```
import pandas as pd
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from \ sklearn. ensemble \ import \ Random Forest Classifier
from \ sklearn.tree \ import \ DecisionTreeClassifier, \ plot\_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt
# Memuat dataset kanker payudara
data = load_breast_cancer()
# Mengonversi dataset menjadi DataFrame pandas
df = pd.DataFrame(data.data, columns=data.feature_names)
df['target'] = data.target
# Menampilkan lima baris pertama dataset
print("Lima baris pertama dataset:\n")
display(df.head())
```

Lima baris pertama dataset:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883

5 rows × 31 columns

# Menampilkan informasi dataset
print("Informasi Dataset:")
df.info()

Informasi Dataset:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):

Data	COTUMNIS (COCAT ST COTUMNI	٥).	
#	Column	Non-Null Count	Dtype
0	mean radius	569 non-null	float64
1	mean texture	569 non-null	float64
2	mean perimeter	569 non-null	float64
3	mean area	569 non-null	float64
4	mean smoothness	569 non-null	float64
5	mean compactness	569 non-null	float64
6	mean concavity	569 non-null	float64
7	mean concave points	569 non-null	float64
8	mean symmetry	569 non-null	float64
9	mean fractal dimension	569 non-null	float64
10	radius error	569 non-null	float64
11	texture error	569 non-null	float64
12	perimeter error	569 non-null	float64
13	area error	569 non-null	float64
14	smoothness error	569 non-null	float64
15	compactness error	569 non-null	float64
16	concavity error	569 non-null	float64
17	concave points error	569 non-null	float64
18	symmetry error	569 non-null	float64
19	fractal dimension error	569 non-null	float64
20	worst radius	569 non-null	float64
21	worst texture	569 non-null	float64
22	worst perimeter	569 non-null	float64
23	worst area	569 non-null	float64
24	worst smoothness	569 non-null	float64
25	worst compactness	569 non-null	float64

```
26 worst concavity 569 non-null float64
27 worst concave points 569 non-null float64
28 worst symmetry 569 non-null float64
29 worst fractal dimension 569 non-null float64
30 target 569 non-null int64
```

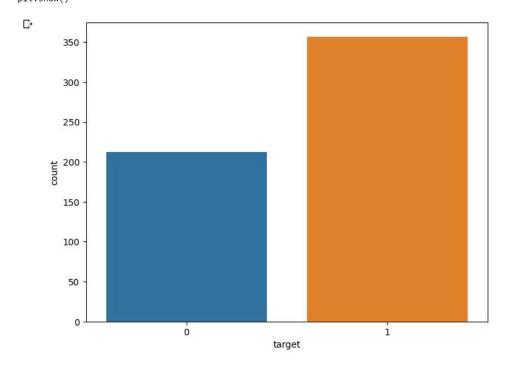
dtypes: float64(30), int64(1)
memory usage: 137.9 KB

# Menampilkan ringkasan statistik dataset
print("\nStatistik Dataset:")
display(df.describe())

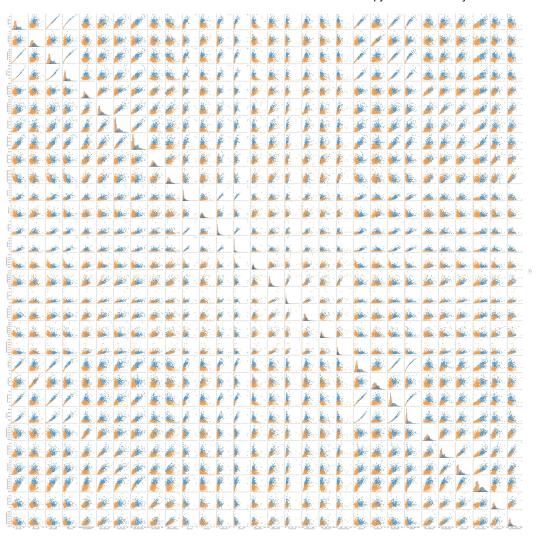
## Statistik Dataset:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mear concavity
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800
8 rows × 31 columns							
4							•

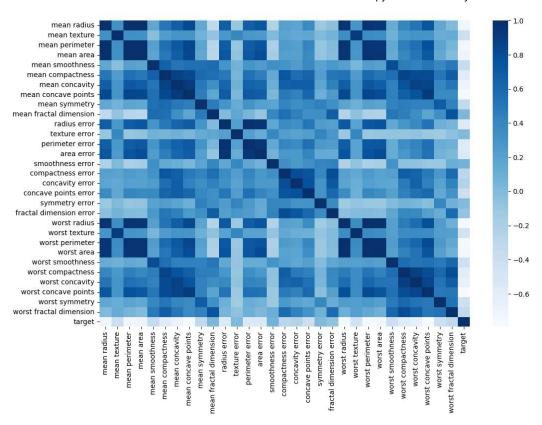
# Menampilkan distribusi variabel target
plt.figure(figsize=(8, 6))
sns.countplot(x='target', data=df)
plt.show()



# Menampilkan matriks korelasi dengan menggunakan fungsi pairplot dari Seaborn
sns.pairplot(df, hue='target', diag\_kind='hist')
plt.show()

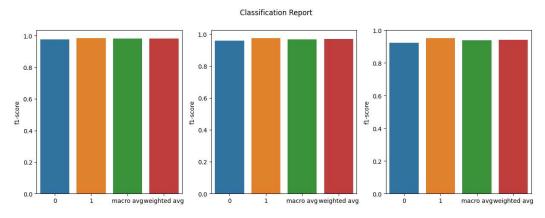


<sup>#</sup> Menampilkan matriks korelasi menggunakan fungsi heatmap dari Seaborn
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), cmap='Blues')
plt.show()



```
# Membagi dataset menjadi set pelatihan dan pengujian
X = df.drop('target', axis=1)
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Melakukan Normalisasi data menggunakan StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Melatih model self training
model1 = LogisticRegression()
model1.fit(X_train_scaled, y_train)
     ▼ LogisticRegression
     LogisticRegression()
# Melatih model random forest
model2 = RandomForestClassifier(n_estimators=100, random_state=42)
model2.fit(X_train_scaled, y_train)
               {\tt RandomForestClassifier}
     RandomForestClassifier(random_state=42)
# Melatih model decission tree
model3 = DecisionTreeClassifier(random_state=42)
model3.fit(X_train, y_train)
```

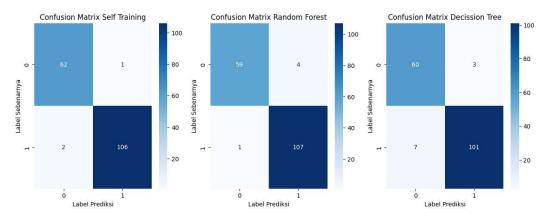
```
DecisionTreeClassifier
                  . . . . .
# Mengevaluasi model pada set pengujian
y pred1 = model1.predict(X test scaled)
y_pred2 = model2.predict(X_test_scaled)
y_pred3 = model3.predict(X_test)
accuracy1 = accuracy_score(y_test, y_pred1)
accuracy2 = accuracy_score(y_test, y_pred2)
accuracy3 = accuracy_score(y_test, y_pred3)
print(f"Akurasi model self training: {accuracy1}")
print(f"Akurasi model random forest: {accuracy2}")
print(f"Akurasi model decission tree: {accuracy3}")
     Akurasi model self training: 0.9824561403508771
    Akurasi model random forest: 0.9707602339181286
    Akurasi model decission tree: 0.9415204678362573
# Menampilkan classification report
report1 = classification_report(y_test, y_pred1, output_dict=True)
report2 = classification_report(y_test, y_pred2, output_dict=True)
report3 = classification_report(y_test, y_pred3, output_dict=True)
df report1 = pd.DataFrame(report1).transpose()
df_report1.drop('support', axis=1, inplace=True)
df_report1.drop('accuracy', axis=0, inplace=True)
df_report2 = pd.DataFrame(report2).transpose()
df_report2.drop('support', axis=1, inplace=True)
df_report2.drop('accuracy', axis=0, inplace=True)
df_report3 = pd.DataFrame(report3).transpose()
df_report3.drop('support', axis=1, inplace=True)
df_report3.drop('accuracy', axis=0, inplace=True)
fig, axs = plt.subplots(1, 3, figsize=(15,5))
fig.suptitle("Classification Report")
sns.barplot(x=df_report1.index, y=df_report1['f1-score'], ax=axs[0])
sns.barplot(x=df_report2.index, y=df_report2['f1-score'], ax=axs[1])
sns.barplot(x=df_report3.index, y=df_report3['f1-score'], ax=axs[2])
plt.show()
```



```
# Menampilkan confusion matrix
cm1 = confusion_matrix(y_test, y_pred1)
cm2 = confusion_matrix(y_test, y_pred2)
cm3 = confusion_matrix(y_test, y_pred3)
```

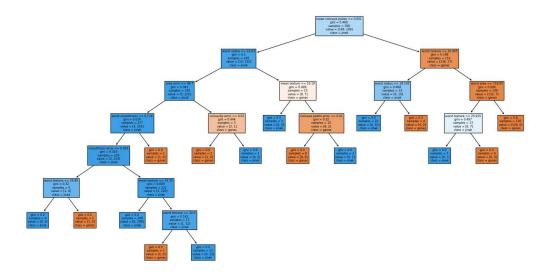
```
plt.figure(figsize=(15,5))
plt.subplot(1, 3, 1)
sns.heatmap(cm1, annot=True, cmap='Blues', fmt='.0f')
plt.title("Confusion Matrix Self Training")
plt.xlabel("Label Prediksi")
plt.ylabel("Label Sebenarnya")
plt.subplot(1, 3, 2)
sns.heatmap(cm2, annot=True, cmap='Blues', fmt='.0f')
plt.title("Confusion Matrix Random Forest")
plt.xlabel("Label Prediksi")
plt.ylabel("Label Sebenarnya")
plt.subplot(1, 3, 3)
sns.heatmap(cm3, annot=True, cmap='Blues', fmt='.0f')
plt.title("Confusion Matrix Decission Tree")
plt.xlabel("Label Prediksi")
plt.ylabel("Label Sebenarnya")
```

## plt.show()



```
# Visualisasi tingkat kepentingan fitur
feature_importance = pd.Series(model2.feature_importances_, index=X.columns)
feature_importance.nlargest(10).plot(kind='barh')
plt.title("10 Fitur Terpenting Random Forest")
plt.show()
```

# Visualisasi pohon keputusan
plt.figure(figsize=(20,10))
plot\_tree(model3, feature\_names=X.columns, class\_names=['ganas', 'jinak'], filled=True)
plt.show()



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