MEX #2 - Geyzson Kristoffer

SN:2023-21036

https://uvle.upd.edu.ph/mod/assign/view.php?id=535541

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from icecream import ic

from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score, f1_score, mean_squared_error, confusion_matrix, ConfusionMatrixDisplay
from sklearn.inspection import DecisionBoundaryDisplay

from sklearn.svm import SVC, SVR
from sklearn.kernel_ridge import KernelRidge
from sklearn.linear_model import LinearRegression

from matplotlib.lines import Line2D
```

Problem #1

In [ ]:
```
penguin_data = pd.read_csv('penguins_size.csv')
penguin_data
```

Out[ ]:

	species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mass_g	sex
0	Adelie	Torgersen	39.1	18.7	181.0	3750.0	MALE
1	Adelie	Torgersen	39.5	17.4	186.0	3800.0	FEMALE
2	Adelie	Torgersen	40.3	18.0	195.0	3250.0	FEMALE
3	Adelie	Torgersen	NaN	NaN	NaN	NaN	NaN
4	Adelie	Torgersen	36.7	19.3	193.0	3450.0	FEMALE
...	...	...	...	...	...	...	...
339	Gentoo	Biscoe	NaN	NaN	NaN	NaN	NaN
340	Gentoo	Biscoe	46.8	14.3	215.0	4850.0	FEMALE
341	Gentoo	Biscoe	50.4	15.7	222.0	5750.0	MALE
342	Gentoo	Biscoe	45.2	14.8	212.0	5200.0	FEMALE
343	Gentoo	Biscoe	49.9	16.1	213.0	5400.0	MALE

344 rows × 7 columns

In [ ]:

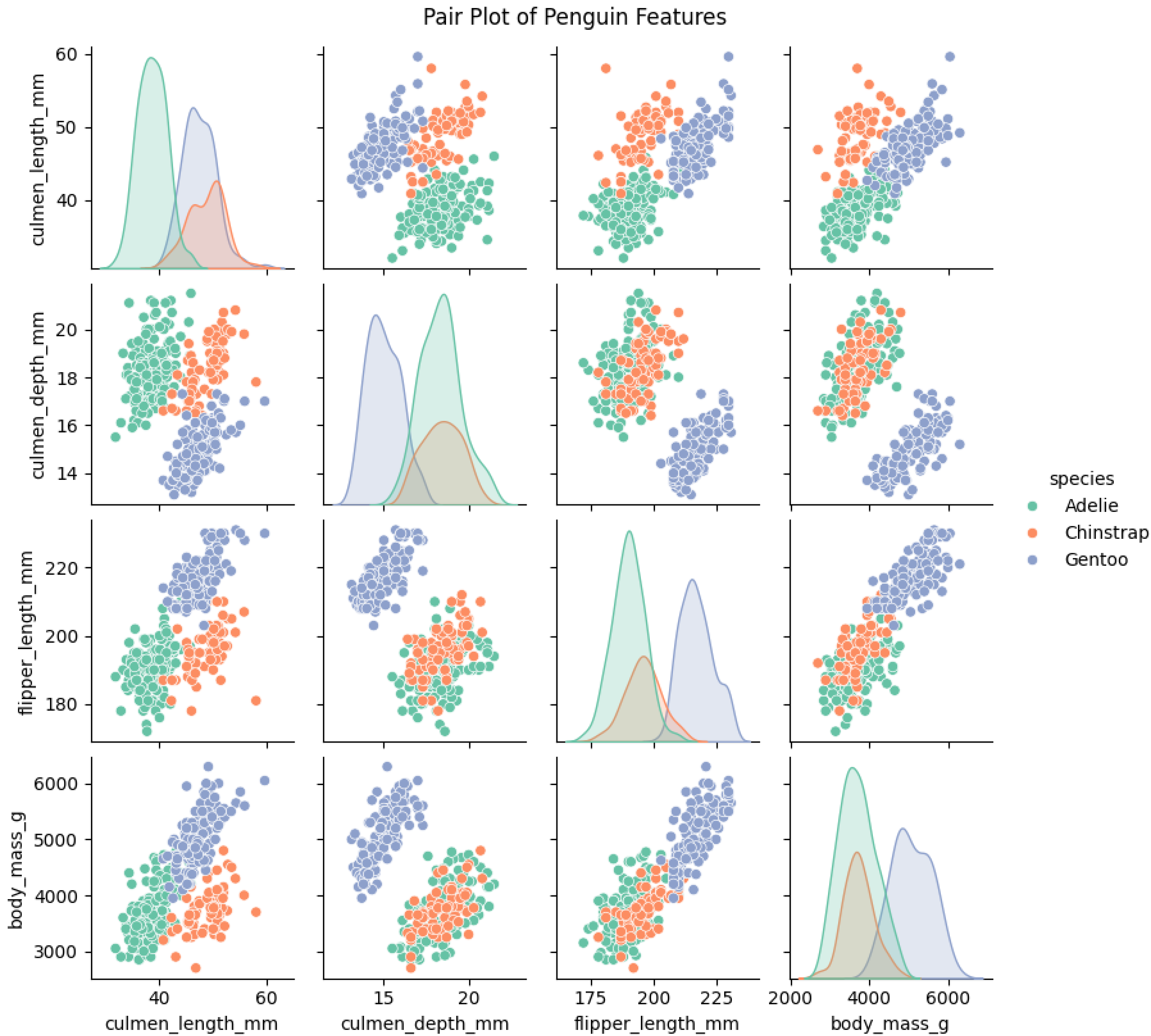
```
ic(penguin_data.isna().sum())
ic(penguin_data.isnull().sum())
```

```
ic| penguin_data.isna().sum(): species              0
                               island               0
                               culmen_length_mm     2
                               culmen_depth_mm      2
                               flipper_length_mm    2
                               body_mass_g          2
                               sex                 10
                               dtype: int64
ic| penguin_data.isnull().sum(): species              0
                                 island               0
                                 culmen_length_mm     2
                                 culmen_depth_mm      2
                                 flipper_length_mm    2
                                 body_mass_g          2
                                 sex                 10
                                 dtype: int64
```

Out[ ]:
```
species              0
island               0
culmen_length_mm     2
culmen_depth_mm      2
flipper_length_mm    2
body_mass_g          2
sex                 10
dtype: int64
```

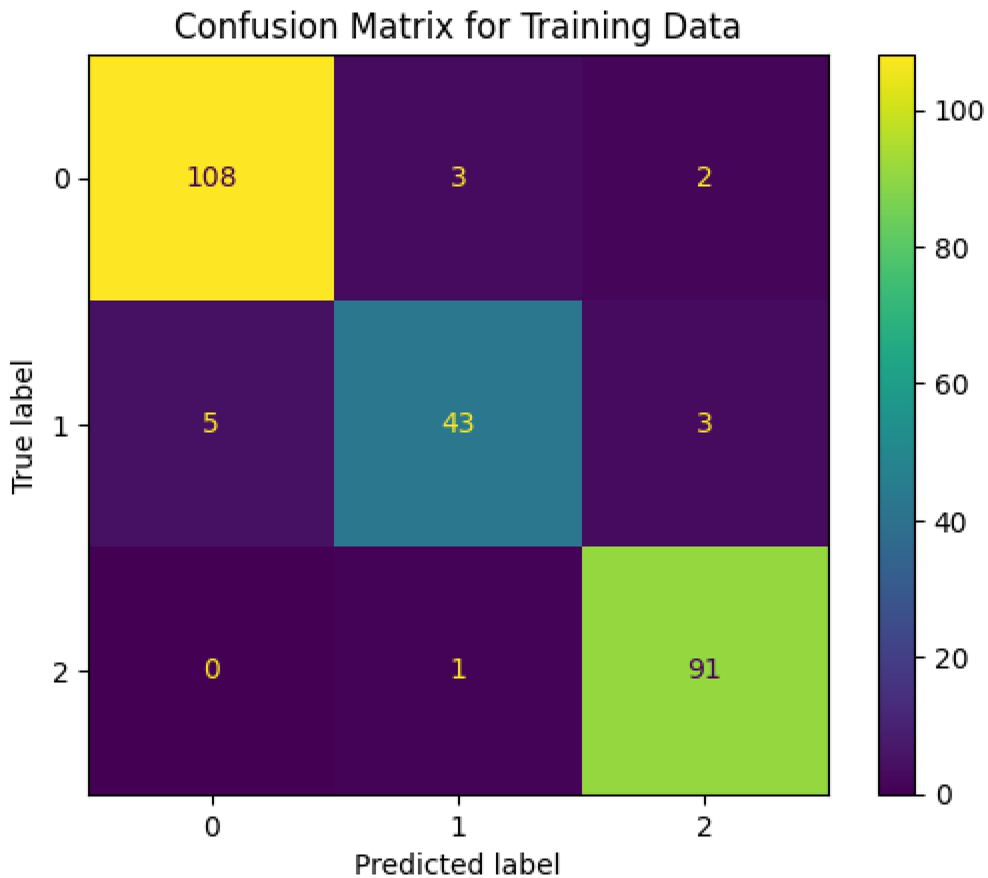
Problem #1-a

In [ ]:
```
columns = ['culmen_length_mm', 'culmen_depth_mm', 'flipper_length_mm', 'body_mass_g', 'species']

penguin_data_clean = penguin_data[columns].dropna()

sns.pairplot(penguin_data_clean, hue='species', palette='Set2', diag_kind='kde', height=2)
plt.suptitle('Pair Plot of Penguin Features', y=1.02)
plt.show()
```

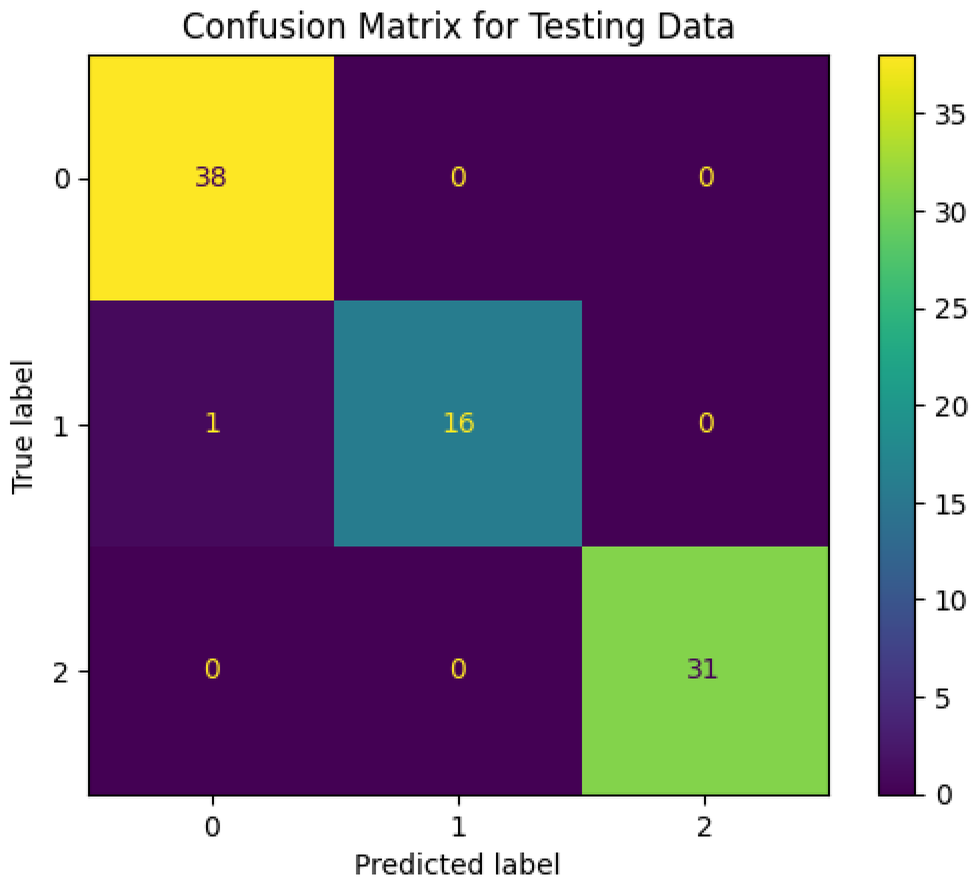

Pair Plot of Penguin Features
culmen_length_mm
culmen_depth_mm
flipper_length_mm
body_mass_g
species
Adelie
Chinstrap
Gentoo
60
50
40
20
18
16
14
220
200
180
6000
5000
4000
3000
15
20
175
200
225
2000
4000
6000

Problem #1-b

In [ ]:
```
X = penguin_data_clean[['culmen_length_mm', 'flipper_length_mm']]
y = penguin_data_clean['species']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, stratify=y, random_state=42)

model = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC())
])

model.fit(X_train, y_train)

y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

train_accuracy = accuracy_score(y_train, y_train_pred)
train_f1 = f1_score(y_train, y_train_pred, average='macro')
train_confusion = confusion_matrix(y_train, y_train_pred)

test_accuracy = accuracy_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred, average='macro')
test_confusion = confusion_matrix(y_test, y_test_pred)

cm_train = ConfusionMatrixDisplay(confusion_matrix = train_confusion)
cm_train.plot()
plt.title('Confusion Matrix for Training Data')
plt.show()
print(f'Train Accuracy: \t{train_accuracy:.5f}')
print(f'Train Macro Avg F1: \t{train_f1:.5f}')

cm_test = ConfusionMatrixDisplay(confusion_matrix = test_confusion)
cm_test.plot()
plt.title('Confusion Matrix for Testing Data')
plt.show()
print(f'Test Accuracy: \t\t{test_accuracy:.5f}')
print(f'Test Macro Avg F1: \t{test_f1:.5f}')
```




```
Train Accuracy:         0.94531
Train Macro Avg F1:     0.93380
```



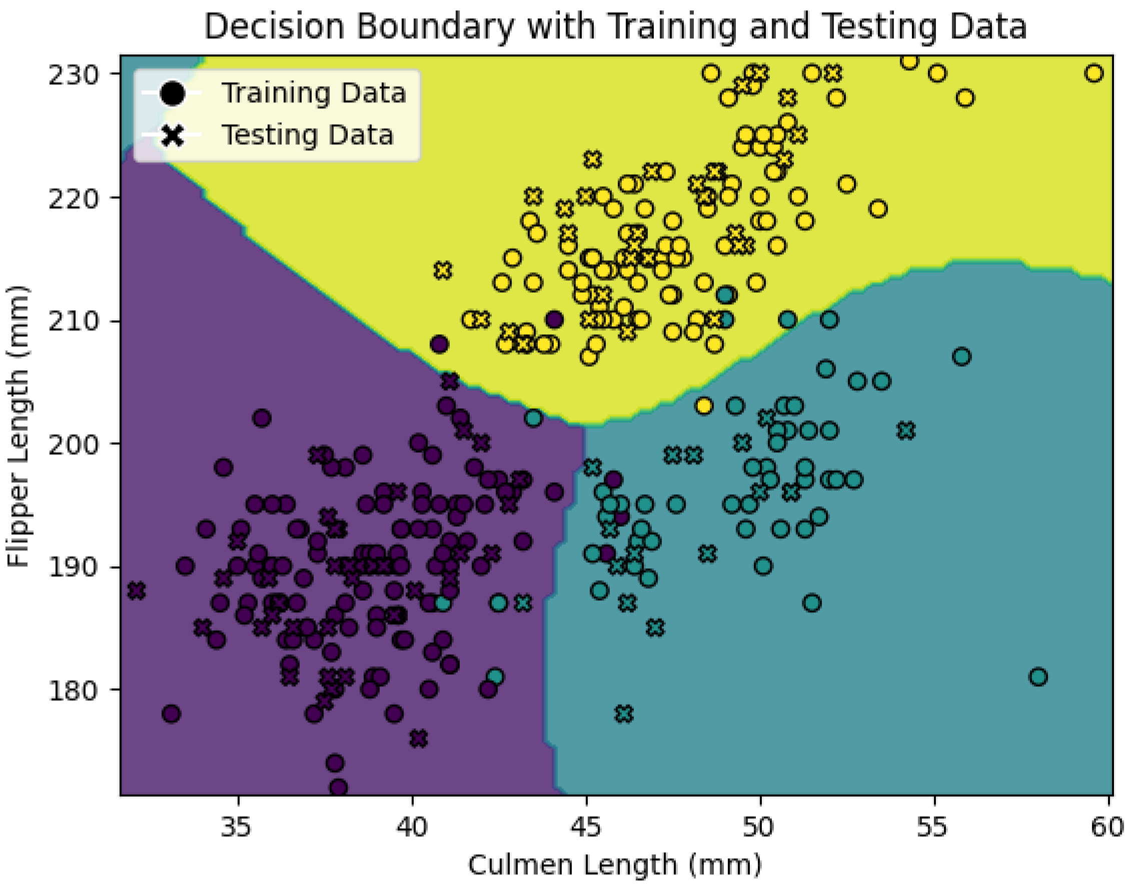

```
Test Accuracy:          0.98837
Test Macro Avg F1:      0.98557
```

Problem #1-c

In [ ]:

```
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)

display = DecisionBoundaryDisplay.from_estimator(model, X, alpha=0.8, eps=0.5)
plt.scatter(X_train['culmen_length_mm'], X_train['flipper_length_mm'], c=y_train_encoded, edgecolors="k", marker='o', label='Train
plt.scatter(X_test['culmen_length_mm'], X_test['flipper_length_mm'], c=y_test_encoded, edgecolors="k", marker='X', label='Testing
plt.title('Decision Boundary with Training and Testing Data')
plt.xlabel('Culmen Length (mm)')
plt.ylabel('Flipper Length (mm)')

legend_elements = [
    Line2D([0], [0], marker='o', color='w', markerfacecolor='k', markersize=10, label='Training Data'),
    Line2D([0], [0], marker='X', color='w', markerfacecolor='k', markersize=10, label='Testing Data')
```

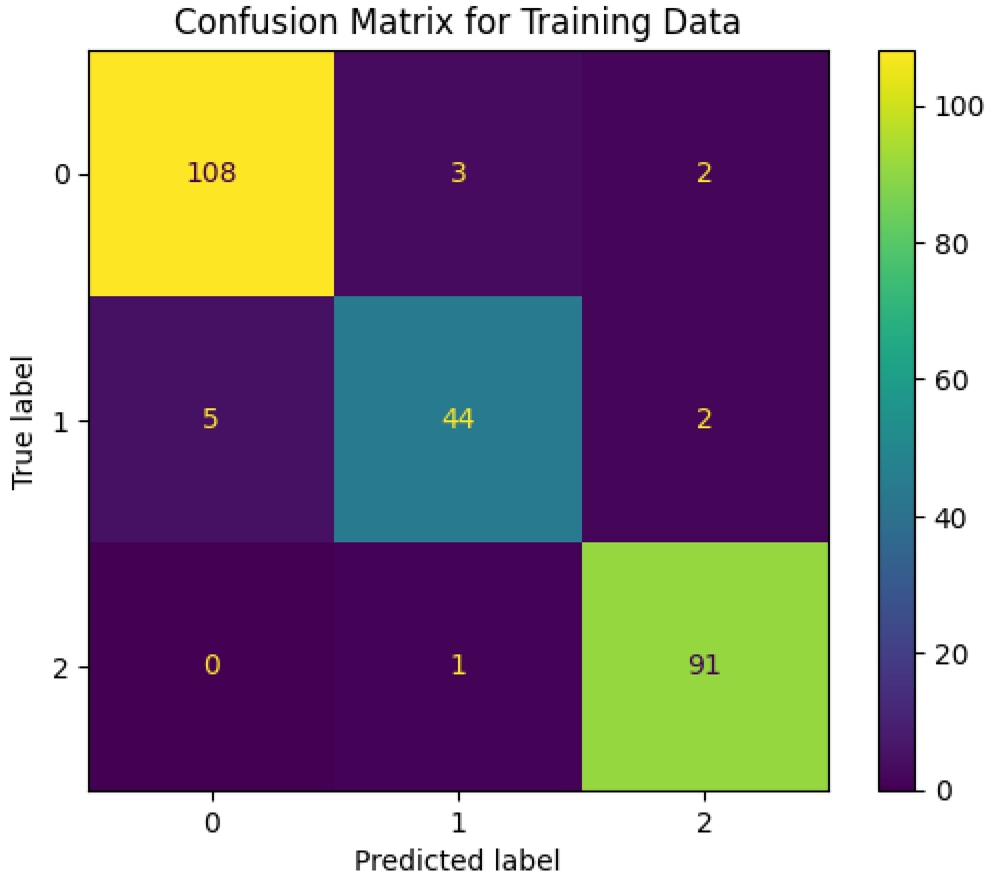
```
]
plt.legend(handles=legend_elements)

plt.show()
```



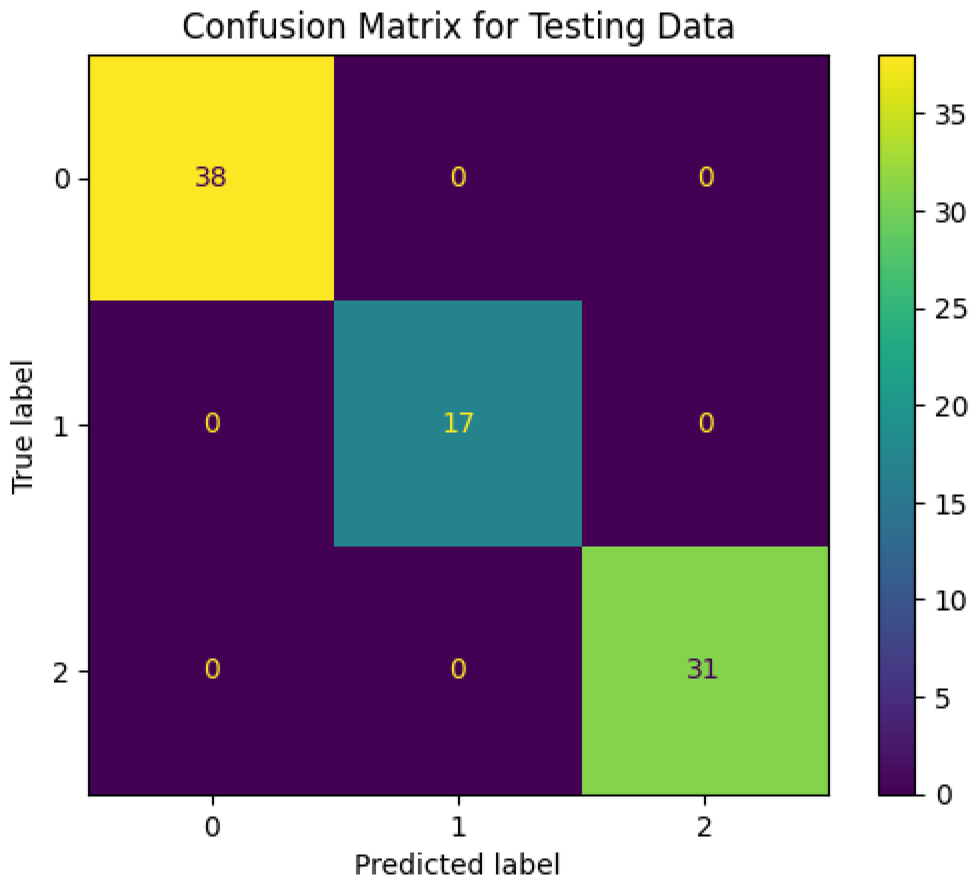
Problem #1-d

In [ ]:
```
parameters = {
    'svc__C': [0.01, 0.1, 1, 10, 100],
    'svc__kernel': ['linear', 'rbf', 'poly', 'sigmoid'],
    'svc__degree': [2, 3, 4, 5],
    'svc__decision_function_shape': ['ovr', 'ovo']
}

random_search = RandomizedSearchCV(model, parameters, n_iter=5, cv=5, scoring='accuracy', n_jobs=-1, random_state=42)
random_search.fit(X_train, y_train)

best_model = random_search.best_estimator_
```

```
y_train_pred = best_model.predict(X_train)
y_test_pred = best_model.predict(X_test)

train_accuracy = accuracy_score(y_train, y_train_pred)
train_f1 = f1_score(y_train, y_train_pred, average='macro')
train_confusion = confusion_matrix(y_train, y_train_pred)

test_accuracy = accuracy_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred, average='macro')
test_confusion = confusion_matrix(y_test, y_test_pred)

cm_train = ConfusionMatrixDisplay(confusion_matrix = train_confusion)
cm_train.plot()
plt.title('Confusion Matrix for Training Data')
plt.show()
print(f'Train Accuracy: \t{train_accuracy:.5f}')
print(f'Train Macro Avg F1: \t{train_f1:.5f}')

cm_test = ConfusionMatrixDisplay(confusion_matrix = test_confusion)
cm_test.plot()
plt.title('Confusion Matrix for Testing Data')
plt.show()
print(f'Test Accuracy: \t\t{test_accuracy:.5f}')
print(f'Test Macro Avg F1: \t{test_f1:.5f}')
```




```
Train Accuracy:        0.94922
Train Macro Avg F1:    0.93930
```

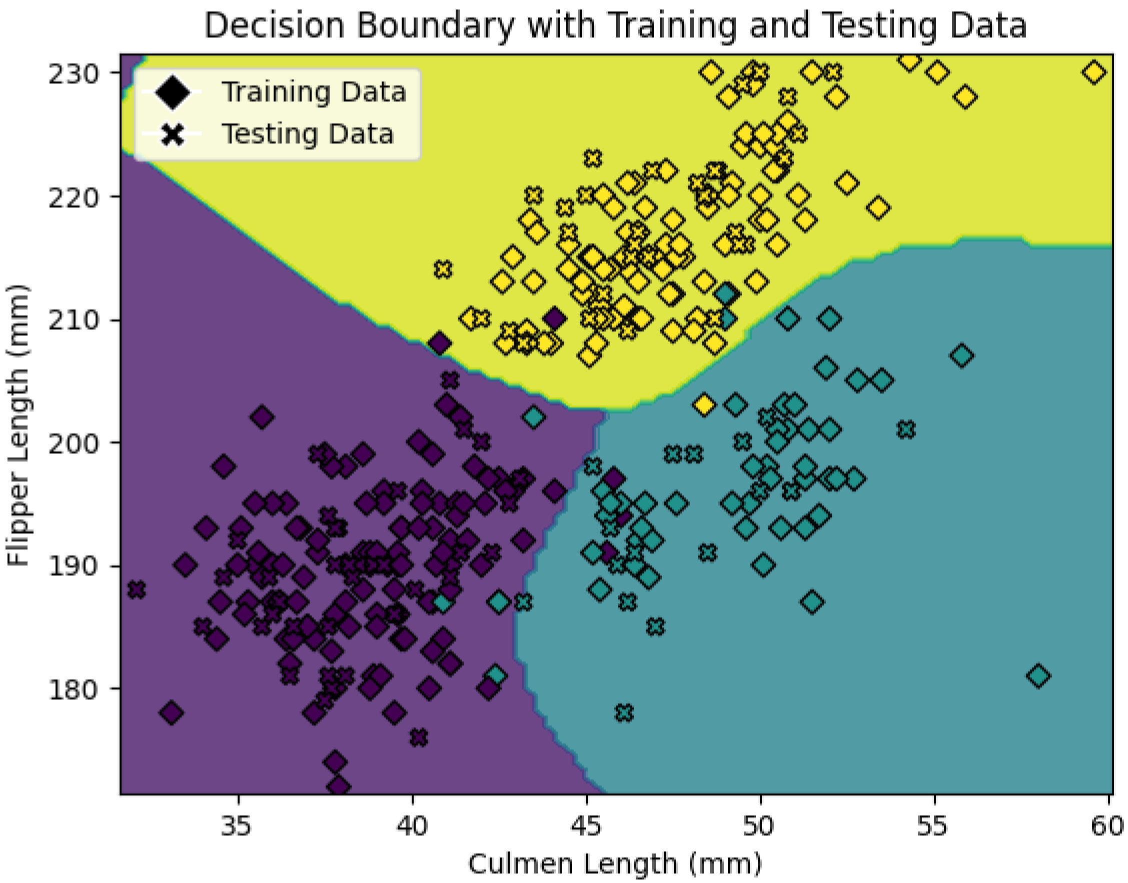



```
Test Accuracy:          1.00000
Test Macro Avg F1:      1.00000
```

In [ ]:

```
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)

display = DecisionBoundaryDisplay.from_estimator(best_model, X, alpha=0.8, eps=0.5)
plt.scatter(X_train['culmen_length_mm'], X_train['flipper_length_mm'], c=y_train_encoded, edgecolors="k", marker='D', label='Train
plt.scatter(X_test['culmen_length_mm'], X_test['flipper_length_mm'], c=y_test_encoded, edgecolors="k", marker='X', label='Testing
plt.title('Decision Boundary with Training and Testing Data')
plt.xlabel('Culmen Length (mm)')
plt.ylabel('Flipper Length (mm)')

legend_elements = [
    Line2D([0], [0], marker='D', color='w', markerfacecolor='k', markersize=10, label='Training Data'),
    Line2D([0], [0], marker='X', color='w', markerfacecolor='k', markersize=10, label='Testing Data')
]
plt.legend(handles=legend_elements)
```

```
plt.show()
```



Problem #2

In [ ]:
```
bike_data = pd.read_csv('SeoulBikeData.csv', encoding='latin1')
bike_data
```

Out[ ]:

	Date	Rented Bike Count	Hour	Temperature(°C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(°C)	Solar Radiation (MJ/m2)	Rainfall(mm)	Snowfall (cm)	Season
0	01/12/2017	254	0	-5.2	37	2.2	2000	-17.6	0.0	0.0	0.0	Winte
1	01/12/2017	204	1	-5.5	38	0.8	2000	-17.6	0.0	0.0	0.0	Winte
2	01/12/2017	173	2	-6.0	39	1.0	2000	-17.7	0.0	0.0	0.0	Winte
3	01/12/2017	107	3	-6.2	40	0.9	2000	-17.6	0.0	0.0	0.0	Winte
4	01/12/2017	78	4	-6.0	36	2.3	2000	-18.6	0.0	0.0	0.0	Winte
...	...	...	...	...	...	...	...	...	...	...	...	.
8755	30/11/2018	1003	19	4.2	34	2.6	1894	-10.3	0.0	0.0	0.0	Autum
8756	30/11/2018	764	20	3.4	37	2.3	2000	-9.9	0.0	0.0	0.0	Autum
8757	30/11/2018	694	21	2.6	39	0.3	1968	-9.9	0.0	0.0	0.0	Autum
8758	30/11/2018	712	22	2.1	41	1.0	1859	-9.8	0.0	0.0	0.0	Autum
8759	30/11/2018	584	23	1.9	43	1.3	1909	-9.3	0.0	0.0	0.0	Autum

8760 rows × 14 columns

In [ ]:

```
ic(bike_data.isna().sum())
ic(bike_data.isnull().sum())
```

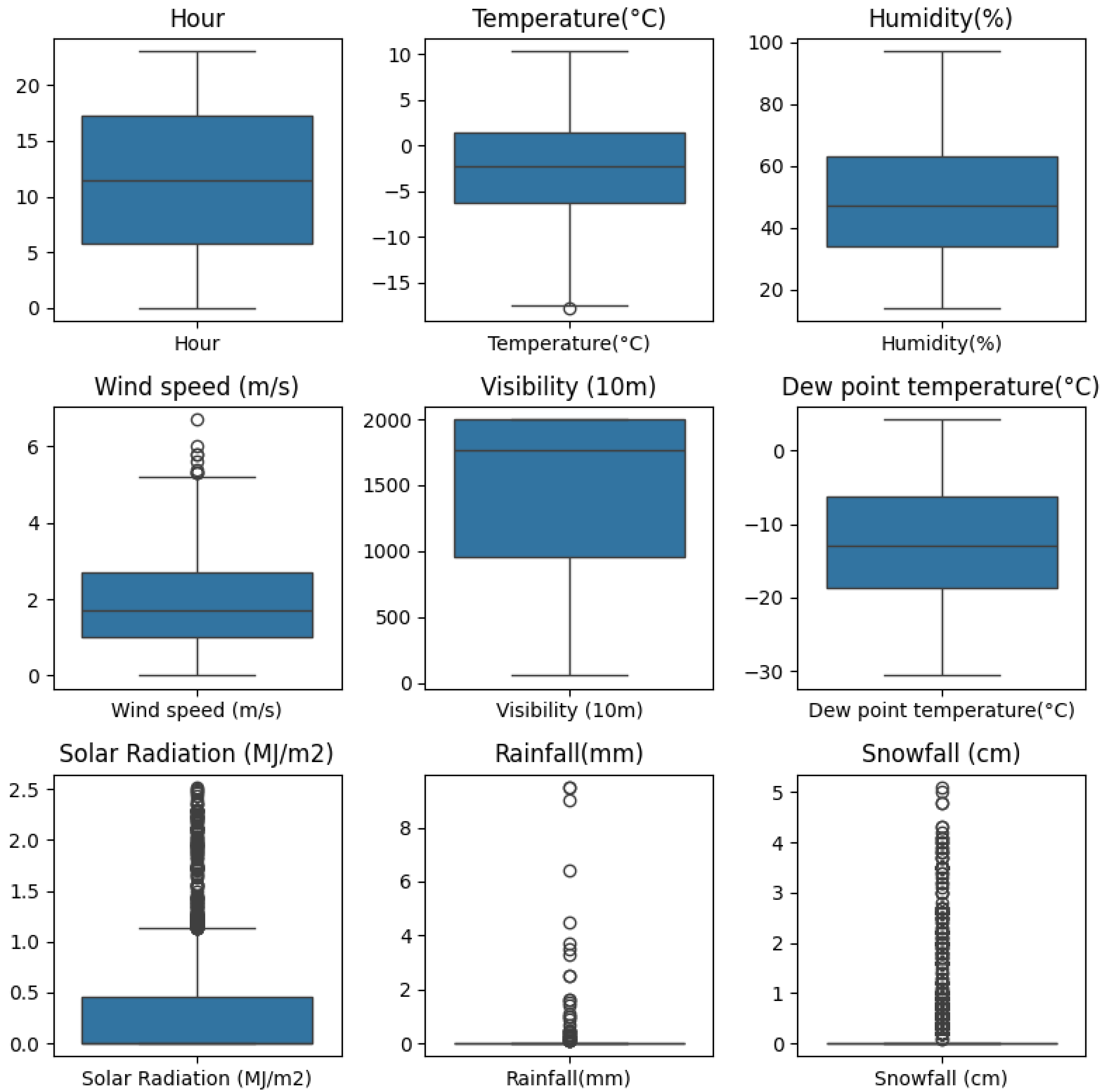
```
ic| bike_data.isna().sum(): Date                         0
                            Rented Bike Count            0
                            Hour                         0
                            Temperature(°C)              0
                            Humidity(%)                  0
                            Wind speed (m/s)             0
                            Visibility (10m)             0
                            Dew point temperature(°C)    0
                            Solar Radiation (MJ/m2)      0
                            Rainfall(mm)                 0
                            Snowfall (cm)                0
                            Seasons                      0
                            Holiday                      0
                            Functioning Day              0
                            dtype: int64
ic| bike_data.isnull().sum(): Date                         0
                              Rented Bike Count            0
                              Hour                         0
                              Temperature(°C)              0
                              Humidity(%)                  0
                              Wind speed (m/s)             0
                              Visibility (10m)             0
                              Dew point temperature(°C)    0
                              Solar Radiation (MJ/m2)      0
                              Rainfall(mm)                 0
                              Snowfall (cm)                0
                              Seasons                      0
                              Holiday                      0
                              Functioning Day              0
                              dtype: int64
```

Out[ ]:
```
Date                         0
Rented Bike Count            0
Hour                         0
Temperature(°C)              0
Humidity(%)                  0
Wind speed (m/s)             0
Visibility (10m)             0
Dew point temperature(°C)    0
Solar Radiation (MJ/m2)      0
Rainfall(mm)                 0
Snowfall (cm)                0
Seasons                      0
Holiday                      0
Functioning Day              0
dtype: int64
```

Problem #2-a

In [ ]:

```
winter_data = bike_data[bike_data['Seasons'] == 'Winter']

columns = [
    'Hour',
    'Temperature(°C)',
    'Humidity(%)',
    'Wind speed (m/s)',
    'Visibility (10m)',
    'Dew point temperature(°C)',
    'Solar Radiation (MJ/m2)',
    'Rainfall(mm)',
    'Snowfall (cm)'
]

plt.figure(figsize=(8, 8))

for i, column in enumerate(columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(data=winter_data[[column]])
    plt.title(column)

plt.tight_layout()
plt.show()
```


Hour
Temperature(°C)
Humidity(%)
Wind speed (m/s)
Visibility (10m)
Dew point temperature(°C)
Solar Radiation (MJ/m2)
Rainfall(mm)
Snowfall (cm)

Problem #2-b

In [ ]:
```
X = winter_data.iloc[:, 2:11]
y = winter_data['Rented Bike Count']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

model_svr = Pipeline([
    ('scaler', StandardScaler()),
    ('svr', SVR())
])

model_svr.fit(X_train, y_train)

y_pred = model_svr.predict(X_test)

rmse_svr = np.sqrt(mean_squared_error(y_test, y_pred))
print(f'RMSE: {rmse_svr:.5f}')
```

```
RMSE: 127.07340
```

Problem #2-b fine tuning

In [ ]:
```
param_grid = {
    'svr__kernel': ['linear', 'rbf', 'poly', 'sigmoid'],
    'svr__C': [0.1, 1, 10, 100],
    'svr__epsilon': [0.01, 0.1, 1]
}

grid_search = GridSearchCV(model_svr, param_grid, scoring='neg_mean_squared_error', cv=5, n_jobs=-1)
grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_svr = grid_search.best_estimator_

y_pred_best_svr = best_svr.predict(X_test)

rmse_best_svr = np.sqrt(mean_squared_error(y_test, y_pred_best_svr))


print(f'Best parameters: {best_params}')
print(f'RMSE: {rmse_best_svr:.5f}')
```

```
Best parameters: {'svr__C': 100, 'svr__epsilon': 1, 'svr__kernel': 'rbf'}
RMSE: 112.86469
```

Problem #2-c

In [ ]:
```
model_krr = Pipeline([
    ('scaler', StandardScaler()),
    ('krr', KernelRidge(kernel='linear'))
])

model_krr.fit(X_train, y_train)

y_pred_krr = model_krr.predict(X_test)

rmse_krr = np.sqrt(mean_squared_error(y_test, y_pred_krr))
print(f'RMSE original: {rmse_krr:.5f}')

param_grid_krr = {
    'krr__alpha': [0.001, 0.01, 0.1, 1, 10, 100],
    'krr__kernel': ['linear', 'poly', 'rbf'],
    'krr__degree': [2, 3, 4],
    'krr__coef0': [0, 1, 2],
    'krr__gamma': [0.01, 0.1, 1, 10]
}

randsearch_krr = RandomizedSearchCV(model_krr, param_grid_krr, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
randsearch_krr.fit(X_train, y_train)

best_params = randsearch_krr.best_params_
best_krr = randsearch_krr.best_estimator_

y_pred_krr = best_krr.predict(X_test)
rmse_krr = np.sqrt(mean_squared_error(y_test, y_pred_krr))
print(f'Best parameters: {best_params}')
print(f'RMSE fine tuned: {rmse_krr:.5f}')
```

```
RMSE original: 253.38630
Best parameters: {'krr__kernel': 'rbf', 'krr__gamma': 0.1, 'krr__degree': 3, 'krr__coef0': 0, 'krr__alpha': 0.01}
RMSE fine tuned: 101.27383
```

Problem #2-d

In [ ]:
```
model_lr = Pipeline([
    ('scaler', StandardScaler()),
```

```
    ('lr', LinearRegression())
])

model_lr.fit(X_train, y_train)
y_pred_lr = model_lr.predict(X_test)

rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
print(f'RMSE original: {rmse_lr:.5f}')

param_grid_lr = {
    'lr__fit_intercept': [True, False]
}

grid_lr = GridSearchCV(model_lr, param_grid_lr, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_lr.fit(X_train, y_train)

best_params = grid_lr.best_params_
best_lr = grid_lr.best_estimator_

y_pred_lr = best_lr.predict(X_test)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
print(f'Best parameters: {best_params}')
print(f'RMSE fine tuned: {rmse_lr:.5f}')
```

```
RMSE original: 120.28687
Best parameters: {'lr__fit_intercept': True}
RMSE fine tuned: 120.28687
```