label='RF Prediction',␣
↪color="yellow", linewidth=2, linestyle="-.")
```

[50]: [<matplotlib.lines.Line2D at 0x199c7e0ce90>]




[51]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

mae_lasso = mean_absolute_error(df_results['price'], df_results['Lasso␣
↪Prediction'])
rmse_lasso = np.sqrt(mean_squared_error(df_results['price'], df_results['Lasso␣
↪Prediction']))
lasso_feature_count = GSCV_Lasso.best_params_['feature_selection__k']

mae_RF = mean_absolute_error(df_results['price'], df_results['RF Prediction'])
rmse_RF = np.sqrt(mean_squared_error(df_results['price'], df_results['RF␣
↪Prediction']))
RF_feature_count = GSCV_rf.best_params_['feature_selection__k']

print(f"Lasso MAE: {mae_lasso}, Lasso RMSE: {rmse_lasso}, Lasso Feature Count:␣
↪{lasso_feature_count}")
print(f"RF MAE: {mae_RF}, RF RMSE: {rmse_RF}, RF Feature Count:␣
↪{RF_feature_count}")
```

```
Lasso MAE: 1500.9684308209926, Lasso RMSE: 1919.3998553484412, Lasso Feature
Count: 21
RF MAE: 55679.41427729769, RF RMSE: 63445.982092762526, RF Feature Count: 17
```

[52]:
```
import pickle

best_model = GSCV_rf.best_estimator_

with open('BestModel_REG_RF_SeaBorn.pkl', 'wb') as f:
```

```python
    pickle.dump(best_model, f)

print("Model terbaik berhasil disimpan ke 'BestModel_REG_RF_SeaBorn.pkl")
```

```
Model terbaik berhasil disimpan ke 'BestModel_REG_RF_SeaBorn.pkl
```

# Kode Streamlit App

```python
import streamlit as st
import pickle
import os
from streamlit_option_menu import option_menu
import numpy as np

with st.sidebar:
    selected = option_menu(
        'Proyek UTS PMDPM_A_Seaborn',
        ['Klasifikasi', 'Regresi', 'Catatan'],
        default_index=0
    )

if selected == 'Klasifikasi':
    st.title('Prediksi Kategori Rumah')

    model_path = r'C:\Kuliah\.Semester 5\ML\Proyek UTS PMDPM_A_Seaborn'
    model = os.path.join(model_path, 'BestModel_CLF_RF_Seaborn.pkl')

    with open(model, 'rb') as f:
        loaded_model = pickle.load(f)

    rf_model = loaded_model

    st.header("Masukkan Fitur Rumah")

    luas_tanah = st.number_input("Luas Tanah (m²)", min_value=0.0, step=0.1)
    jumlah_kamar = st.number_input("Jumlah Kamar", min_value=1, step=1)
    lantai = st.number_input("Jumlah Lantai", min_value=1, step=1)
    kota_kode = st.selectbox("Kode Kota", [310, 340, 350, 390])
    area_kota = st.selectbox("Kode Area Kota", [1, 2, 3, 4, 5])
    pemilik_sebelumnnya = st.number_input("Jumlah Pemilik Sebelumnya", min_value=0)
    dibuat = st.number_input("Tahun Dibuat", min_value=1900, max_value=2024)

    hasyard = st.selectbox("Ada Halaman?", ["Tidak", "Ya"])
    haspool = st.selectbox("Ada Kolam Renang?", ["Tidak", "Ya"])
    isnewbuilt = st.selectbox("Bangunan Baru?", ["Tidak", "Ya"])
    hasstormprotector = st.selectbox("Ada Pelindung Badai?", ["Tidak", "Ya"])
    hasstorageroom = st.selectbox("Ada Gudang?", ["Tidak", "Ya"])

    basement = st.number_input("Luas Basement (m²)", min_value=0.0, step=0.1)
    attic = st.number_input("Luas Attic (m²)", min_value=0.0, step=0.1)
    garage = st.number_input("Luas Garasi (m²)", min_value=0.0, step=0.1)

    hasyard = 1 if hasyard == "Ya" else 0
    haspool = 1 if haspool == "Ya" else 0
    isnewbuilt = 1 if isnewbuilt == "Ya" else 0
    hasstormprotector = 1 if hasstormprotector == "Ya" else 0
    hasstorageroom = 1 if hasstorageroom == "Ya" else 0

    input_data = np.array([[luas_tanah, jumlah_kamar, lantai, kota_kode, area_kota, pemilik_sebelumnnya, dibuat, hasyard,
                            haspool, isnewbuilt, hasstormprotector, hasstorageroom,
                            basement, attic, garage, 0, 0, 0, 0, 0, 0,]])

    if st.button("Prediksi Kategori"):
        try:
            rf_model_prediction = rf_model.predict(input_data)
            outcome = {'Basic': 'Basic', 'Luxury': 'Luxury', 'Middle': 'Middle'}
            st.success(f"Prediksi Kategori Rumah Adalah :  {outcome[rf_model_prediction[0]]}")
        except Exception as e:
            st.error(f"Terjadi kesalahan saat melakukan prediksi: {str(e)}")

if selected == 'Regresi':
    st.title('Prediksi Harga Rumah')

    model_path = r'C:\Kuliah\.Semester 5\ML\Proyek UTS PMDPM_A_Seaborn'
    model = os.path.join(model_path, 'BestModel_REG_SVR_Seaborn.pkl')

    with open(model, 'rb') as f:
        loaded_model = pickle.load(f)

    rf_model = loaded_model

    st.header("Masukkan Fitur Rumah")

    luas_tanah = st.number_input("Luas Tanah (m²)", min_value=0.0, step=0.1)
    jumlah_kamar = st.number_input("Jumlah Kamar", min_value=1, step=1)
    lantai = st.number_input("Jumlah Lantai", min_value=1, step=1)
    kota_kode = st.selectbox("Kode Kota", [310, 340, 350, 390])
    area_kota = st.selectbox("Kode Area Kota", [1, 2, 3, 4, 5])
    pemilik_sebelumnnya = st.number_input("Jumlah Pemilik Sebelumnya", min_value=0)
    dibuat = st.number_input("Tahun Dibuat", min_value=1900, max_value=2024)

    hasyard = st.selectbox("Ada Halaman?", ["Tidak", "Ya"])
    haspool = st.selectbox("Ada Kolam Renang?", ["Tidak", "Ya"])
    isnewbuilt = st.selectbox("Bangunan Baru?", ["Tidak", "Ya"])
    hasstormprotector = st.selectbox("Ada Pelindung Badai?", ["Tidak", "Ya"])
    hasstorageroom = st.selectbox("Ada Gudang?", ["Tidak", "Ya"])

    basement = st.number_input("Luas Basement (m²)", min_value=0.0, step=0.1)
    attic = st.number_input("Luas Attic (m²)", min_value=0.0, step=0.1)
    garage = st.number_input("Luas Garasi (m²)", min_value=0.0, step=0.1)

    hasyard = 1 if hasyard == "Ya" else 0
    haspool = 1 if haspool == "Ya" else 0
    isnewbuilt = 1 if isnewbuilt == "Ya" else 0
    hasstormprotector = 1 if hasstormprotector == "Ya" else 0
    hasstorageroom = 1 if hasstorageroom == "Ya" else 0

    input_data = np.array([[luas_tanah, jumlah_kamar, lantai, kota_kode, area_kota, pemilik_sebelumnnya, dibuat, hasyard,
                            haspool, isnewbuilt, hasstormprotector, hasstorageroom,
                            basement, attic, garage, 0, 0, 0, 0, 0, 0,]])

    if st.button("Prediksi Harga"):
        try:
            prediksi_harga = rf_model.predict(input_data)
            st.success(f"Prediksi Harga Rumah: Rp {prediksi_harga[0]:,.0f}")
        except Exception as e:
            st.error(f"Terjadi kesalahan saat melakukan prediksi: {str(e)}")
```