

```

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.feature_selection import SelectFromModel, SelectKBest,
SelectPercentile, RFECV
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier,
RandomForestRegressor
from sklearn.svm import SVC, SVR
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
from pandas.api.types import is_numeric_dtype
from sklearn.linear_model import Ridge, Lasso
import matplotlib.pyplot as plt

```

```

properti = pd.read_csv('/Users/saktiyoga/Downloads/UTS_PMDPM/Dataset
UTS_Gasal 2425.csv')
properti.head(100)
# from google.colab import drive
# drive.mount('/content/drive')
# properti=pd.read_csv('/content/drive/MyDrive/Colab
Notebooks/paris_housing.csv')
# properti.head(100)

```

	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	
..	...	...	...	...	...	...	
95	98868	41	no	yes	67	85917	
96	83110	43	yes	no	75	55046	
97	71154	67	no	yes	53	8762	
98	90841	48	yes	no	15	25300	
99	68416	87	yes	no	48	60979	

	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						
..	...	...	...	...		...
...						
95	7	3	2021	new		yes
2146						
96	7	10	2001	new		no
4108						
97	2	6	2021	new		yes
8418						
98	6	5	2003	old		no
3333						
99	8	7	2010	old		no
1811						

	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
..	...	...	...	...	...	...
95	1077	623	yes	3	9892300.1	Luxury
96	5663	380	yes	7	8321631.1	Luxury
97	7187	706	no	8	7122699.1	Luxury
98	149	842	no	9	9086177.3	Luxury
99	6776	424	no	6	6846709.0	Middle

[100 rows x 18 columns]

```

propti2 = propti.drop('price', axis=1)
propti2.head(100)

```

	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	
..	...	...	...	...	...	...	
95	98868	41	no	yes	67	85917	
96	83110	43	yes	no	75	55046	
97	71154	67	no	yes	53	8762	
98	90841	48	yes	no	15	25300	
99	68416	87	yes	no	48	60979	

	citypar	range	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						
..	...		...	...	...	...
...						
95		7	3	2021	new	yes
2146						
96		7	10	2001	new	no
4108						
97		2	6	2021	new	yes
8418						
98		6	5	2003	old	no
3333						
99		8	7	2010	old	no
1811						

	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
..	...		...	...	...
95	1077	623	yes	3	Luxury
96	5663	380	yes	7	Luxury
97	7187	706	no	8	Luxury
98	149	842	no	9	Luxury
99	6776	424	no	6	Middle

[100 rows x 17 columns]

```
print("data null \n", properti2.isnull().sum())
print("data kosong \n", properti2.empty)
print("data nan \n", properti2.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
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

```

```

print("Sebelum drop missing value", properti2.shape)
properti2 = properti2.dropna(how="any", inplace=False)
print("Setelah drop missing value", properti2.shape)

```

```

Sebelum drop missing value (10000, 17)
Setelah drop missing value (10000, 17)

```

```

print("Sebelum Pengecekan data duplikat", properti2.shape)
properti3 = properti2.drop_duplicates(keep='last')
print("Setelah Pengecekan data duplikat", properti3.shape)

```

```

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

```

```

kolom_kategori=['hasyard', 'haspool', 'isnewbuilt',
               'hasstormprotector', 'hasstorageroom']
transform = make_column_transformer(
    (OneHotEncoder(), kolom_kategori),
    remainder = 'passthrough'
)

x=properti3.drop('category',axis=1)
y=properti3.category

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.20, random_state=84)

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

(8000, 16)
(2000, 16)

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(10)
df_test_enc.head(10)

```

	onehotencoder__hasyard_no	onehotencoder__hasyard_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	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__haspool_no	onehotencoder__haspool_yes \
0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
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	0.0	1.0
onehotencoder__isnewbuilt_new   onehotencoder__isnewbuilt_old \		
0	0.0	1.0
1	1.0	0.0
2	1.0	0.0
3	1.0	0.0
4	1.0	0.0
5	1.0	0.0
6	1.0	0.0
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	1.0	
0.0		
2	1.0	
0.0		
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	1.0	
0.0		
9	1.0	
0.0		
onehotencoder__hasstorageroom_no   onehotencoder__hasstorageroom_yes		
...	\	
0	1.0	0.0
...		
1	1.0	0.0
...		
2	0.0	1.0
...		
3	1.0	0.0
...		
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	0.0	1.0
...		

	remainder__numberofrooms	remainder__floors	remainder__citycode	\
0	97.0	45.0	62899.0	
1	76.0	54.0	82737.0	
2	72.0	26.0	7812.0	
3	46.0	51.0	91317.0	
4	4.0	30.0	8424.0	
5	47.0	14.0	50927.0	
6	54.0	15.0	61691.0	
7	42.0	50.0	50833.0	
8	97.0	3.0	68804.0	
9	18.0	26.0	67302.0	

	remainder__citypartrange	remainder__numprevowners	remainder__made	\
0	1.0	9.0	1990.0	
1	7.0	3.0	1998.0	
2	6.0	3.0	1995.0	
3	5.0	3.0	2020.0	
4	4.0	10.0	2003.0	
5	9.0	6.0	1993.0	
6	2.0	2.0	2002.0	
7	3.0	8.0	2009.0	
8	10.0	5.0	1991.0	
9	6.0	2.0	2005.0	

	remainder__basement	remainder__attic	remainder__garage	\
0	4110.0	1675.0	599.0	
1	4010.0	8343.0	260.0	
2	6972.0	3804.0	828.0	

3	3337.0	7250.0	337.0
4	5655.0	1684.0	453.0
5	4078.0	315.0	767.0
6	5925.0	9705.0	342.0
7	9320.0	5752.0	936.0
8	5804.0	2070.0	846.0
9	6111.0	771.0	500.0

	remainder__hasguestroom
0	4.0
1	10.0
2	8.0
3	1.0
4	8.0
5	10.0
6	8.0
7	3.0
8	9.0
9	10.0

[10 rows x 21 columns]

```

pipe_GBT_kbest = Pipeline([
    ('scaler', StandardScaler()),
    ('feature_selection', SelectKBest()),
    ('classifier', GradientBoostingClassifier(random_state=84))
])

pipe_GBT_percentile = Pipeline([
    ('scaler', StandardScaler()),
    ('feature_selection', SelectPercentile()),
    ('classifier', GradientBoostingClassifier(random_state=84))
])

param_grid_GBT_kbest = {
    'feature_selection__k': [3, 5],
    'classifier__n_estimators': [50, 100],
    'classifier__learning_rate': [0.005, 0.01],
    'classifier__max_depth': [3]
}

param_grid_GBT_percentile = {
    'feature_selection__percentile': [30, 50],
    'classifier__n_estimators': [50, 100],
    'classifier__learning_rate': [0.005, 0.01],
    'classifier__max_depth': [3]
}

gscv_GBT_kbest = GridSearchCV(pipe_GBT_kbest, param_grid_GBT_kbest,
cv=StratifiedKFold(n_splits=5))

```



```

gscv_GBT_kbest.fit(x_train_enc, y_train)
print("GSCV finished")

gscv_GBT_percentile = GridSearchCV(pipe_GBT_percentile,
param_grid_GBT_percentile, cv=StratifiedKFold(n_splits=5))
gscv_GBT_percentile.fit(x_train_enc, y_train)
print("GSCV finished")

GSCV finished
GSCV finished

mask =
gscv_GBT_kbest.best_estimator_.named_steps['feature_selection'].get_support()

print("Best model:{}".format(gscv_GBT_kbest.best_estimator_))
print("Selected features:{}".format(df_train_enc.columns[mask]))

print("Best CV score: {:.2f}".format(gscv_GBT_kbest.best_score_))
print("Train set score:
{:.2f}".format(gscv_GBT_kbest.score(x_test_enc,y_test)))

GBT_pred = gscv_GBT_kbest.predict(x_test_enc)

import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, GBT_pred,
labels=gscv_GBT_kbest.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=gscv_GBT_kbest.classes_)
disp.plot()
plt.title("GBT Confusion Matrix KBest")
plt.show()
#tampilkan classification report
print("Classification report GBT KBest: \n",
classification_report(y_test,GBT_pred))

mask =
gscv_GBT_percentile.best_estimator_.named_steps['feature_selection'].get_support()

print("Best model:{}".format(gscv_GBT_percentile.best_estimator_))
print("Selected features:{}".format(df_train_enc.columns[mask]))

print("Best CV score: {:.2f}".format(gscv_GBT_percentile.best_score_))
print("Train set score:
{:.2f}".format(gscv_GBT_percentile.score(x_test_enc,y_test)))

GBT_pred = gscv_GBT_percentile.predict(x_test_enc)

import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, GBT_pred,

```

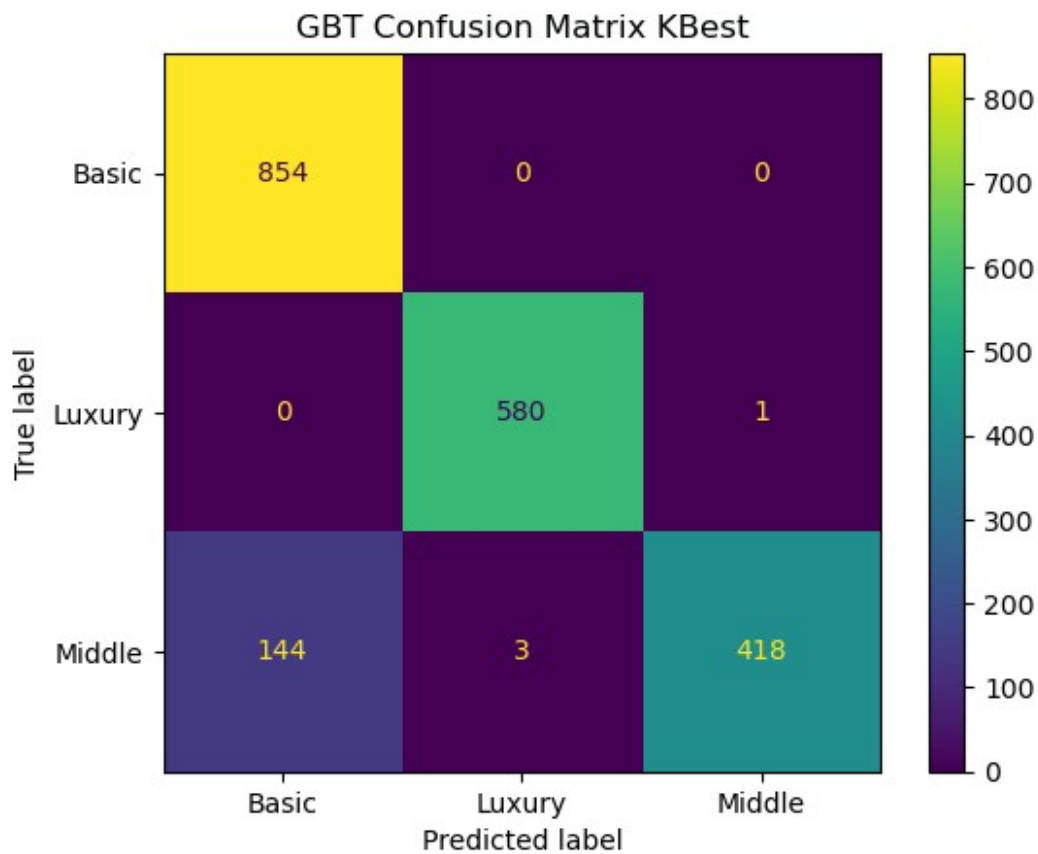
```

labels=gscv_GBT_percentile.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=gscv_GBT_percentile.classes_)
disp.plot()
plt.title("GBT Confusion Matrix Percentile")
plt.show()
#tampilkan classification report
print("Classification report GBT Percentile: \n",
classification_report(y_test,GBT_pred))

Best model:Pipeline(steps=[('scaler', StandardScaler()),
                           ('feature_selection', SelectKBest(k=3)),
                           ('classifier',
                           GradientBoostingClassifier(learning_rate=0.005,
                                                         n_estimators=50,
                                                         random_state=84))])

Selected features:Index(['onehotencoder__haspool_no',
                        'onehotencoder__haspool_yes',
                        'remainder__squaremeters'],
                        dtype='object')
Best CV score: 0.94
Train set score: 0.93

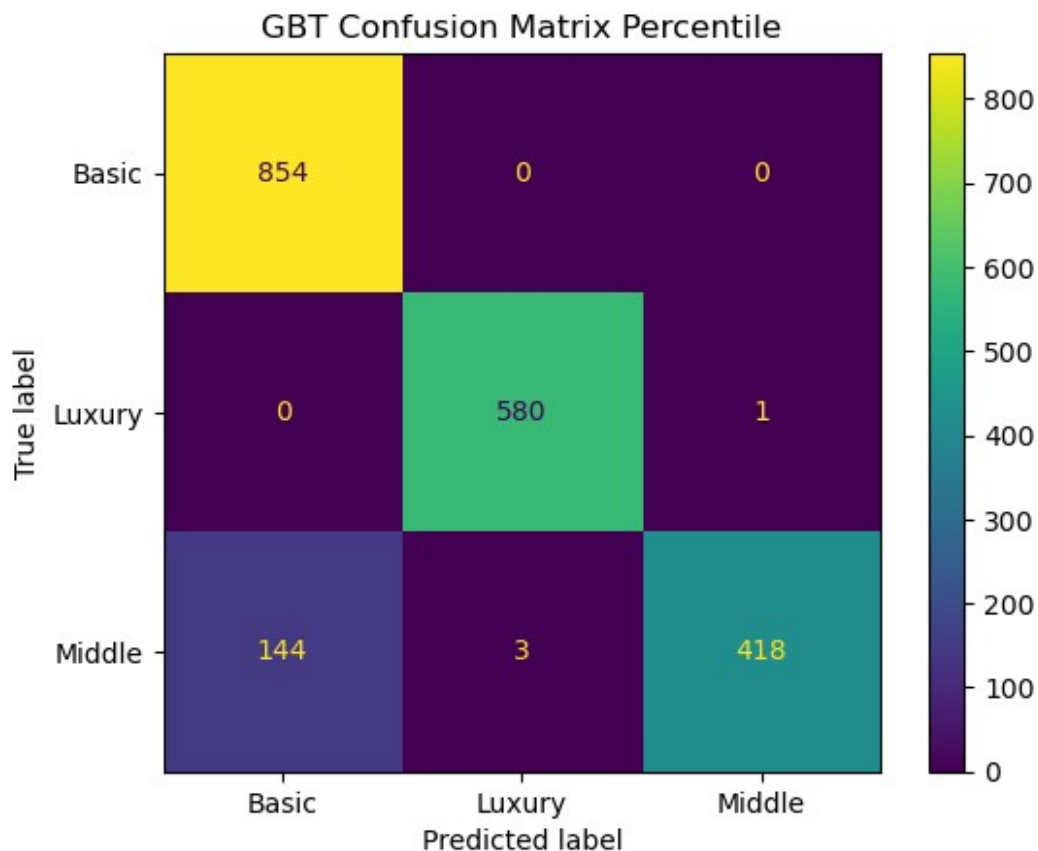
```



Classification report GBT KBest:

	precision	recall	f1-score	support
Basic	0.86	1.00	0.92	854
Luxury	0.99	1.00	1.00	581
Middle	1.00	0.74	0.85	565
accuracy			0.93	2000
macro avg	0.95	0.91	0.92	2000
weighted avg	0.94	0.93	0.92	2000

```
Best model:Pipeline(steps=[('scaler', StandardScaler()),
                             ('feature_selection',
                              SelectPercentile(percentile=30)),
                             ('classifier',
                              GradientBoostingClassifier(learning_rate=0.005,
                                                            n_estimators=50,
                                                            random_state=84))])
Selected features:Index(['onehotencoder__hasyard_no',
                         'onehotencoder__hasyard_yes',
                         'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
                         'onehotencoder__isnewbuilt_new', 'remainder__squaremeters'],
                        dtype='object')
Best CV score: 0.94
Train set score: 0.93
```



Classification report GBT Percentile:

	precision	recall	f1-score	support
Basic	0.86	1.00	0.92	854
Luxury	0.99	1.00	1.00	581
Middle	1.00	0.74	0.85	565
accuracy			0.93	2000
macro avg	0.95	0.91	0.92	2000
weighted avg	0.94	0.93	0.92	2000

```

pipe_svm_percentile = Pipeline([
    ('scaler', StandardScaler()),
    ('feature_selection', SelectPercentile()),
    ('classifier', SVC(random_state=84))
])

pipe_svm_kbest = Pipeline([
    ('scaler', MinMaxScaler()),
    ('feature_selection', SelectKBest()),
    ('classifier', SVC(random_state=84))
])

```

```

param_grid_svm_kbest = {
    'feature_selection__k': [2, 3, 5],
    'classifier__C': [0.01, 0.1, 1],
    'classifier__kernel': ['rbf', 'linear']
}

param_grid_svm_percentile = {
    'feature_selection__percentile': [20, 30, 50],
    'classifier__C': [0.01, 0.1, 1],
    'classifier__kernel': ['rbf', 'linear']
}

gscv_SVM_kbest = GridSearchCV(pipe_svm_kbest, param_grid_svm_kbest,
cv=StratifiedKFold(n_splits=5))
gscv_SVM_kbest.fit(x_train_enc, y_train)
print("GSCV finished")

gscv_SVM_percentile = GridSearchCV(pipe_svm_percentile,
param_grid_svm_percentile, cv=StratifiedKFold(n_splits=5))
gscv_SVM_percentile.fit(x_train_enc, y_train)
print("GSCV finished")

GSCV finished
GSCV finished

mask =
gscv_SVM_kbest.best_estimator_.named_steps['feature_selection'].get_support()

print("Best model:{}".format(gscv_SVM_kbest.best_estimator_))
print("Selected features:{}".format(df_train_enc.columns[mask]))

print("Best CV score: {:.2f}".format(gscv_SVM_kbest.best_score_))
print("Train set score:
{:.2f}".format(gscv_SVM_kbest.score(x_test_enc,y_test)))

SVM_pred = gscv_SVM_kbest.predict(x_test_enc)

import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, SVM_pred,
labels=gscv_GBT_kbest.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=gscv_SVM_kbest.classes_)
disp.plot()
plt.title("SVM Confusion Matrix KBest")
plt.show()
#tampilkan classification report
print("Classification report SVM KBest: \n",
classification_report(y_test,SVM_pred))

```

```

mask =
gscv_SVM_percentile.best_estimator_.named_steps['feature_selection'].get_support()

print("Best model:{}".format(gscv_SVM_percentile.best_estimator_))
print("Selected features:{}".format(df_train_enc.columns[mask]))

print("Best CV score: {:.2f}".format(gscv_SVM_percentile.best_score_))
print("Train set score:
{:.2f}".format(gscv_SVM_percentile.score(x_test_enc,y_test)))

SVM_pred = gscv_SVM_percentile.predict(x_test_enc)

import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, SVM_pred,
labels=gscv_SVM_percentile.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=gscv_SVM_percentile.classes_)
disp.plot()
plt.title("SVM Confusion Matrix Percentile")
plt.show()
#tampilkan classification report
print("Classification report SVM Percentile: \n",
classification_report(y_test,SVM_pred))

Best model:Pipeline(steps=[('scaler', MinMaxScaler()),
                           ('feature_selection', SelectKBest(k=2)),
                           ('classifier', SVC(C=1, random_state=84))])
Selected features:Index(['onehotencoder__haspool_yes',
'remainder__squaremeters'], dtype='object')
Best CV score: 0.93
Train set score: 0.92

```



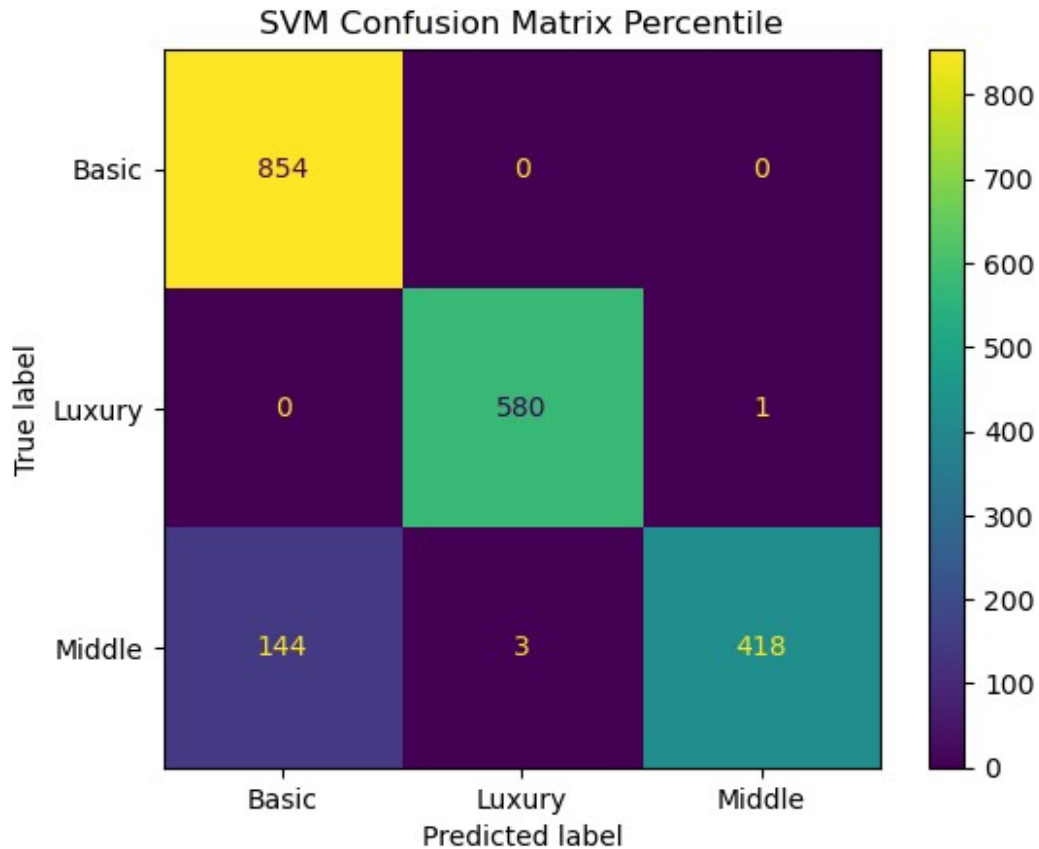
#### Classification report SVM KBest:

	precision	recall	f1-score	support
Basic	0.86	0.97	0.91	854
Luxury	1.00	1.00	1.00	581
Middle	0.95	0.75	0.84	565
accuracy			0.92	2000
macro avg	0.93	0.91	0.92	2000
weighted avg	0.92	0.92	0.92	2000

Best model: Pipeline(steps=[('scaler', StandardScaler()),  
('feature\_selection',  
SelectPercentile(percentile=30)),  
('classifier', SVC(C=1, random\_state=84))])

Selected features: Index(['onehotencoder\_\_hasyard\_no',  
'onehotencoder\_\_hasyard\_yes',  
'onehotencoder\_\_haspool\_no', 'onehotencoder\_\_haspool\_yes',  
'onehotencoder\_\_isnewbuilt\_new', 'remainder\_\_squaremeters'],  
dtype='object')

Best CV score: 0.99  
Train set score: 0.98



Classification report SVM Percentile:

	precision	recall	f1-score	support
Basic	0.99	0.99	0.99	854
Luxury	0.99	0.99	0.99	581
Middle	0.97	0.98	0.97	565
accuracy			0.98	2000
macro avg	0.98	0.98	0.98	2000
weighted avg	0.99	0.98	0.99	2000

```
import pickle
best_model = gscv_SVM_percentile.best_estimator_

with open('BestModel_CLF_gscv_SVM_percentile_matplotlib.pkl', 'wb') as f:
    pickle.dump(best_model, f)
print("Model Terbaik berhasil disimpan ke
'BestModel_CLF_gscv_SVM_percentile_matplotlib.pkl.pkl'")

Model Terbaik berhasil disimpan ke
'BestModel_CLF_gscv_SVM_percentile_matplotlib.pkl.pkl'
```



```

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.feature_selection import SelectFromModel, SelectKBest,
SelectPercentile, RFECV
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier,
RandomForestRegressor
from sklearn.svm import SVC, SVR
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
from pandas.api.types import is_numeric_dtype
from sklearn.linear_model import Ridge, Lasso
import matplotlib.pyplot as plt

```

```

properti = pd.read_csv('Dataset_UTS_Gasal_2425.csv')
properti.head(100)

```

	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	
..	...	...	...	...	...	...	
95	98868	41	no	yes	67	85917	
96	83110	43	yes	no	75	55046	
97	71154	67	no	yes	53	8762	
98	90841	48	yes	no	15	25300	
99	68416	87	yes	no	48	60979	

	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
...
...
95          7          3  2021      new          yes
2146
96          7          10  2001      new          no
4108
97          2          6  2021      new          yes
8418
98          6          5  2003      old          no
3333
99          8          7  2010      old          no
1811

```

```

      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
..      ...      ...          ...          ...      ...
95     1077    623          yes          3  9892300.1  Luxury
96     5663    380          yes          7  8321631.1  Luxury
97     7187    706          no          8  7122699.1  Luxury
98      149    842          no          9  9086177.3  Luxury
99     6776    424          no          6  6846709.0  Middle

```

[100 rows x 18 columns]

```

propti2 = propti.drop('price', axis=1)
propti2.head(100)

```

```

      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
..           ...           ...         ...         ...      ...
95          98868          41         no      yes      67      85917
96          83110          43        yes      no       75      55046
97          71154          67         no      yes      53       8762
98          90841          48        yes      no       15      25300
99          68416          87        yes      no       48      60979

```

```

      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					
..	...	...	...	...	...
...					
95	7	3	2021	new	yes
2146					
96	7	10	2001	new	no
4108					
97	2	6	2021	new	yes
8418					
98	6	5	2003	old	no
3333					
99	8	7	2010	old	no
1811					

	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
..	...	...	...	...	...
95	1077	623	yes	3	Luxury
96	5663	380	yes	7	Luxury
97	7187	706	no	8	Luxury
98	149	842	no	9	Luxury
99	6776	424	no	6	Middle

[100 rows x 17 columns]

```
print("data null \n", properti2.isnull().sum())
print("data kosong \n", properti2.empty)
print("data nan \n", properti2.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
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

```

```

print("Sebelum drop missing value", properti2.shape)
properti2 = properti2.dropna(how="any", inplace=False)
print("Setelah drop missing value", properti2.shape)

```

```

Sebelum drop missing value (10000, 17)
Setelah drop missing value (10000, 17)

```

```

print("Sebelum Pengecekan data duplikat", properti2.shape)
properti3 = properti2.drop_duplicates(keep='last')
print("Setelah Pengecekan data duplikat", properti3.shape)

```

```

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

```

```

kolom_kategori=['hasyard', 'haspool', 'isnewbuilt',
                'hasstormprotector', 'hasstorageroom']
transform = make_column_transformer(
    (OneHotEncoder(), kolom_kategori),
    remainder = 'passthrough'
)

```

```

x=propti3.drop('category',axis=1)
y=propti3.category

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.20, random_state=84)

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

(8000, 16)
(2000, 16)

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(10)
df_test_enc.head(10)

```

	onehotencoder__hasyard_no	onehotencoder__hasyard_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	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__haspool_no	onehotencoder__haspool_yes \
0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
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	0.0	1.0

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

3	1.0	0.0
4	1.0	0.0
5	1.0	0.0
6	1.0	0.0
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	1.0
0.0	
2	1.0
0.0	
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	1.0
0.0	
9	1.0
0.0	

onehotencoder__hasstorageroom_no	onehotencoder__hasstorageroom_yes
...	\
0	1.0 0.0
...	
1	1.0 0.0
...	
2	0.0 1.0
...	
3	1.0 0.0
...	
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	0.0	1.0
...		

	remainder__numberofrooms	remainder__floors	remainder__citycode	\
0	97.0	45.0	62899.0	
1	76.0	54.0	82737.0	
2	72.0	26.0	7812.0	
3	46.0	51.0	91317.0	
4	4.0	30.0	8424.0	
5	47.0	14.0	50927.0	
6	54.0	15.0	61691.0	
7	42.0	50.0	50833.0	
8	97.0	3.0	68804.0	
9	18.0	26.0	67302.0	

	remainder__citypartrange	remainder__numprevowners	remainder__made	\
0	1.0	9.0	1990.0	
1	7.0	3.0	1998.0	
2	6.0	3.0	1995.0	
3	5.0	3.0	2020.0	
4	4.0	10.0	2003.0	
5	9.0	6.0	1993.0	
6	2.0	2.0	2002.0	
7	3.0	8.0	2009.0	
8	10.0	5.0	1991.0	
9	6.0	2.0	2005.0	

	remainder__basement	remainder__attic	remainder__garage	\
0	4110.0	1675.0	599.0	
1	4010.0	8343.0	260.0	
2	6972.0	3804.0	828.0	
3	3337.0	7250.0	337.0	
4	5655.0	1684.0	453.0	
5	4078.0	315.0	767.0	
6	5925.0	9705.0	342.0	
7	9320.0	5752.0	936.0	
8	5804.0	2070.0	846.0	

9	6111.0	771.0	500.0
---	--------	-------	-------

	remainder__hasguestroom
0	4.0
1	10.0
2	8.0
3	1.0
4	8.0
5	10.0
6	8.0
7	3.0
8	9.0
9	10.0

[10 rows x 21 columns]

*#import Library yang dibutuhkan*

```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectKBest, SelectPercentile
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, StratifiedKFold
import numpy as np
```

*#buat rancangan pipeline mulai dari data scaling hingga classifier*

```
pipe_RF = [
    ('data scaling', StandardScaler()),
    ('feature select', SelectKBest()),
    ('clf', RandomForestClassifier(random_state=84,
class_weight='balanced'))
]
```

*#buat parameter grid untuk step feature selection dan classifier*

```
params_grid_RF = [
    {
        'data scaling': [StandardScaler()],
        'feature select__k': np.arange(2, 6),
        'clf__max_depth': np.arange(4, 6), # Ubah dari 4-5 menjadi 4-
6
        'clf__n_estimators': [50, 100] # Ubah dari 100, 150 menjadi
50, 100
    },
    {
        'data scaling': [MinMaxScaler()],
        'feature select__k': np.arange(2, 6),
        'clf__max_depth': np.arange(4, 6), # Ubah dari 4-5 menjadi 4-
6
        'clf__n_estimators': [50, 100] # Ubah dari 100, 150 menjadi
50, 100
    }
]
```



```

    },
]

#muat tancangan pipeline ke dalam objek pipeline
estimator_RF = Pipeline(pipe_RF)

#muat pipeline dan parameter grid ke dalam objek GSCV dengan
Stratified 5-fold CV
SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=84) #
RANDOM STATE MENGGUNAKAN 2 atau 1 DIGIT
GSCV_RF = GridSearchCV(estimator_RF, params_grid_RF, cv=SKF)

#jalankan objek GSCV untuk melatih model dengan train set menggunakan
fungsi fit
GSCV_RF.fit(x_train_enc, y_train)
print("GSCV training finished")

GSCV training finished

#tampilkan skor cross-validation
print("CV Score: {}".format(GSCV_RF.best_score_))
#tampilkan skor model terbaik GSCV pada test set
print("Test Score:
{}".format(GSCV_RF.best_estimator_.score(x_test_enc, y_test)))
#tampilkan best model dan best features
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])

#buat prediksi dari test set
RF_pred = GSCV_RF.predict(x_test_enc)

import matplotlib.pyplot as plt
#buat confusion matrix
cm = confusion_matrix(y_test, RF_pred, labels=GSCV_RF.classes_)
#buat confusion matrix display
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=GSCV_RF.classes_)
disp.plot()

plt. title("Random Forest Confusion Matrix")
plt.show()
#tampilkan Classification report
print("Classification report RF: \n", classification_report(y_test,
RF_pred))

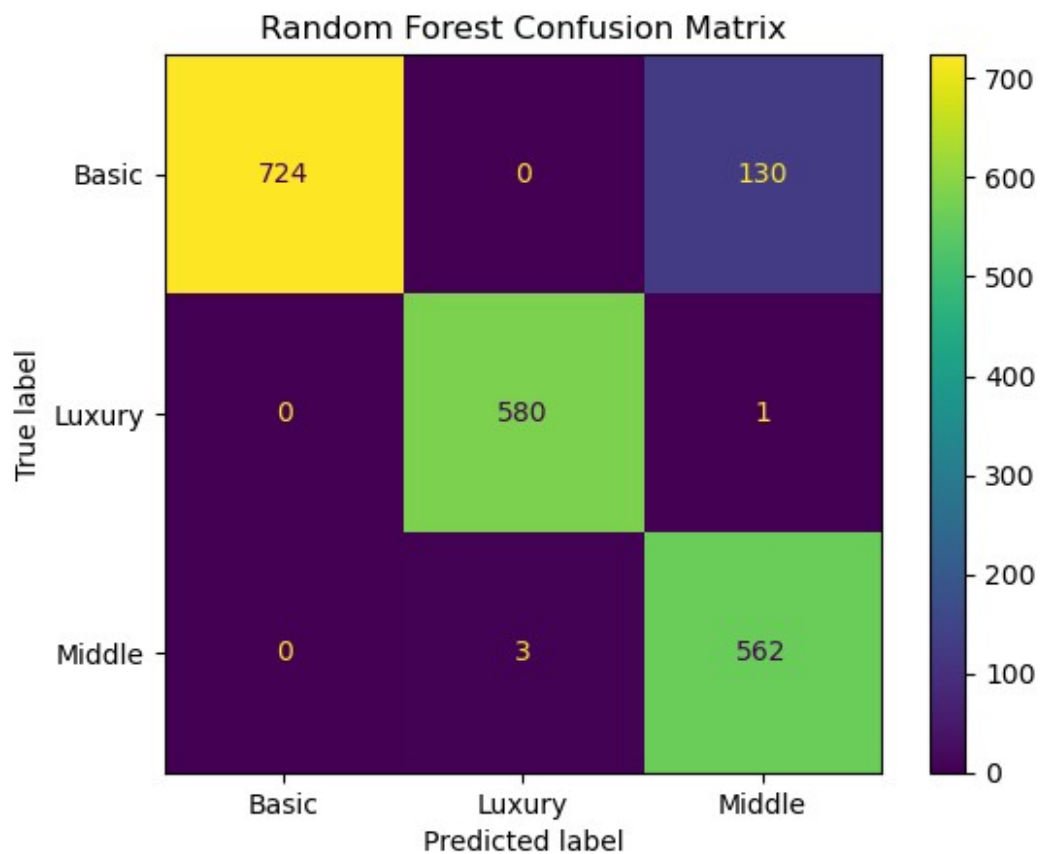
CV Score: 0.937875
Test Score: 0.933
Best model: Pipeline(steps=[('data scaling', StandardScaler()),

```

```

('feature select', SelectKBest(k=4)),
('clf',
 RandomForestClassifier(class_weight='balanced',
max_depth=4,
n_estimators=50,
random_state=84)))
Best features: Index(['onehotencoder__hasyard_yes',
'onehotencoder__haspool_no',
'onehotencoder__haspool_yes', 'remainder__squaremeters'],
dtype='object')

```



Classification report RF:

	precision	recall	f1-score	support
Basic	1.00	0.85	0.92	854
Luxury	0.99	1.00	1.00	581
Middle	0.81	0.99	0.89	565
accuracy			0.93	2000
macro avg	0.94	0.95	0.94	2000
weighted avg	0.95	0.93	0.93	2000

```

#import Library yang dibutuhkan
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectPercentile
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, StratifiedKFold
import numpy as np

# Buat rancangan pipeline mulai dari data scaling hingga classifier
pipe_RF_percentil = [('data_scaling', StandardScaler()),
                     ('feature_select', SelectPercentile()),
                     ('clf', RandomForestClassifier(random_state=84,
class_weight='balanced'))]

# Buat parameter grid untuk step feature selection dan classifier
params_grid_RF_percentil = [{
    'data_scaling': [StandardScaler()],
    'feature_select': [SelectPercentile()],
    'feature_select__percentile': np.arange(30, 51),
    'clf__max_depth': np.arange(4, 6),
    'clf__n_estimators': [50, 100, 150, 200]
},
{
    'data_scaling': [MinMaxScaler()],
    'feature_select': [SelectPercentile()],
    'feature_select__percentile': np.arange(30, 51),
    'clf__max_depth': np.arange(4, 6),
    'clf__n_estimators': [50, 100, 150, 200]
}]

# Definisikan StratifiedKFold
SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=84)

# Muat tancangan pipeline ke dalam objek pipeline
estimator_RF = Pipeline(pipe_RF_percentil)

# Muat pipeline dan parameter grid ke dalam objek GSCV dengan
Stratified 5-fold CV
GSCV_RF = GridSearchCV(estimator_RF, params_grid_RF_percentil, cv=SKF)

# Jalankan objek GSCV untuk melatih model dengan train set menggunakan
fungsi fit
GSCV_RF.fit(x_train_enc, y_train)
print("GSCV training finished")

GSCV training finished

#tampilkan skor cross-validation
print("CV Score: {}".format(GSCV_RF.best_score_))
#tampilkan skor model terbaik GSCV pada test set

```

```

print("Test Score:
{}".format(GSCV_RF.best_estimator_.score(x_test_enc, y_test)))
#tampilkan best model dan best features
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])

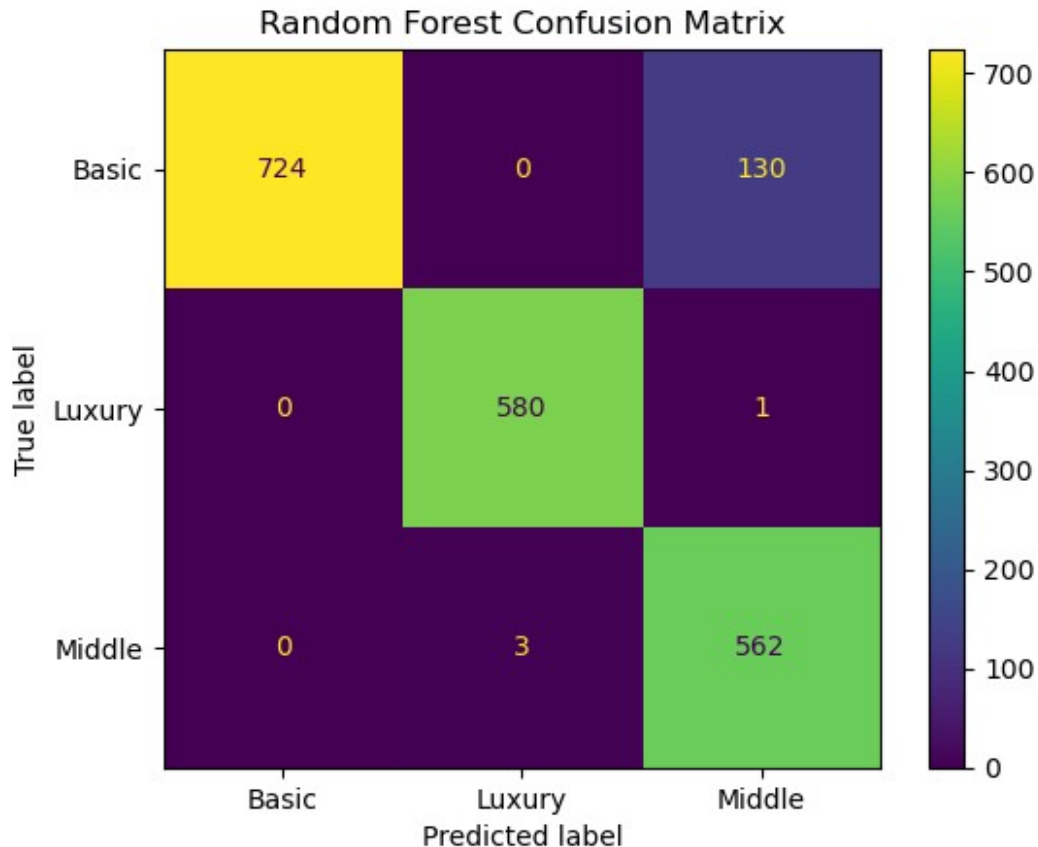
#buat prediksi dari test set
RF_pred = GSCV_RF.predict(x_test_enc)

import matplotlib.pyplot as plt
#buat confusion matrix
cm = confusion_matrix(y_test, RF_pred, labels=GSCV_RF.classes_)
#buat confusion matrix display
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=GSCV_RF.classes_)
disp.plot()

plt. title("Random Forest Confusion Matrix")
plt.show()
#tampilkan Classification report
print("Classification report RF: \n", classification_report(y_test,
RF_pred))

CV Score: 0.937875
Test Score: 0.933
Best model: Pipeline(steps=[('data scaling', StandardScaler()),
                             ('feature select', SelectKBest(k=4)),
                             ('clf',
                             RandomForestClassifier(class_weight='balanced',
max_depth=4,
n_estimators=50,
random_state=84))])
Best features: Index(['onehotencoder__hasyard_yes',
'onehotencoder__haspool_no',
'onehotencoder__haspool_yes', 'remainder__squaremeters'],
dtype='object')

```



Classification report RF:

	precision	recall	f1-score	support
Basic	1.00	0.85	0.92	854
Luxury	0.99	1.00	1.00	581
Middle	0.81	0.99	0.89	565
accuracy			0.93	2000
macro avg	0.94	0.95	0.94	2000
weighted avg	0.95	0.93	0.93	2000

*#import Library yang dibutuhkan*

```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectPercentile
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, StratifiedKFold
import numpy as np
```

*# Buat rancangan pipeline mulai dari data scaling hingga classifier*

```
pipe_LR_percentil = [('data_scaling', StandardScaler()),
                     ('feature_select', SelectPercentile()),
```

```

        ('clf', LogisticRegression(random_state=84,
class_weight='balanced', solver='liblinear'))]

# Buat parameter grid untuk step feature selection dan classifier
params_grid_LR_percentil = [{
    'data_scaling': [StandardScaler()],
    'feature_select': [SelectPercentile()],
    'feature_select_percentile': np.arange(30, 51),
    'clf_C': [0.01, 0.1, 1, 10],
    'clf_penalty': ['l1', 'l2']
},
{
    'data_scaling': [MinMaxScaler()],
    'feature_select': [SelectPercentile()],
    'feature_select_percentile': np.arange(30, 51),
    'clf_C': [0.01, 0.1, 1, 10],
    'clf_penalty': ['l1', 'l2']
}]

# Definisikan StratifiedKfold
SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=84)

# Muat tancangan pipeline ke dalam objek pipeline
estimator_LR = Pipeline(pipe_LR_percentil)

# Muat pipeline dan parameter grid ke dalam objek GSCV dengan
Stratified 5-fold CV
GSCV_LR = GridSearchCV(estimator_LR, params_grid_LR_percentil, cv=SKF)

# Jalankan objek GSCV untuk melatih model dengan train set menggunakan
fungsi fit
GSCV_LR.fit(x_train_enc, y_train)
print("GSCV training finished")

c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  warnings.warn(
c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  warnings.warn(
c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  warnings.warn(
c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  warnings.warn(

```

[illegible]

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]

```

warnings.warn(
c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
warnings.warn(
c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
warnings.warn(

GSCV training finished

c:\Users\capsl\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
warnings.warn(

# tampilkan skor cross-validation
print("CV Score: {}".format(GSCV_LR.best_score_))

# tampilkan skor model terbaik GSCV pada test set
print("Test Score:
{}".format(GSCV_LR.best_estimator_.score(x_test_enc, y_test)))

# tampilkan best model dan best features
print("Best model:", GSCV_LR.best_estimator_)

# Mendapatkan fitur terbaik berdasarkan seleksi fitur
mask =
GSCV_LR.best_estimator_.named_steps['feature_select'].get_support()
print("Best features:", df_train_enc.columns[mask])

# buat prediksi dari test set
LR_pred = GSCV_LR.predict(x_test_enc)

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

# buat confusion matrix
cm = confusion_matrix(y_test, LR_pred, labels=GSCV_LR.classes_)

# buat confusion matrix display
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=GSCV_LR.classes_)
disp.plot()

plt.title("Logistic Regression Confusion Matrix")
plt.show()

# tampilkan Classification report

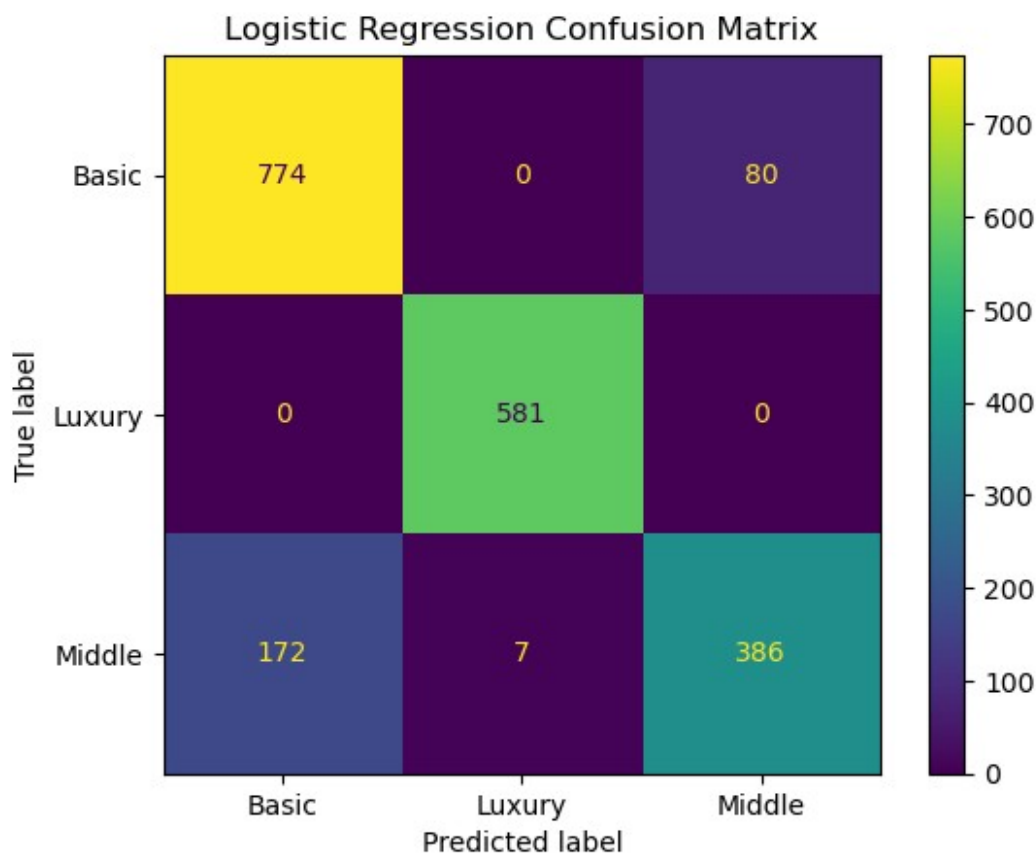
```

```

print("Classification report LR: \n", classification_report(y_test,
LR_pred))

CV Score: 0.88025
Test Score: 0.8705
Best model: Pipeline(steps=[('data_scaling', StandardScaler()),
                             ('feature_select', SelectPercentile(percentile=41)),
                             ('clf',
                              LogisticRegression(C=10, class_weight='balanced',
penalty='l1',
random_state=84,
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__numberofrooms',
'remainder__basement'],
dtype='object')

```



Classification report LR:				
	precision	recall	f1-score	support
Basic	0.82	0.91	0.86	854
Luxury	0.99	1.00	0.99	581
Middle	0.83	0.68	0.75	565
accuracy			0.87	2000
macro avg	0.88	0.86	0.87	2000
weighted avg	0.87	0.87	0.87	2000

```

#import Library yang dibutuhkan
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.feature_selection import SelectKBest
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, StratifiedKFold
import numpy as np

# buat rancangan pipeline mulai dari data scaling hingga classifier
pipe_LR = [
    ('data scaling', StandardScaler()),
    ('feature select', SelectKBest()),
    ('clf', LogisticRegression(random_state=84,
class_weight='balanced', solver='liblinear')) # Menentukan solver
]

# buat parameter grid untuk step feature selection dan classifier
params_grid_LR = [
    {
        'data scaling': [StandardScaler()],
        'feature select_k': np.arange(2, 6),
        'clf_C': [0.01, 0.1, 1, 10], # Regularization strength
        'clf_penalty': ['l1', 'l2'] # Jenis penalty
    },
    {
        'data scaling': [MinMaxScaler()],
        'feature select_k': np.arange(2, 6),
        'clf_C': [0.01, 0.1, 1, 10],
        'clf_penalty': ['l1', 'l2']
    },
]

# muat tancangan pipeline ke dalam objek pipeline
estimator_LR = Pipeline(pipe_LR)

# muat pipeline dan parameter grid ke dalam objek GSCV dengan
Stratified 5-fold CV
SKF = StratifiedKFold(n_splits=5, shuffle=True, random_state=84)

```

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]

```

select'].get_support()
print("Best features:", df_train_enc.columns[mask])

# buat prediksi dari test set
LR_pred = GSCV_LR.predict(x_test_enc)

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

# buat confusion matrix
cm = confusion_matrix(y_test, LR_pred, labels=GSCV_LR.classes_)

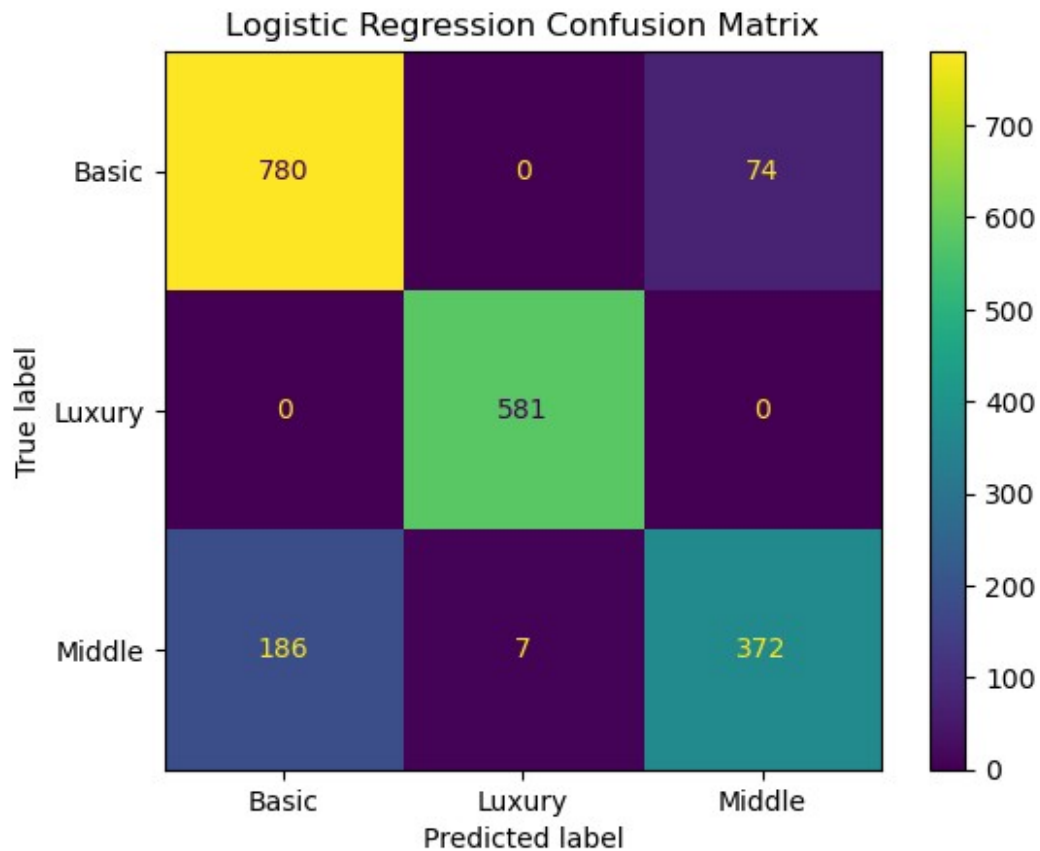
# buat confusion matrix display
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=GSCV_LR.classes_)
disp.plot()

plt.title("Logistic Regression Confusion Matrix")
plt.show()

# tampilkan Classification report
print("Classification report LR: \n", classification_report(y_test,
LR_pred))

CV Score: 0.882
Test Score: 0.8665
Best model: Pipeline(steps=[('data scaling', StandardScaler()),
                             ('feature select', SelectKBest(k=5)),
                             ('clf',
                              LogisticRegression(C=10, class_weight='balanced',
penalty='l1',
random_state=84,
solver='liblinear'))])
Best features: Index(['onehotencoder__hasyard_no',
'onehotencoder__hasyard_yes',
'onehotencoder__haspool_no', 'onehotencoder__haspool_yes',
'remainder__squaremeters'],
dtype='object')

```



Classification report LR:				
	precision	recall	f1-score	support
Basic	0.81	0.91	0.86	854
Luxury	0.99	1.00	0.99	581
Middle	0.83	0.66	0.74	565
accuracy			0.87	2000
macro avg	0.88	0.86	0.86	2000
weighted avg	0.87	0.87	0.86	2000

```

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.feature_selection import SelectFromModel, SelectKBest,
SelectPercentile, RFECV
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier,
RandomForestRegressor
from sklearn.svm import SVC, SVR
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
from pandas.api.types import is_numeric_dtype
from sklearn.linear_model import Ridge, Lasso
import matplotlib.pyplot as plt

```

```

properti_price =
pd.read_csv('/Users/saktiyoga/Downloads/UTS_PMDPM/Dataset UTS_Gasal
2425.csv')
properti_price.head(100)

```

	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
..	...	...	...	...	...	...
95	98868	41	no	yes	67	85917
96	83110	43	yes	no	75	55046
97	71154	67	no	yes	53	8762
98	90841	48	yes	no	15	25300
99	68416	87	yes	no	48	60979

	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					
..	...	...	...	...	...
...					
95	7	3	2021	new	yes
2146					
96	7	10	2001	new	no
4108					
97	2	6	2021	new	yes
8418					
98	6	5	2003	old	no
3333					
99	8	7	2010	old	no
1811					

	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
..	...	...	...	...	...	...
95	1077	623	yes	3	9892300.1	Luxury
96	5663	380	yes	7	8321631.1	Luxury
97	7187	706	no	8	7122699.1	Luxury
98	149	842	no	9	9086177.3	Luxury
99	6776	424	no	6	6846709.0	Middle

[100 rows x 18 columns]

```

propti_price2 = propti_price.drop('category', axis=1)
propti_price2.head(100)

```

	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	
..	...	...	...	...	...	...	
95	98868	41	no	yes	67	85917	
96	83110	43	yes	no	75	55046	
97	71154	67	no	yes	53	8762	
98	90841	48	yes	no	15	25300	
99	68416	87	yes	no	48	60979	

	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
..         ...         ...         ...         ...
...
95          7          3  2021      new          yes
2146
96          7          10  2001      new          no
4108
97          2          6  2021      new          yes
8418
98          6          5  2003      old          no
3333
99          8          7  2010      old          no
1811

```

```

      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
..     ...     ...         ...         ...     ...
95   1077    623          yes          3  9892300.1
96   5663    380          yes          7  8321631.1
97   7187    706          no          8  7122699.1
98    149    842          no          9  9086177.3
99   6776    424          no          6  6846709.0

```

[100 rows x 17 columns]

properti\_price2.info

```

<bound method DataFrame.info of
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
...         ...         ...     ...     ...     ...     ...
9995         341         83      no      no       8      1960
9996        21514          5      no      yes     11      91373
9997        1726         89      no      yes      5      73133

```

9998	44403	29	yes	yes	12	34606
9999	1440	84	no	no	49	18412
	citypartrange	numprevowners	made	isnewbuilt	hasstormprotector	
\						
0	3	8	2005	old	yes	
1	6	8	2021	old	no	
2	3	4	2003	new	no	
3	8	3	2012	new	yes	
4	4	2	2011	new	yes	
...	...	...	...	...	...	...
9995	4	4	1993	new	yes	
9996	1	1	1999	old	no	
9997	7	6	2009	old	yes	
9998	9	4	1990	old	yes	
9999	6	10	1994	new	no	
	basement	attic	garage	hasstorageroom	hasguestroom	price
0	4313	9005	956	no	7	7559081.5
1	2937	8852	135	yes	9	5574642.1
2	6326	4748	654	no	10	8696869.3
3	632	5792	807	yes	5	5154055.2
4	5414	1172	716	yes	9	9652258.1
...	...	...	...	...	...	...
9995	2366	4016	229	yes	5	35371.3
9996	2584	5266	787	no	3	2153602.9
9997	9311	1698	218	no	4	176425.9
9998	9061	1742	230	no	0	4448474.0
9999	8485	2024	278	yes	6	146708.4

```
[10000 rows x 17 columns]>
```

```
properti_price2.describe()
```

	squaremeters	numberofrooms	floors	citycode
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	49870.13120	50.358400	50.276300	50225.486100
std	28774.37535	28.816696	28.889171	29006.675799
min	89.000000	1.000000	1.000000	3.000000
25%	25098.50000	25.000000	25.000000	24693.750000
50%	50105.50000	50.000000	50.000000	50693.000000
75%	74609.75000	75.000000	76.000000	75683.250000
max	99999.00000	100.000000	100.000000	99953.000000

	numprevowners	made	basement	attic
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	5.521700	2005.48850	5033.103900	5028.01060
std	2.856667	9.30809	2876.729545	2894.33221
min	1.000000	1990.00000	0.000000	1.000000
25%	3.000000	1997.00000	2559.750000	2512.000000
50%	5.000000	2005.50000	5092.500000	5045.000000
75%	8.000000	2014.00000	7511.250000	7540.500000
max	10.000000	2021.00000	10000.000000	10000.000000

	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%	8.000000	7.469092e+06
max	10.000000	1.000677e+07

```
print(properti_price2['price'].value_counts())
```

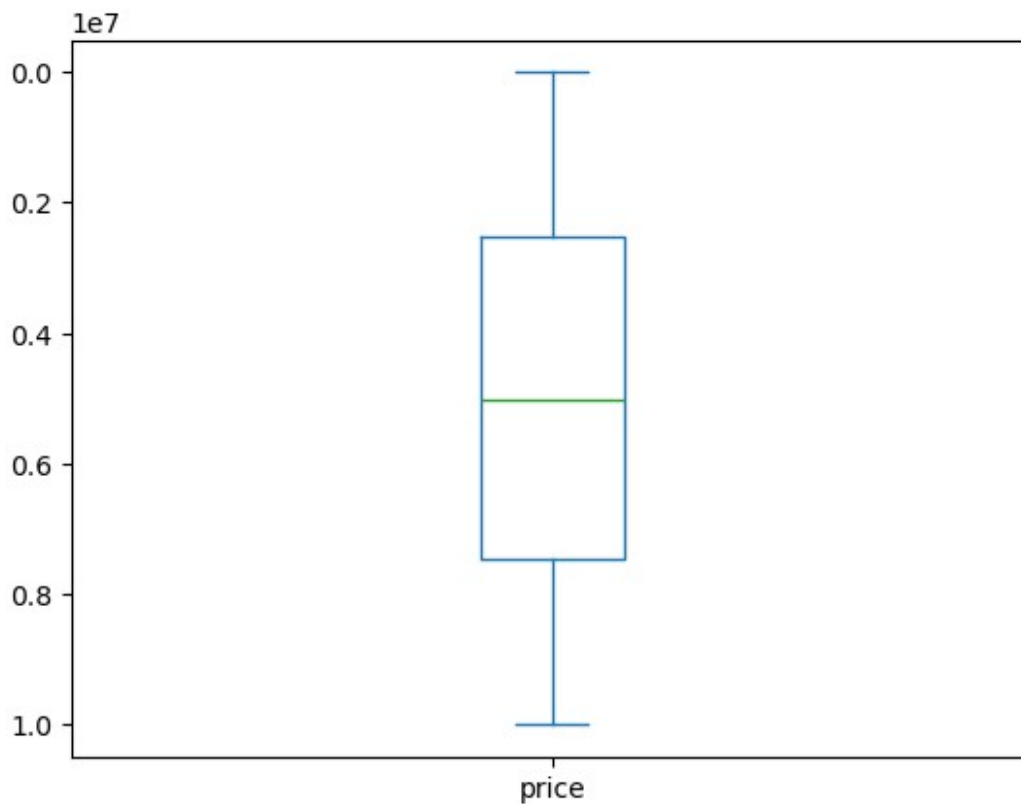
```
price
7559081.5    1
2600292.1    1
3804577.4    1
3658559.7    1
2316639.4    1
..
5555606.6    1
5501007.5    1
9986201.2    1
9104801.8    1
146708.4     1
Name: count, Length: 10000, dtype: int64
```

```
print("data null \n", properti_price2.isnull().sum())
print("data kosong \n", properti_price2.empty)
print("data nan \n", properti_price2.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
```

```
property_price2.price.plot(kind='box')
plt.gca().invert_yaxis()
plt.show()
```



```
def remove_outlier(df_in):
    for col_name in list(df_in):
        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+(iqr*1.5)
batas_bawah = q1-(iqr*1.5)

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

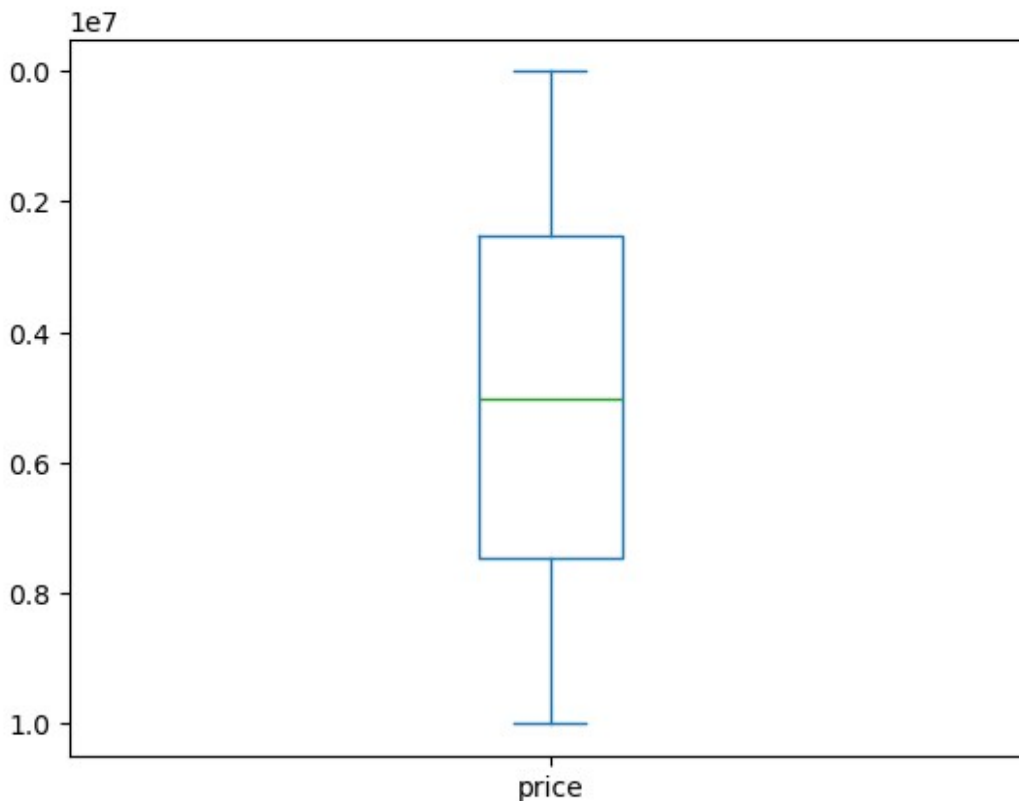
return df_out

properti_price_clean = remove_outlier(properti_price2)
print("Jumlah baris DataFrame sebelum di
outlier",properti_price2.shape[0])
print("Jumlah baris DataFrame sesudah di
outlier",properti_price_clean.shape[0])
properti_price_clean.price.plot(kind='box', vert=True)

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

Jumlah baris DataFrame sebelum di outlier 10000
Jumlah baris DataFrame sesudah di outlier 10000

```



```

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

```
X_regress=properti_price_clean.drop('price',axis=1)
```

```
y_regress=properti_price_clean.price
```

```
X_train_price, X_test_price, y_train_price, y_test_price =
```

```

train_test_split(X_regress, y_regress, test_size=0.20,
random_state=84)

X_regress=properti_price_clean.drop('price',axis=1)
y_regress=properti_price_clean.price

X_train_ins, X_test_ins, y_train_ins, y_test_ins =
train_test_split(X_regress, y_regress, test_size=0.20,
random_state=84)
cat_cols =
X_train_ins.select_dtypes(include=['object']).columns.tolist()
print("Kolom kategorik:",cat_cols)

transformer = make_column_transformer(
    (OneHotEncoder(), cat_cols),
    remainder = 'passthrough'
)

X_train_enc = transformer.fit_transform(X_train_ins)
X_test_enc = transformer.transform(X_test_ins)

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

df_train_enc.head(10)
df_test_enc.head(10)

Kolom kategorik: ['hasyard', 'haspool', 'isnewbuilt',
'hasstormprotector', 'hasstorageroom']

```

	onehotencoder__hasyard_no	onehotencoder__hasyard_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	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__haspool_no	onehotencoder__haspool_yes \
0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
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	0.0	1.0

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

	onehotencoder__hasstorageroom_no	onehotencoder__hasstorageroom_yes
...		
0	1.0	0.0
...		
1	1.0	0.0
...		
2	0.0	1.0
...		
3	1.0	0.0
...		

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	0.0	1.0
...		

	remainder__numberofrooms	remainder__floors	remainder__citycode	\
0	97.0	45.0	62899.0	
1	76.0	54.0	82737.0	
2	72.0	26.0	7812.0	
3	46.0	51.0	91317.0	
4	4.0	30.0	8424.0	
5	47.0	14.0	50927.0	
6	54.0	15.0	61691.0	
7	42.0	50.0	50833.0	
8	97.0	3.0	68804.0	
9	18.0	26.0	67302.0	

	remainder__citypartrange	remainder__numprevowners	remainder__made	\
0	1.0	9.0	1990.0	
1	7.0	3.0	1998.0	
2	6.0	3.0	1995.0	
3	5.0	3.0	2020.0	
4	4.0	10.0	2003.0	
5	9.0	6.0	1993.0	
6	2.0	2.0	2002.0	
7	3.0	8.0	2009.0	
8	10.0	5.0	1991.0	
9	6.0	2.0	2005.0	

	remainder__basement	remainder__attic	remainder__garage	\
0	4110.0	1675.0	599.0	

1	4010.0	8343.0	260.0
2	6972.0	3804.0	828.0
3	3337.0	7250.0	337.0
4	5655.0	1684.0	453.0
5	4078.0	315.0	767.0
6	5925.0	9705.0	342.0
7	9320.0	5752.0	936.0
8	5804.0	2070.0	846.0
9	6111.0	771.0	500.0

	remainder__hasguestroom
0	4.0
1	10.0
2	8.0
3	1.0
4	8.0
5	10.0
6	8.0
7	3.0
8	9.0
9	10.0

[10 rows x 21 columns]

```

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

pipe_Lasso_KBest = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection',
SelectKBest(score_func=f_regression)),
    ('reg', Lasso(max_iter=1000)) #max_iter digunakan untuk
menen
    ])

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

GSCV_Lasso = GridSearchCV(pipe_Lasso_KBest, param_grid_Lasso_KBest,
cv=5, scoring='neg_mean_squared_error')

GSCV_Lasso.fit(X_train_enc, y_train_price)
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_price, Lasso_predict)
mae_Lasso = mean_absolute_error(y_test_price, 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=19,
                                           score_func=<function f_regression at
0x12e0b7380>)),
                             ('reg', Lasso(alpha=10))])
Lasso best parameters: {'feature_selection__k': 19, 'reg__alpha': 10}
Koefisien/bobot:[-1.48625529e+03  7.33416528e-12 -1.50225115e+03
1.53522706e-12
 7.27030018e+01 -1.23691279e-13 -6.74320323e+01  0.00000000e+00
-3.53814701e+00  1.93569576e-10  2.88436146e+06  0.00000000e+00
 1.58134765e+03  1.38057483e+02 -3.70828982e+00 -8.77399024e+00
-1.03200436e+00  2.18869143e+01 -0.00000000e+00]
Intercept/bias:5008877.674924995
Lasso Mean Squared Error (MSE): 3535757.3574986807
Lasso Mean Absolute Error (MAE): 1462.234583543154
Lasso Root Mean Squared Error: 1880.3609646816967

# df_results['Lasso KBest Prediction']=Lasso_predict
df_results = pd.DataFrame(y_test_price)
df_results['Lasso KBest Prediction']=Lasso_predict

df_results['Selisih Price Lasso KBest'] = df_results['Lasso KBest
Prediction'] - df_results['price']
df_results.head()


```

	price	Lasso KBest Prediction	Selisih Price Lasso KBest
2457	6033313.0	6.035400e+06	2087.414519
4865	5290006.8	5.285274e+06	-4733.001285
5288	9235289.5	9.234512e+06	-777.323262
1063	7616002.0	7.616129e+06	126.814548
5197	9390420.3	9.391625e+06	1204.251593

```

df_results.describe()

```

	price	Lasso KBest Prediction	Selisih Price Lasso KBest
count	2.000000e+03	2.000000e+03	2000.000000
mean	4.931727e+06	4.931789e+06	61.835861
std	2.848679e+06	2.848584e+06	1879.813963
min	2.381840e+04	2.881419e+04	-6905.546378
25%	2.494605e+06	2.493396e+06	-1087.464237
50%	5.014176e+06	5.014615e+06	39.206169
75%	7.338401e+06	7.338065e+06	1234.037636
max	9.994474e+06	9.994805e+06	6211.922919

```

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 SelectPercentile, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_Lasso_percentile = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectPercentile(score_func=f_regression)),
    # Menggunakan SelectPercentile
    ('reg', Lasso(max_iter=1000))
])

param_grid_Lasso_percentile = {
    'reg__alpha': [0.01, 0.1, 1, 10, 100],
    'feature_selection__percentile': np.arange(10, 100, 10) #
    Menggunakan persentase fitur terbaik
}

GSCV_Lasso = GridSearchCV(pipe_Lasso_percentile,
    param_grid_Lasso_percentile, cv=5, scoring='neg_mean_squared_error')

# Fit ke data latih
GSCV_Lasso.fit(X_train_enc, y_train_price)

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

# Koefisien dan intercept dari model terbaik
print("Koefisien/bobot:
{}".format(GSCV_Lasso.best_estimator_.named_steps['reg'].coef_))
print("Intercept/bias:
{}".format(GSCV_Lasso.best_estimator_.named_steps['reg'].intercept_))

# Prediksi terhadap data uji
Lasso_predict = GSCV_Lasso.predict(X_test_enc)

# Menghitung error

```

```

mse_Lasso = mean_squared_error(y_test_price, Lasso_predict)
mae_Lasso = mean_absolute_error(y_test_price, 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',
                              SelectPercentile(percentile=90,
                                                  score_func=<function f_regression at
0x12e0b7380>)),
                             ('reg', Lasso(alpha=10))])
Lasso best parameters: {'feature_selection__percentile': 90,
'reg__alpha': 10}
Koefisien/bobot:[ 1.48625529e+03 -1.50225115e+03  1.32422429e-12
7.27030018e+01
-2.91038305e-14 -6.74320323e+01  0.00000000e+00 -3.53814701e+00
1.93609594e-10  2.88436146e+06  0.00000000e+00  1.58134765e+03
1.38057483e+02 -3.70828982e+00 -8.77399024e+00 -1.03200436e+00
2.18869143e+01 -0.00000000e+00]
Intercept/bias:5008877.6749249995
Lasso Mean Squared Error (MSE): 3535757.3574986784
Lasso Mean Absolute Error (MAE): 1462.2345835431515
Lasso Root Mean Squared Error: 1880.360964681696

df_results['Lasso Percentile Prediction']=Lasso_predict
df_results = pd.DataFrame(y_test_price)
df_results['Lasso Percentile Prediction']=Lasso_predict

df_results['Selisih Price Lasso Percentile'] = df_results['Lasso
Percentile Prediction'] - df_results['price']
df_results.head()

   price  Lasso Percentile Prediction  Selisih Price Lasso
Percentile
2457  6033313.0                    6.035400e+06
2087.414519
4865  5290006.8                    5.285274e+06 -
4733.001285
5288  9235289.5                    9.234512e+06 -
777.323262
1063  7616002.0                    7.616129e+06
126.814548
5197  9390420.3                    9.391625e+06
1204.251593

df_results.describe()

   price  Lasso Percentile Prediction  \
count  2.000000e+03                2.000000e+03

```

mean	4.931727e+06	4.931789e+06
std	2.848679e+06	2.848584e+06
min	2.381840e+04	2.881419e+04
25%	2.494605e+06	2.493396e+06
50%	5.014176e+06	5.014615e+06
75%	7.338401e+06	7.338065e+06
max	9.994474e+06	9.994805e+06

	Selisih Price Lasso Percentile
count	2000.000000
mean	61.835861
std	1879.813963
min	-6905.546378
25%	-1087.464237
50%	39.206169
75%	1234.037636
max	6211.922919

```

from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectPercentile, f_regression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

```

```

# Pipeline for Random Forest Regressor

```

```

pipe_RF = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectPercentile(score_func=f_regression)),
    ('reg', RandomForestRegressor(random_state=84)) # Random Forest
])

```

```

# Parameter grid untuk GridSearchCV

```

```

param_grid_RF = {
    'reg__n_estimators': [100, 200], # Jumlah pohon lebih
    'reg__max_depth': [2,3], # Variasi kedalaman terbatas
    'feature_selection__percentile': np.arange(10, 50) # Langkah 10
}

```

```

# GridSearchCV to find the best parameters

```

```

GSCV_RF = GridSearchCV(pipe_RF, param_grid_RF, cv=5,
    scoring='neg_mean_squared_error')

```

```

# Fit to the training data

```

```

GSCV_RF.fit(X_train_enc, y_train_price)

```

```

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

# Make predictions on the test set
RF_predict = GSCV_RF.predict(X_test_enc)

# Calculate metrics
mse_RF = mean_squared_error(y_test_price, RF_predict)
mae_RF = mean_absolute_error(y_test_price, RF_predict)

print("Random Forest Mean Squared Error (MSE): {}".format(mse_RF))
print("Random Forest Mean Absolute Error (MAE): {}".format(mae_RF))
print("Random Forest Root Mean Squared Error:
{}".format(np.sqrt(mse_RF)))

Best model:Pipeline(steps=[('scale', StandardScaler()),
                             ('feature_selection',
                              SelectPercentile(percentile=41,
                                                  score_func=<function f_regression at
0x12e0b7380>)),
                             ('reg', RandomForestRegressor(max_depth=3,
                                                             random_state=84))])
Random Forest best parameters: {'feature_selection__percentile': 41,
'__reg__max_depth': 3, '__reg__n_estimators': 100}
Random Forest Mean Squared Error (MSE): 111333999223.2568
Random Forest Mean Absolute Error (MAE): 289241.46874328353
Random Forest Root Mean Squared Error: 333667.4980025127

df_results['Random Forest Percentile Prediction']=RF_predict
df_results = pd.DataFrame(y_test_price)
df_results['Random Forest Percentile Prediction']=RF_predict

df_results['Selisih Price RF Percentile'] = df_results['Random Forest
Percentile Prediction'] - df_results['price']
df_results.head()

```

	price	Random Forest Percentile Prediction \
2457	6033313.0	5.610185e+06
4865	5290006.8	5.610185e+06
5288	9235289.5	9.373249e+06
1063	7616002.0	8.145797e+06
5197	9390420.3	9.373249e+06

	Selisih Price RF Percentile
2457	-423128.277191
4865	320177.922809
5288	137959.866135



```
1063          529794.777347
5197          -17170.933865
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Pipeline for Random Forest Regressor
pipe_RF_Kbest = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectKBest(score_func=f_regression)), #
    ('reg', RandomForestRegressor(random_state=84)) # Random Forest
    ])

# Parameter grid untuk GridSearchCV
param_grid_RF_Kbest = {
    'reg_n_estimators': [100, 200], # Jumlah pohon lebih
    'reg_max_depth': [2,3], # Variasi kedalaman terbatas
    'feature_selection_k': np.arange(10, 50) # Langkah 10 untuk
}

# GridSearchCV to find the best parameters
GSCV_RF = GridSearchCV(pipe_RF_Kbest, param_grid_RF_Kbest, cv=5,
    scoring='neg_mean_squared_error')

# Fit to the training data
GSCV_RF.fit(X_train_enc, y_train_price)

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

# Make predictions on the test set
RF_predict = GSCV_RF.predict(X_test_enc)

# Calculate metrics
mse_RF = mean_squared_error(y_test_price, RF_predict)
mae_RF = mean_absolute_error(y_test_price, RF_predict)

print("Random Forest Mean Squared Error (MSE): {}".format(mse_RF))
print("Random Forest Mean Absolute Error (MAE): {}".format(mae_RF))
```

```
print("Random Forest Root Mean Squared Error:
{}".format(np.sqrt(mse_RF)))
```

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```
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=27 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=28 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=28 is greater than
n_features=21. All the features will be returned.
warnings.warn(
```

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```
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=28 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=28 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=28 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=29 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=29 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=29 is greater than  
n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=29 is greater than  
n_features=21. All the features will be returned.
```

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```
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=30 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=31 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=31 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=31 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=31 is greater than
```



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```
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=33 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=34 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=34 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=34 is greater than
n_features=21. All the features will be returned.
  warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=34 is greater than
n_features=21. All the features will be returned.
```

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```
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=38 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=39 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=39 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=39 is greater than
n_features=21. All the features will be returned.
warnings.warn(
```

[illegible]

[illegible]

[illegible]



[illegible]

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=41 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=42 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=42 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=42 is greater than n_features=21. All the features will be returned.  
warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/_univariate_selection.py:776: UserWarning: k=42 is greater than
```

[illegible]

[illegible]

[illegible]

[illegible]

```
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=44 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=44 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=44 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=44 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=44 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=45 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=45 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=45 is greater than  
n_features=21. All the features will be returned.  
    warnings.warn(  
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/  
_univariate_selection.py:776: UserWarning: k=45 is greater than  
n_features=21. All the features will be returned.
```

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```

warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.
warnings.warn(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/feature_selection/
_univariate_selection.py:776: UserWarning: k=49 is greater than
n_features=21. All the features will be returned.

```

```

Best model: Pipeline(steps=[('scale', StandardScaler()),
                             ('feature_selection',
                              SelectKBest(k=15,
                                           score_func=<function f_regression at
0x12e0b7380>))),

```

```

                             ('reg', RandomForestRegressor(max_depth=3,
random_state=84))])
Random Forest best parameters: {'feature_selection__k': 15,
'__reg__max_depth': 3, '__reg__n_estimators': 100}
Random Forest Mean Squared Error (MSE): 111333999223.2568
Random Forest Mean Absolute Error (MAE): 289241.46874328353
Random Forest Root Mean Squared Error: 333667.4980025127

```

```

df_results['Random Forest KBest Prediction']=RF_predict
df_results = pd.DataFrame(y_test_price)
df_results['Random Forest KBest Prediction']=RF_predict

```

```
df_results['Selisih Price RF KBest'] = df_results['Random Forest KBest Prediction'] - df_results['price']
df_results.head()
```

	price	Random Forest KBest Prediction	Selisih Price RF KBest
2457	6033313.0	5.610185e+06	-
4231	28.277191		
4865	5290006.8	5.610185e+06	
3201	77.922809		
5288	9235289.5	9.373249e+06	
1379	59.866135		
1063	7616002.0	8.145797e+06	
5297	94.777347		
5197	9390420.3	9.373249e+06	-
1717	0.933865		

```
import pandas as pd
import matplotlib.pyplot as plt

# Misalkan Ridge_predict dan SVR_predict sudah didefinisikan sebelumnya
# Ridge_predict = model_ridge.predict(X_test)
# SVR_predict = model_svr.predict(X_test)

# Mengonversi y_test_price menjadi DataFrame
df_results = pd.DataFrame(y_test_price)

# Menambahkan kolom prediksi
df_results['Lasso KBest Prediction']=Lasso_predict
df_results['Random Forest KBest Prediction']=RF_predict

# Jika ada kolom lain yang perlu ditambahkan
df_results['Lasso Percentile Prediction']=Lasso_predict
df_results['Random Forest Percentile Prediction']=RF_predict

# Menghitung selisih

df_results['Selisih Price Lasso KBest'] = df_results['Lasso KBest Prediction'] - df_results['price']
df_results['Selisih Price RF KBest'] = df_results['Random Forest KBest Prediction'] - df_results['price']

# Menampilkan beberapa data teratas
print(df_results.head())

# Membuat plot
plt.figure(figsize=(20, 5))
data_len = range(len(y_test_price))
plt.scatter(data_len, df_results['price'], label="Actual",
```



```

color="blue")
plt.plot(data_len, df_results['Lasso KBest Prediction'], label="Lasso
KBest Prediction", color="green", linewidth=1, linestyle="dashed")
plt.plot(data_len, df_results['Lasso Percentile Prediction'],
label="Lasso Percentile Prediction", color="red", linewidth=1,
linestyle="dashed")
plt.plot(data_len, df_results['Random Forest KBest Prediction'],
label="Random Forest KBest Prediction", color="yellow", linewidth=1,
linestyle="-.")
plt.plot(data_len, df_results['Random Forest Percentile Prediction'],
label="Random Forest Percentile Prediction", color="black",
linewidth=1, linestyle="-.")

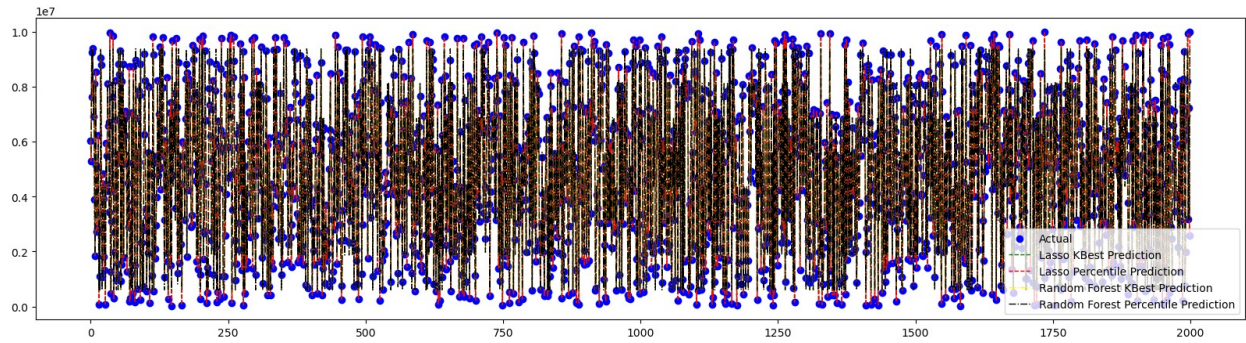
# Menambahkan legenda dan menampilkan plot
plt.legend()
plt.show()

```

	price	Lasso KBest Prediction	Random Forest KBest
Prediction \			
2457	6033313.0	6.035400e+06	
5.610185e+06			
4865	5290006.8	5.285274e+06	
5.610185e+06			
5288	9235289.5	9.234512e+06	
9.373249e+06			
1063	7616002.0	7.616129e+06	
8.145797e+06			
5197	9390420.3	9.391625e+06	
9.373249e+06			

	Lasso Percentile Prediction	Random Forest Percentile Prediction
\		
2457	6.035400e+06	5.610185e+06
4865	5.285274e+06	5.610185e+06
5288	9.234512e+06	9.373249e+06
1063	7.616129e+06	8.145797e+06
5197	9.391625e+06	9.373249e+06

	Selisih Price Lasso KBest	Selisih Price RF KBest
2457	2087.414519	-423128.277191
4865	-4733.001285	320177.922809
5288	-777.323262	137959.866135
1063	126.814548	529794.777347
5197	1204.251593	-17170.933865



```
import pickle
best_model = GSCV_RF.best_estimator_

with open('BestModel_REG_GSCV_RF_matplotlib.pkl', 'wb') as f:
    pickle.dump(best_model, f)
print("Model Terbaik berhasil disimpan ke  
'BestModel_REG_GSCV_RF_matplotlib.pkl'")

Model Terbaik berhasil disimpan ke  
'BestModel_REG_GSCV_RF_matplotlib.pkl'
```

```

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.feature_selection import SelectFromModel, SelectKBest,
SelectPercentile, RFECV
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier,
RandomForestRegressor
from sklearn.svm import SVC, SVR
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error
from pandas.api.types import is_numeric_dtype
from sklearn.linear_model import Ridge, Lasso
import matplotlib.pyplot as plt

```

```

properti_price = pd.read_csv('Dataset UTS_Gasal 2425.csv')
properti_price.head(100)

```

	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	
..	...	...	...	...	...	...	
95	98868	41	no	yes	67	85917	
96	83110	43	yes	no	75	55046	
97	71154	67	no	yes	53	8762	
98	90841	48	yes	no	15	25300	
99	68416	87	yes	no	48	60979	

	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
...
...
95      7      3  2021      new      yes
2146
96      7      10  2001      new      no
4108
97      2      6  2021      new      yes
8418
98      6      5  2003      old      no
3333
99      8      7  2010      old      no
1811

```

```

      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
...      ...      ...      ...      ...      ...
95     1077    623          yes          3  9892300.1  Luxury
96     5663    380          yes          7  8321631.1  Luxury
97     7187    706          no          8  7122699.1  Luxury
98      149    842          no          9  9086177.3  Luxury
99     6776    424          no          6  6846709.0  Middle

```

[100 rows x 18 columns]

```

propterti_price2 = propterti_price.drop('category', axis=1)
propterti_price2.head(100)

```

```

      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
...      ...      ...      ...      ...      ...
95     98868          41          no      yes      67      85917
96     83110          43          yes      no      75      55046
97     71154          67          no      yes      53      8762
98     90841          48          yes      no      15      25300
99     68416          87          yes      no      48      60979

```

```

      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
...      ...      ...      ...      ...      ...
...
95          7          3  2021          new          yes
2146
96          7          10  2001          new          no
4108
97          2          6  2021          new          yes
8418
98          6          5  2003          old          no
3333
99          8          7  2010          old          no
1811

```

```

      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
...      ...      ...      ...      ...      ...
95     1077      623             yes             3  9892300.1
96     5663      380             yes             7  8321631.1
97     7187      706             no             8  7122699.1
98       149      842             no             9  9086177.3
99     6776      424             no             6  6846709.0

```

[100 rows x 17 columns]

properti\_price2.info

```

<bound method DataFrame.info of
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
...      ...      ...      ...      ...      ...      ...
9995          341          83      no      no       8      1960
9996         21514          5      no      yes     11      91373
9997          1726          89      no      yes      5      73133
9998         44403          29     yes     yes     12      34606
9999          1440          84      no      no     49      18412

```

	city	par	range	numprev	owners	made	isnew	built	hasstorm	protector
\0		3		8		2005		old		yes
1		6		8		2021		old		no
2		3		4		2003		new		no
3		8		3		2012		new		yes
4		4		2		2011		new		yes
...		...		...		...		...		...
9995		4		4		1993		new		yes
9996		1		1		1999		old		no
9997		7		6		2009		old		yes
9998		9		4		1990		old		yes
9999		6		10		1994		new		no
	basement	attic	garage	hasstorageroom	hasguestroom	price				
0	4313	9005	956	no	7	7559081.5				
1	2937	8852	135	yes	9	5574642.1				
2	6326	4748	654	no	10	8696869.3				
3	632	5792	807	yes	5	5154055.2				
4	5414	1172	716	yes	9	9652258.1				
...	...	...	...	...	...	...				
9995	2366	4016	229	yes	5	35371.3				
9996	2584	5266	787	no	3	2153602.9				
9997	9311	1698	218	no	4	176425.9				
9998	9061	1742	230	no	0	4448474.0				
9999	8485	2024	278	yes	6	146708.4				
[10000 rows x 17 columns]>										

```
propti_price2.describe()
```

	squaremeters	numberofrooms	floors	citycode
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	49870.13120	50.358400	50.276300	50225.486100
std	28774.37535	28.816696	28.889171	29006.675799
min	89.000000	1.000000	1.000000	3.000000
25%	25098.50000	25.000000	25.000000	24693.750000
50%	50105.50000	50.000000	50.000000	50693.000000
75%	74609.75000	75.000000	76.000000	75683.250000
max	99999.00000	100.000000	100.000000	99953.000000

	numprevowners	made	basement	attic
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	5.521700	2005.48850	5033.103900	5028.01060
std	2.856667	9.30809	2876.729545	2894.33221
min	1.000000	1990.00000	0.000000	1.000000
25%	3.000000	1997.00000	2559.750000	2512.000000
50%	5.000000	2005.50000	5092.500000	5045.000000
75%	8.000000	2014.00000	7511.250000	7540.500000
max	10.000000	2021.00000	10000.000000	10000.000000

	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

```
print(properti_price2['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
```

```
print("data null \n", properti_price2.isnull().sum())
```

```
print("data kosong \n", properti_price2.empty)
```

```
print("data nan \n", properti_price2.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
```

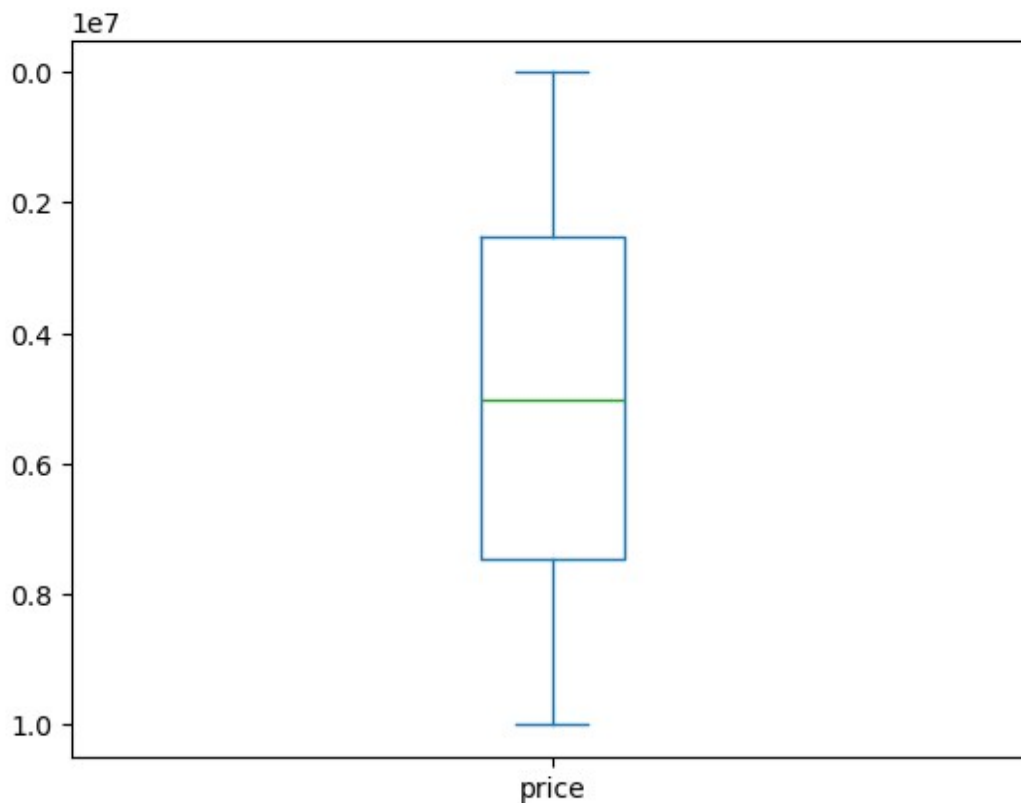
```
data nan
```

```
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
```

```
properti_price2.price.plot(kind='box')
plt.gca().invert_yaxis()
plt.show()
```



```
def remove_outlier(df_in):
    for col_name in list(df_in):
        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+(iqr*1.5)
            batas_bawah = q1-(iqr*1.5)
```

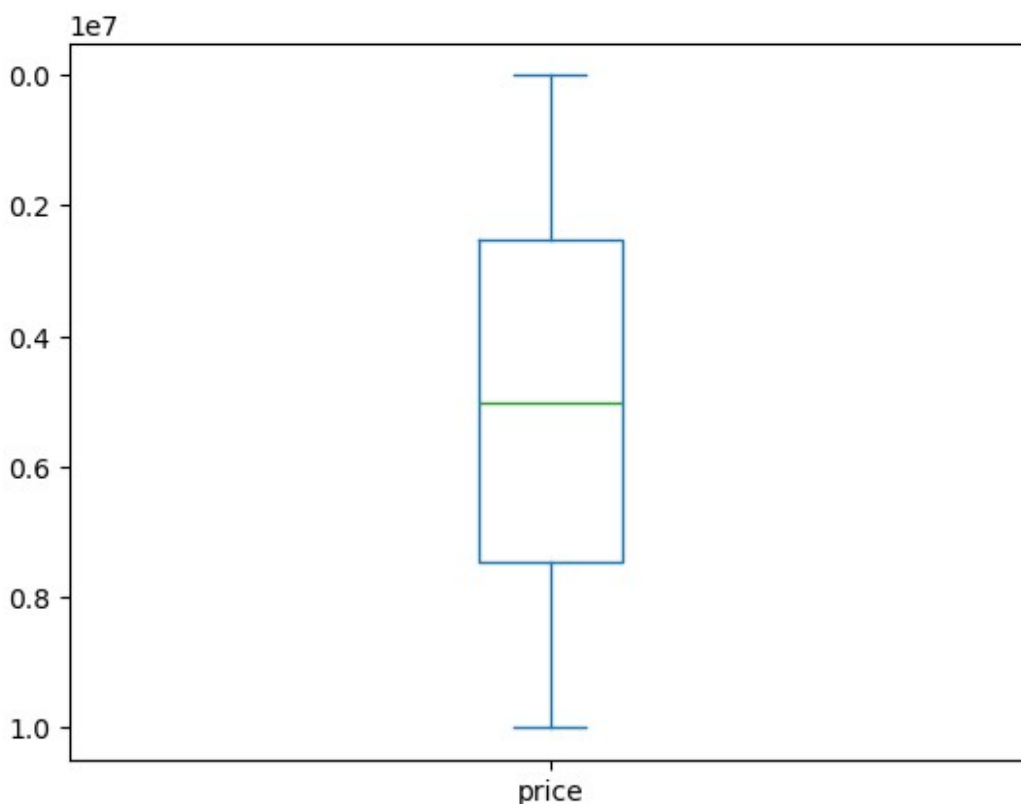
```
df_out = df_in.loc[(df_in[col_name]>=batas_bawah) &
(df_in[col_name]<=batas_atas)]
```

```
return df_out
```

```
properti_price_clean = remove_outlier(properti_price2)
print("Jumlah baris DataFrame sebelum di outlier",properti_price2.shape[0])
print("Jumlah baris DataFrame sesudah di outlier",properti_price_clean.shape[0])
properti_price_clean.price.plot(kind='box', vert=True)
```

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

Jumlah baris DataFrame sebelum di outlier 10000  
Jumlah baris DataFrame sesudah di outlier 10000



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

```
X_regress=properti_price_clean.drop('price',axis=1)
```

```
y_regress=properti_price_clean.price
```

```
X_train_price, X_test_price, y_train_price, y_test_price =
train_test_split(X_regress, y_regress, test_size=0.20,
random_state=84)
```

```
X_regress=properti_price_clean.drop('price',axis=1)
```

```
y_regress=properti_price_clean.price
```

```

X_train_ins, X_test_ins, y_train_ins, y_test_ins =
train_test_split(X_regress, y_regress, test_size=0.20,
random_state=84)
cat_cols =
X_train_ins.select_dtypes(include=['object']).columns.tolist()
print("Kolom kategorik:", cat_cols)

transformer = make_column_transformer(
    (OneHotEncoder(), cat_cols),
    remainder = 'passthrough'
)

X_train_enc = transformer.fit_transform(X_train_ins)
X_test_enc = transformer.transform(X_test_ins)

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

df_train_enc.head(10)
df_test_enc.head(10)

Kolom kategorik: ['hasyard', 'haspool', 'isnewbuilt',
'hasstormprotector', 'hasstorageroom']

```

	onehotencoder__hasyard_no	onehotencoder__hasyard_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	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__haspool_no	onehotencoder__haspool_yes \
0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
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	0.0	1.0

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

	onehotencoder__hasstorageroom_no	onehotencoder__hasstorageroom_yes
...	\	
0	1.0	0.0
...		
1	1.0	0.0
...		
2	0.0	1.0
...		
3	1.0	0.0
...		
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	0.0	1.0
...		

	remainder__numberofrooms	remainder__floors	remainder__citycode	\
0	97.0	45.0	62899.0	
1	76.0	54.0	82737.0	
2	72.0	26.0	7812.0	
3	46.0	51.0	91317.0	
4	4.0	30.0	8424.0	
5	47.0	14.0	50927.0	
6	54.0	15.0	61691.0	
7	42.0	50.0	50833.0	
8	97.0	3.0	68804.0	
9	18.0	26.0	67302.0	

	remainder__citypartrange	remainder__numprevowners	remainder__made	\
0	1.0	9.0	1990.0	
1	7.0	3.0	1998.0	
2	6.0	3.0	1995.0	
3	5.0	3.0	2020.0	
4	4.0	10.0	2003.0	
5	9.0	6.0	1993.0	
6	2.0	2.0	2002.0	
7	3.0	8.0	2009.0	
8	10.0	5.0	1991.0	
9	6.0	2.0	2005.0	

	remainder__basement	remainder__attic	remainder__garage	\
0	4110.0	1675.0	599.0	
1	4010.0	8343.0	260.0	
2	6972.0	3804.0	828.0	
3	3337.0	7250.0	337.0	
4	5655.0	1684.0	453.0	

5	4078.0	315.0	767.0
6	5925.0	9705.0	342.0
7	9320.0	5752.0	936.0
8	5804.0	2070.0	846.0
9	6111.0	771.0	500.0

	remainder__hasguestroom
0	4.0
1	10.0
2	8.0
3	1.0
4	8.0
5	10.0
6	8.0
7	3.0
8	9.0
9	10.0

[10 rows x 21 columns]

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

```
pipe_Ridge = Pipeline(steps=[
    ('scale', MinMaxScaler()),
    ('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(2, 11)
}
```

```
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_price)
```

```
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_price, Ridge_predict)
mae_Ridge = mean_absolute_error(y_test_price, Ridge_predict)

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

Best model:Pipeline(steps=[('scale', MinMaxScaler()),
                             ('feature_selection',
                              SelectKBest(score_func=<function f_regression at
0x0000020133634CC0>)),
                             ('reg', Ridge(alpha=0.01))])
Ridge best parameters: {'feature_selection__k': 10, 'reg__alpha': 0.01}
Koefisien/bobot: [-1.53069804e+03  1.53069804e+03  8.37049891e+01 -
8.37049878e+01
-5.36117068e+01  5.36117075e+01  9.99077325e+06  4.76218243e+02
-3.30900310e+01 -4.68782145e+01]
Intercept/bias: 15269.991580400616
Ridge Mean Squard Error (MSE): 8244727.333072739
Ridge Mean Absolute Error (MAE): 2337.7145753501745
Ridge Root Mean Squared Error: 2871.3633230701994

df_results['Ridge Prediction'] = Ridge_predict
df_results = pd.DataFrame(y_test_price)
df_results['Ridge Prediction'] = Ridge_predict

df_results['Selisih_price_RR'] = df_results['Ridge Prediction'] -
df_results['price']

df_results.head()

```

	price	Ridge Prediction	Selisih_price_RR
2457	6033313.0	6.034185e+06	872.342258
4865	5290006.8	5.283703e+06	-6304.221330
5288	9235289.5	9.234346e+06	-943.386054
1063	7616002.0	7.617647e+06	1644.933213
5197	9390420.3	9.391224e+06	804.087296

```

df_results.describe()

```

	price	Ridge Prediction	Selisih_price_RR
count	2.000000e+03	2.000000e+03	2000.000000
mean	4.931727e+06	4.931782e+06	55.352778
std	2.848679e+06	2.848562e+06	2871.547718
min	2.381840e+04	2.787007e+04	-10833.184798
25%	2.494605e+06	2.495427e+06	-1843.724940
50%	5.014176e+06	5.017360e+06	297.079502



75%	7.338401e+06	7.339645e+06	2355.146005
max	9.994474e+06	9.998520e+06	5919.050249

```

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],
    'reg__epsilon': [0.1, 0.2, 0.5, 1],
    'feature_selection__k': np.arange(2, 11)
}

```

```

GSCV_SVR = GridSearchCV(pipe_SVR, param_grid_SVR, cv=5,
    scoring='neg_mean_squared_error')

```

```

GSCV_SVR.fit(X_train_enc, y_train_price)

```

```

print("Best model:{}".format(GSCV_SVR.best_estimator_))
print("Ridge best parameters:{}".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_price, SVR_predict)
mae_SVR = mean_absolute_error(y_test_price, 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(k=2,
            score_func=<function f_regression at
0x0000020133634CC0>)),
    ('reg', SVR(C=10, kernel='linear'))])
Ridge best parameters: {'feature_selection__k': 2, 'reg__C': 10,

```

```
'reg_epsilon': 0.1}
Koefisien/bobot:[[69203.83142266 1771.44667832]]
Intercept/bias:[5017389.52551094]
SVR Mean Squared Error (MSE): 7733494955101.608
SVR Mean Absolute Error (MAE): 2392029.6675750944
SVR Root Mean Squared Error: 2780916.2078533773
```

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

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

	price	SVR Prediction	Selisih_price_SVR
2457	6033313.0	5.044114e+06	-9.891985e+05
4865	5290006.8	5.022385e+06	-2.676220e+05
5288	9235289.5	5.117175e+06	-4.118115e+06
1063	7616002.0	5.078386e+06	-2.537616e+06
5197	9390420.3	5.125272e+06	-4.265149e+06

```
df_results.describe()
```

	price	SVR Prediction	Selisih_price_SVR
count	2.000000e+03	2.000000e+03	2.000000e+03
mean	4.931727e+06	5.015550e+06	8.382343e+04
std	2.848679e+06	6.835477e+04	2.780348e+06
min	2.381840e+04	4.896081e+06	-4.858343e+06
25%	2.494605e+06	4.957087e+06	-2.266067e+06
50%	5.014176e+06	5.018407e+06	2.438072e+03
75%	7.338401e+06	5.072981e+06	2.461521e+06
max	9.994474e+06	5.138576e+06	4.874318e+06

```
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 SelectPercentile, f_regression
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
```

```
# Membuat pipeline dengan SelectPercentile
```

```
pipe_SVR_percentile = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectPercentile(score_func=f_regression)),
    ('reg', SVR(kernel='linear'))
])
```

```
# Parameter grid untuk GridSearchCV
```

```
param_grid_SVR_percentile = {
```

```

    'reg__C': [0.01,0.1,1,10],
    'reg__epsilon': [0.1, 0.2, 0.5, 1],
    'feature_selection__percentile': [10, 20, 30, 40, 50, 60, 70, 80,
90] # Menggunakan percentile
}

# Membuat objek GridSearchCV
GSCV_SVR = GridSearchCV(pipe_SVR_percentile,
    param_grid_SVR_percentile, cv=5, scoring='neg_mean_squared_error')

# Fitting model
GSCV_SVR.fit(X_train_enc, y_train_price)

# Output hasil terbaik
print("Best model: {}".format(GSCV_SVR.best_estimator_))
print("SVR best parameters: {}".format(GSCV_SVR.best_params_))

# Menghitung koefisien dan intercept
try:
    print("Koefisien/bobot:
{}".format(GSCV_SVR.best_estimator_.named_steps['reg'].coef_))
    print("Intercept/bias:
{}".format(GSCV_SVR.best_estimator_.named_steps['reg'].intercept_))
except AttributeError:
    print("SVR tidak memiliki koefisien yang dapat diakses secara
langsung.")

# Melakukan prediksi
SVR_predict = GSCV_SVR.predict(X_test_enc)

# Menghitung MSE dan MAE
mse_SVR = mean_squared_error(y_test_price, SVR_predict)
mae_SVR = mean_absolute_error(y_test_price, SVR_predict)

# Menampilkan hasil
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',
        SelectPercentile(score_func=<function f_regression at
0x0000020133634CC0>)),
    ('reg', SVR(C=10, kernel='linear'))])
SVR best parameters: {'feature_selection__percentile': 10, 'reg__C':
10, 'reg__epsilon': 0.1}
Koefisien/bobot: [[69203.83142266 1771.44667832]]
Intercept/bias: [5017389.52551094]
SVR Mean Squared Error (MSE): 7733494955101.608

```

SVR Mean Absolute Error (MAE): 2392029.6675750944  
SVR Root Mean Squared Error: 2780916.2078533773

```
df_results['SVR Percentile Prediction'] =SVR_predict  
df_results = pd.DataFrame(y_test_price)  
df_results['SVR Percentile Prediction'] =SVR_predict
```

```
df_results['Selisih_price_SVR_percentile'] = df_results['SVR  
Percentile Prediction'] - df_results['price']  
df_results.head()
```

	price	SVR Percentile Prediction	
Selisih_price_SVR_percentile			
2457	6033313.0	5.044114e+06	-
9.891985e+05			
4865	5290006.8	5.022385e+06	-
2.676220e+05			
5288	9235289.5	5.117175e+06	-
4.118115e+06			
1063	7616002.0	5.078386e+06	-
2.537616e+06			
5197	9390420.3	5.125272e+06	-
4.265149e+06			

```
df_results.describe()
```

	price	SVR Percentile Prediction	
Selisih_price_SVR_percentile			
count	2.000000e+03	2.000000e+03	
2.000000e+03			
mean	4.931727e+06	5.015550e+06	
8.382343e+04			
std	2.848679e+06	6.835477e+04	
2.780348e+06			
min	2.381840e+04	4.896081e+06	-
4.858343e+06			
25%	2.494605e+06	4.957087e+06	-
2.266067e+06			
50%	5.014176e+06	5.018407e+06	
2.438072e+03			
75%	7.338401e+06	5.072981e+06	
2.461521e+06			
max	9.994474e+06	5.138576e+06	
4.874318e+06			

```
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 SelectPercentile, f_regression
```

```

from sklearn.metrics import mean_absolute_error, mean_squared_error

pipe_Ridge_percentile = Pipeline(steps=[
    ('scale', StandardScaler()),
    ('feature_selection', SelectPercentile(score_func=f_regression)),
    ('reg', Ridge())
])

param_grid_Ridge_percentile = {
    'reg__alpha': [0.01, 0.1, 1, 10, 100],
    'feature_selection__percentile': [10, 20, 30, 40, 50, 60, 70, 80,
90] # Mengganti 'k' dengan 'percentile'
}

GSCV_RR = GridSearchCV(pipe_Ridge_percentile,
param_grid_Ridge_percentile, cv=5,
                        scoring='neg_mean_squared_error',
error_score='raise')

GSCV_RR.fit(X_train_enc, y_train_price)

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_price, Ridge_predict)
mae_Ridge = mean_absolute_error(y_test_price, 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 Error: {}".format(np.sqrt(mse_Ridge)))

Best model: Pipeline(steps=[('scale', StandardScaler()),
                             ('feature_selection',
                             SelectPercentile(percentile=90,
                             score_func=<function f_regression at
0x0000020133634CC0>)),
                             ('reg', Ridge(alpha=0.01))])
Ridge best parameters: {'feature_selection__percentile': 90,
'reg__alpha': 0.01}
Koefisien/bobot: [ 1.49636141e+03 -7.55922006e+02  7.55922004e+02
4.14416376e+01
-4.14416377e+01 -3.87150865e+01  3.87150862e+01 -6.77404283e+00
6.77404323e+00  2.88436798e+06 -4.56405366e-02  1.59112848e+03

```

```

1.48200813e+02 -1.43371744e+01 -1.86279947e+01 -1.15977886e+01
3.17189986e+01 -8.23109475e+00]
Intercept/bias: 5008877.6749249995
Ridge Mean Squared Error (MSE): 3540144.7107716934
Ridge Mean Absolute Error (MAE): 1463.0366330413735
Ridge Root Mean Squared Error: 1881.527228283368

```

```

df_results['Ridge Percentile Prediction'] = Ridge_predict
df_results = pd.DataFrame(y_test_price)
df_results['Ridge Percentile Prediction'] = Ridge_predict

```

```

df_results['Selisih_price_RR_percentile'] = df_results['Ridge
Percentile Prediction'] - df_results['price']

```

```
df_results.head()
```

	price	Ridge Percentile Prediction	Selisih_price_RR_percentile
2457	6033313.0	6.034185e+06	872.342258
4865	5290006.8	5.283703e+06	6304.221330
5288	9235289.5	9.234346e+06	943.386054
1063	7616002.0	7.617647e+06	1644.933213
5197	9390420.3	9.391224e+06	804.087296

```
df_results.describe()
```

	price	Ridge Percentile Prediction	Selisih_price_RR_percentile
count	2.000000e+03	2.000000e+03	2000.000000
mean	4.931727e+06	4.931782e+06	55.352778
std	2.848679e+06	2.848562e+06	2871.547718
min	2.381840e+04	2.787007e+04	10833.184798
25%	2.494605e+06	2.495427e+06	1843.724940
50%	5.014176e+06	5.017360e+06	297.079502
75%	7.338401e+06	7.339645e+06	2355.146005
max	9.994474e+06	9.998520e+06	5919.050249

```

import pandas as pd
import matplotlib.pyplot as plt

# Misalkan Ridge_predict dan SVR_predict sudah didefinisikan
sebelumnya
# Ridge_predict = model_ridge.predict(X_test)
# SVR_predict = model_svr.predict(X_test)

# Mengonversi y_test_price menjadi DataFrame
df_results = pd.DataFrame(y_test_price)

# Menambahkan kolom prediksi
df_results['Ridge Prediction'] = Ridge_predict
df_results['SVR Prediction'] = SVR_predict # Pastikan ini ada

# Jika ada kolom lain yang perlu ditambahkan
df_results['Ridge Percentile Prediction'] = Ridge_predict
df_results['SVR Percentile Prediction'] = SVR_predict # Pastikan kamu
sudah menambahkan ini juga

# Menghitung selisih
df_results['Selisih_price_RR'] = df_results['Ridge Prediction'] -
df_results['price']
df_results['Selisih_price_SVR'] = df_results['SVR Prediction'] -
df_results['price']
df_results['Selisih_price_RR_percentile'] = df_results['Ridge
Percentile Prediction'] - df_results['price']
df_results['Selisih_price_SVR_percentile'] = df_results['SVR
Percentile Prediction'] - df_results['price']

# Menampilkan beberapa data teratas
print(df_results.head())

# Membuat plot
plt.figure(figsize=(20, 5))
data_len = range(len(y_test_price))
plt.scatter(data_len, df_results['price'], label="Actual",
color="blue")
plt.plot(data_len, df_results['Ridge Prediction'], label="Ridge
Prediction KBest", color="green", linewidth=1, linestyle="dashed")
plt.plot(data_len, df_results['Ridge Percentile Prediction'],
label="Ridge Prediction Percentile", color="red", linewidth=1,
linestyle="dashed")
plt.plot(data_len, df_results['SVR Prediction'], label="SVR Prediction
KBest", color="yellow", linewidth=1, linestyle="-.")
plt.plot(data_len, df_results['SVR Percentile Prediction'], label="SVR
Prediction Percentile", color="blue", linewidth=1, linestyle="-.")

# Menambahkan legenda dan menampilkan plot

```



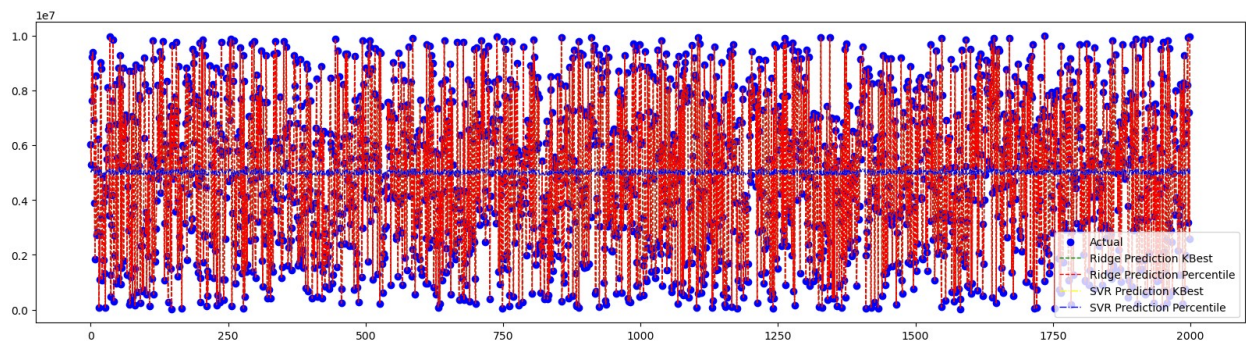
```
plt.legend()
plt.show()
```

	price	Ridge Prediction	SVR Prediction \
2457	6033313.0	6.034185e+06	5.044114e+06
4865	5290006.8	5.283703e+06	5.022385e+06
5288	9235289.5	9.234346e+06	5.117175e+06
1063	7616002.0	7.617647e+06	5.078386e+06
5197	9390420.3	9.391224e+06	5.125272e+06

	Ridge Percentile Prediction	SVR Percentile Prediction \
2457	6.034185e+06	5.044114e+06
4865	5.283703e+06	5.022385e+06
5288	9.234346e+06	5.117175e+06
1063	7.617647e+06	5.078386e+06
5197	9.391224e+06	5.125272e+06

	Selisih_price_RR	Selisih_price_SVR	Selisih_price_RR_percentile
2457	872.342258	-9.891985e+05	872.342258
4865	-6304.221330	-2.676220e+05	-6304.221330
5288	-943.386054	-4.118115e+06	-943.386054
1063	1644.933213	-2.537616e+06	1644.933213
5197	804.087296	-4.265149e+06	804.087296

	Selisih_price_SVR_percentile
2457	-9.891985e+05
4865	-2.676220e+05
5288	-4.118115e+06
1063	-2.537616e+06
5197	-4.265149e+06





```

import streamlit as st
import pandas as pd
import pickle
import os
from streamlit_option_menu import option_menu

import numpy as np

# Navigasi sidebar
with st.sidebar:
    selected = option_menu('Prediksi Harga Properti',
                           ['Klasifikasi', 'Regresi'],
                           default_index=0)

# Fungsi untuk memuat model
def load_model():
    with open('gscv_SVM_percentile_model.pkl', 'rb') as file:
        model = pickle.load(file)
    return model

gscv_SVM_percentile_model = load_model()

def load_model1():
    with open('GSCV_RF_model.pkl', 'rb') as file:
        model1 = pickle.load(file)
    return model1

GSCV_RF_model = load_model1()

# Muat model

# Halaman Klasifikasi
if selected == 'Klasifikasi':
    st.title('Klasifikasi')

    # Inputan file dataset CSV
    file = st.file_uploader("Masukkan File", type=["csv", "txt"])

    # Input data properti
    squaremeters = st.number_input("Masukkan luas tanah dalam meter persegi", min_value=0)
    numberofrooms = st.number_input("Masukkan jumlah kamar", min_value=0)

    # Input untuk kategori yang terpisah
    hasyard_yes = st.selectbox("Memiliki halaman (Ya)", [1, 0])
    hasyard_no = 1 - hasyard_yes

    haspool_yes = st.selectbox("Memiliki kolam renang (Ya)", [1, 0])
    haspool_no = 1 - haspool_yes

    floors = st.number_input("Masukkan jumlah lantai", min_value=0)
    citycode = st.number_input("Masukkan kode lokasi", min_value=0)
    citypartrange = st.number_input("Masukkan eksklusivitas kawasan", min_value=0)
    numprevowners = st.number_input("Masukkan jumlah pemilik sebelumnya", min_value=0)
    made = st.number_input("Masukkan tahun pembuatan", min_value=0)

    isnewbuilt_new = st.selectbox("Bangunan baru (Ya)", [1, 0])
    isnewbuilt_old = 1 - isnewbuilt_new

    hasstormprotector_yes = st.selectbox("Memiliki pelindung badai (Ya)", [1, 0])
    hasstormprotector_no = 1 - hasstormprotector_yes

    basement = st.number_input("Masukkan luas basement", min_value=0)
    attic = st.number_input("Masukkan luas loteng", min_value=0)
    garage = st.number_input("Masukkan luas garase", min_value=0)

    hasstorageroom_yes = st.selectbox("Memiliki gudang (Ya)", [1, 0])

```

```

hasstorageroom_no = 1 - hasstorageroom_yes+1 # Inversi dari hasstorageroom_yes

hasguestroom = st.number_input("Masukkan jumlah ruang tamu", min_value=0)

# Siapkan data input
input_data = np.array([[
    squaremeters,
    numberofrooms,
    hasyard_yes,
    hasyard_no,
    haspool_yes,
    haspool_no,
    floors,
    citycode,
    citypartrange,
    numprevowners,
    made,
    isnewbuilt_new,
    isnewbuilt_old,
    hasstormprotector_yes,
    hasstormprotector_no,
    basement,
    attic,
    garage,
    hasstorageroom_yes,
    hasstorageroom_no,
    hasguestroom
]])

# Tombol untuk prediksi
hitung = st.button("Prediksi")

if hitung:
    # Debug info sebelum prediksi
    st.write("Data yang akan diprediksi:", input_data)

    # Gunakan model untuk prediksi
    rf_model_prediction = gscv_SVM_percentile_model.predict(input_data)

    # Tampilkan hasil dengan format yang lebih baik
    kategori = rf_model_prediction[0]

    st.write("predik:", kategori)

    # Tampilkan hasil dengan warna dan format yang lebih baik
    if kategori == "Basic":
        st.success(f"🏠 Properti termasuk kategori Basic")
    elif kategori == "Middle":
        st.warning(f"🏠 Properti termasuk kategori Middle")
    else:
        st.error(f"🏠 Properti termasuk kategori Luxury")

if selected == 'Regresi':
    st.title('Regresi')

    # Inputan file dataset CSV
    file = st.file_uploader("Masukkan File", type=["csv", "txt"])

    # Input data properti
    squaremeters = st.number_input("Masukkan luas tanah dalam meter persegi", min_value=0)
    numberofrooms = st.number_input("Masukkan jumlah kamar", min_value=0)

    # Perbaikan untuk variabel kategorikal
    hasyard_yes = st.selectbox("Memiliki halaman", [0, 1])

```

```

hasyard_no = 1 - hasyard_yes

haspool_yes = st.selectbox("Memiliki kolam renang", [0, 1])
haspool_no = 1 - haspool_yes

floors = st.number_input("Masukkan jumlah lantai", min_value=0)
citycode = st.number_input("Masukkan kode lokasi", min_value=0)
citypartrange = st.number_input("Masukkan eksklusivitas kawasan", min_value=0)
numprevowners = st.number_input("Masukkan jumlah pemilik sebelumnya", min_value=0)
made = st.number_input("Masukkan tahun pembuatan", min_value=0)

isnewbuilt_new = st.selectbox("Bangunan baru", [0, 1])
isnewbuilt_old = 1 - isnewbuilt_new

hasstormprotector_yes = st.selectbox("Memiliki pelindung badai", [0, 1])
hasstormprotector_no = 1 - hasstormprotector_yes

basement = st.number_input("Masukkan luas basement", min_value=0)
attic = st.number_input("Masukkan luas loteng", min_value=0)
garage = st.number_input("Masukkan luas garase", min_value=0)

hasstorageroom_yes = st.selectbox("Memiliki gudang", [0, 1])
hasstorageroom_no = 1 - hasstorageroom_yes

hasguestroom = st.number_input("Masukkan jumlah ruang tamu", min_value=0)

# Siapkan data input
input_data = np.array([[
    squaremeters,
    numberofrooms,
    hasyard_yes,
    hasyard_no,
    haspool_yes,
    haspool_no,
    floors,
    citycode,
    citypartrange,
    numprevowners,
    made,
    isnewbuilt_new,
    isnewbuilt_old,
    hasstormprotector_yes,
    hasstormprotector_no,
    basement,
    attic,
    garage,
    hasstorageroom_yes,
    hasstorageroom_no,
    hasguestroom
]])

# Tombol untuk prediksi
hitung = st.button("Prediksi")

if hitung:
    try:
        # Gunakan model untuk prediksi
        rf_model_prediction = GSCV_RF_model.predict(input_data)
        # Format hasil prediksi dengan 1 angka di belakang koma
        formatted_prediction = "{:,.1f}".format(rf_model_prediction[0])
        st.success(f"Harga properti yang diprediksi: Rp {formatted_prediction}")
    except Exception as e:
        st.error(f"Terjadi kesalahan dalam prediksi: {str(e)}")

```