1.- Letter recognition using three ML models.

Load the letter recognition dataset.

In [ ]:
```
from ucimlrepo import fetch_ucirepo

# fetch dataset
letter_recognition = fetch_ucirepo(id=59)

# data (as pandas dataframes)
X = letter_recognition.data.features
y = letter_recognition.data.targets

# metadata
print(letter_recognition.metadata)
```

```
  letter  feature_1  feature_2  feature_3  feature_4  feature_5  feature_6  \
0      T          2          8          3          5          1          8
1      I          5         12          3          7          2         10
2      D          4         11          6          8          6         10
3      N          7         11          6          6          3          5
4      G          2          1          3          1          1          8

   feature_7  feature_8  feature_9  feature_10  feature_11  feature_12  \
0         13          0          6           6          10           8
1          5          5          4          13           3           9
2          6          2          6          10           3           7
3          9          4          6           4           4          10
4          6          6          6           6           5           9

   feature_13  feature_14  feature_15  feature_16
0           0           8           0           8
1           2           8           4          10
2           3           7           3           9
3           6          10           2           8
4           1           7           5          10
```

In [ ]:
```
# variable information
print(letter_recognition.variables)
```

```
     name     role         type demographic                   description  \
0   lettr   Target  Categorical        None                 capital letter
1   x-box  Feature      Integer        None     horizontal position of box
2   y-box  Feature      Integer        None       vertical position of box
3   width  Feature      Integer        None                   width of box
4    high  Feature      Integer        None                  height of box
5   onpix  Feature      Integer        None              total # on pixels
6   x-bar  Feature      Integer        None     mean x of on pixels in box
7   y-bar  Feature      Integer        None     mean y of on pixels in box
8   x2bar  Feature      Integer        None                 mean x variance
9   y2bar  Feature      Integer        None                 mean y variance
10  xybar  Feature      Integer        None           mean x y correlation
11  x2ybr  Feature      Integer        None              mean of x * x * y
12  xy2br  Feature      Integer        None              mean of x * y * y
13  x-ege  Feature      Integer        None  mean edge count left to right
14  xegvy  Feature      Integer        None    correlation of x-ege with y
15  y-ege  Feature      Integer        None  mean edge count bottom to top
16  yegvx  Feature      Integer        None    correlation of y-ege with x

   units missing_values
0   None             no
1   None             no
2   None             no
3   None             no
4   None             no
5   None             no
6   None             no
7   None             no
8   None             no
9   None             no
10  None             no
11  None             no
12  None             no
13  None             no
14  None             no
15  None             no
16  None             no
```

Split the data into traind and test (using 70% of the data for training and 30% for testing)

In [ ]:
```
#!pip install -U scikit-learn
```

```
Collecting scikit-learn
  Downloading scikit_learn-1.5.2-cp312-cp312-macosx_12_0_arm64.whl.metadata (13 kB)
Requirement already satisfied: numpy>=1.19.5 in /Users/cdr_c/anaconda3/envs/my_env/lib/python3.12/site-packages (from s
cikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /Users/cdr_c/anaconda3/envs/my_env/lib/python3.12/site-packages (from sc
ikit-learn) (1.14.1)
Collecting joblib>=1.2.0 (from scikit-learn)
  Using cached joblib-1.4.2-py3-none-any.whl.metadata (5.4 kB)
Collecting threadpoolctl>=3.1.0 (from scikit-learn)
  Using cached threadpoolctl-3.5.0-py3-none-any.whl.metadata (13 kB)
Downloading scikit_learn-1.5.2-cp312-cp312-macosx_12_0_arm64.whl (11.0 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11.0/11.0 MB 6.1 MB/s eta 0:00:0000:0100:01
Using cached joblib-1.4.2-py3-none-any.whl (301 kB)
Using cached threadpoolctl-3.5.0-py3-none-any.whl (18 kB)
Installing collected packages: threadpoolctl, joblib, scikit-learn
Successfully installed joblib-1.4.2 scikit-learn-1.5.2 threadpoolctl-3.5.0
```

In [ ]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
```

In [ ]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

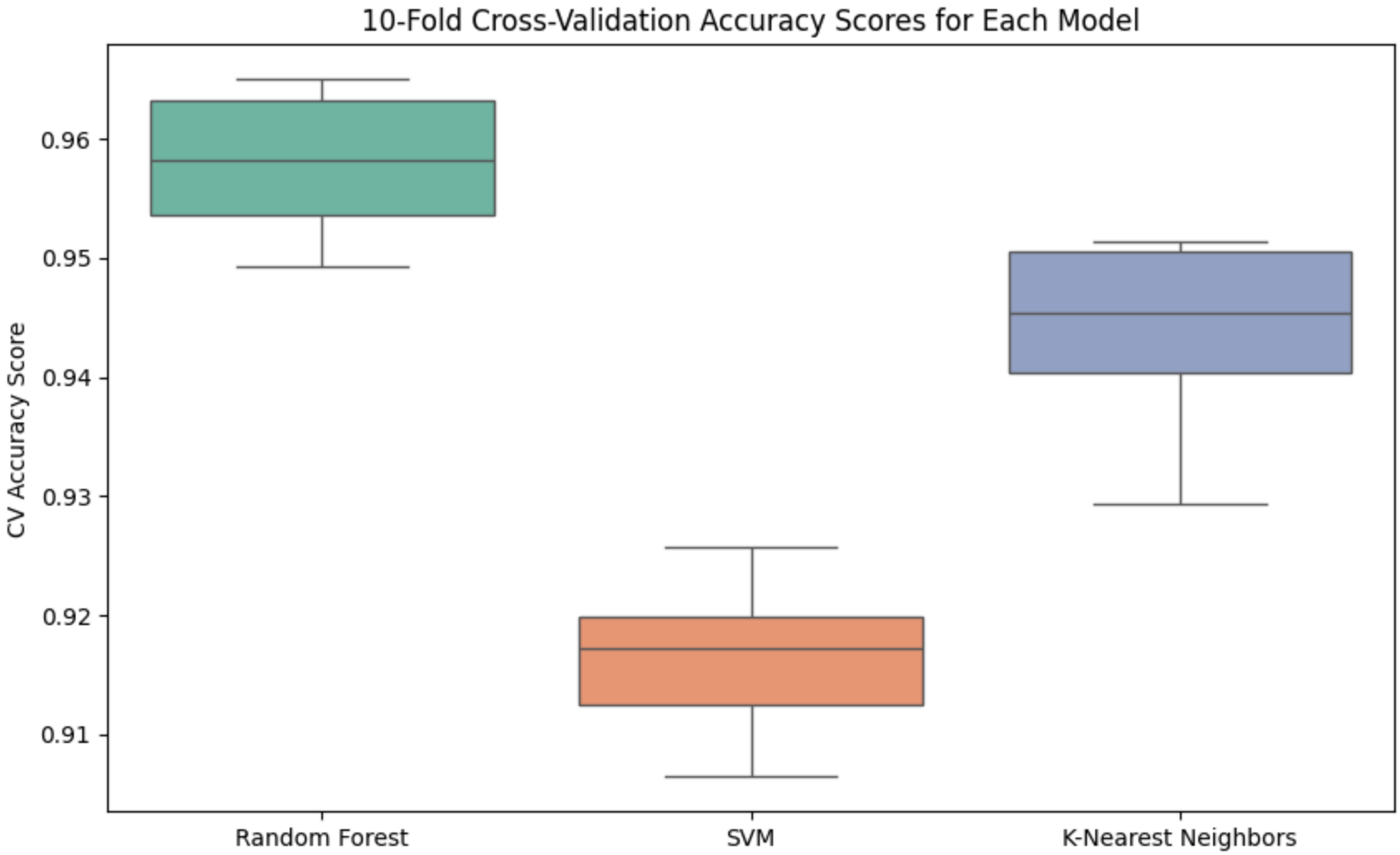
Train and evaluate the models Random Forest, SVM and KNN

In [ ]:
```python
models = {
    'Random Forest': RandomForestClassifier(),
    'SVM': SVC(),
    'K-Nearest Neighbors': KNeighborsClassifier()
}

cv_results = {}
for model_name, model in models.items():
    cv_score = cross_val_score(model, X_train, y_train.values.ravel(), cv=10, scoring='accuracy')
    cv_results[model_name] = cv_score
    print(f'{model_name} 10-fold CV Mean Accuracy: {np.mean(cv_score):.3f}')
```

```
Random Forest 10-fold CV Mean Accuracy: 0.958
SVM 10-fold CV Mean Accuracy: 0.916
K-Nearest Neighbors 10-fold CV Mean Accuracy: 0.944
```

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=list(cv_results.values()), palette="Set2")
plt.xticks(range(len(models)), list(models.keys()))
plt.ylabel("CV Accuracy Score")
plt.title("10-Fold Cross-Validation Accuracy Scores for Each Model")
plt.show()
```



Hyperparameter tuning

In [ ]:
```
param_grids = {
    'Random Forest': {'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20]},
    'SVM': {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']},
    'K-Nearest Neighbors': {'n_neighbors': [3, 5, 7], 'weights': ['uniform', 'distance']}
}
```

```
best_models = {}
for model_name, model in models.items():
    grid_search = GridSearchCV(model, param_grids[model_name], cv=10, scoring='accuracy')
    grid_search.fit(X_train, y_train.values.ravel())
    best_models[model_name] = grid_search.best_estimator_
    print(f'{model_name} Best Hyperparameters: {grid_search.best_params_}')
```

```
Random Forest Best Hyperparameters: {'max_depth': None, 'n_estimators': 200}
SVM Best Hyperparameters: {'C': 10, 'kernel': 'rbf'}
K-Nearest Neighbors Best Hyperparameters: {'n_neighbors': 5, 'weights': 'distance'}
```

Evaluate the models with the best parameters

In [ ]:
```
for model_name, model in best_models.items():
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f'{model_name} Hold-out Test Accuracy: {accuracy:.3f}')
```

```
Random Forest Hold-out Test Accuracy: 0.961
SVM Hold-out Test Accuracy: 0.962
K-Nearest Neighbors Hold-out Test Accuracy: 0.955
```

As we can see, the model with the highest accuracy was Random Forest.

In [ ]:
```

```