```
import pandas as pd
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.linear model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy score, confusion matrix
from sklearn.model selection import cross val score
from sklearn.model selection import GridSearchCV, train test split
from sklearn.datasets import make classification
dataset = pd.read csv('sonar.csv')
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test size=0.2, random state=42)
```

Split the dataset into Training and Test groups (use 20-80 split, i.e. 20% of data will be used for the Test group and 80% for training).

```
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)
```

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier (with nb_trees = 10)
- K- Nearest Neighbors (K-NN)
- Support Vector Machine (SVM) use the 'rbf' kernel

Train each of the above models and make predictions.

```
logistic_regression = LogisticRegression(random_state=42)
decision_tree = DecisionTreeClassifier(random_state=42)
random_forest = RandomForestClassifier(n_estimators=10,
random_state=42)
knn = KNeighborsClassifier()
naive_bayes = GaussianNB()
svm = SVC(kernel='rbf', random_state=42)
logistic_regression.fit(X_train_scaled, y_train)
decision_tree.fit(X_train_scaled, y_train)
```

```
random forest.fit(X train scaled, y train)
knn.fit(X train scaled, y train)
naive bayes.fit(X train scaled, y train)
svm.fit(X train scaled, y train)
y pred logistic regression =
logistic_regression.predict(X_test_scaled)
y pred decision tree = decision tree.predict(X test scaled)
y pred random forest = random forest.predict(X test scaled)
y pred knn = knn.predict(X test scaled)
y_pred_naive_bayes = naive_bayes.predict(X_test_scaled)
y pred svm = svm.predict(X test scaled)
results = pd.DataFrame({
    'Actual': y test,
    'Logistic Regression': y_pred_logistic_regression,
    'Decision Tree': y pred decision tree,
    'Random Forest': y_pred_random_forest,
    'K-NN': y pred knn,
    'Naive Bayes': y pred naive bayes,
    'SVM': y pred svm
})
print(results)
    Actual Logistic Regression Decision Tree Random Forest K-NN Naive
Bayes \
161
      Mine
                          Mine
                                         Mine
                                                       Mine Mine
Mine
15
                          Rock
                                         Mine
                                                       Mine Rock
      Rock
Rock
73
      Rock
                          Mine
                                                       Rock Rock
                                         Rock
Rock
96
      Rock
                          Rock
                                         Rock
                                                       Rock Rock
Rock
166
      Mine
                          Mine
                                         Mine
                                                       Mine Mine
Mine
9
                          Mine
                                         Mine
                                                       Rock Rock
      Rock
Rock
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100
      Mine
                          Mine
                                         Mine
Mine
135
      Mine
                          Mine
                                         Mine
                                                       Mine Mine
Mine
18
                                                       Rock Rock
      Rock
                          Rock
                                         Rock
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148
      Mine
                          Rock
                                         Mine
                                                       Mine Rock
Mine
171
      Mine
                          Mine
                                         Mine
                                                       Mine Mine
Mine
                                                       Rock Rock
30
      Rock
                          Rock
                                         Mine
```

Rock					
155	Mine	Rock	Rock	Rock	Mine
Rock 180	Mine	Mine	Mine	Mine	Mine
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125	Mine	Mine	Mine	Mine	Mine
Mine	M	N4 :	M	N4 :	N4 :
197 Rock	Mine	Mine	Mine	Mine	Mine
164	Mine	Mine	Mine	Mine	Mine
Rock					
190	Mine	Mine	Mine	Mine	Mine
Rock 84	Rock	Rock	Rock	Mine	Rock
o4 Rock	NUCK	NUCK	NUCK	ытпе	NUCK
75	Rock	Rock	Rock	Rock	Rock
Rock					
124 Mino	Mine	Mine	Mine	Mine	Mine
Mine 170	Mine	Mine	Rock	Rock	Mine
Rock	TITILE	TITILE	Nock	NOCK	111110
104	Mine	Rock	Mine	Mine	Mine
Mine	Mina	Mina	Mina	N4.	M
101 Mine	Mine	Mine	Mine	Mine	Mine
69	Rock	Rock	Rock	Rock	Rock
Rock					
25	Rock	Rock	Rock	Rock	Rock
Rock	Pock	Pock	Mino	Pock	Doole
95 Rock	Rock	Rock	Mine	Rock	Rock
16	Rock	Rock	Mine	Mine	Mine
Mine					
141 Mino	Mine	Mine	Mine	Mine	Mine
Mine 185	Mine	Mine	Mine	Mine	Mine
Mine	TIETIC	TITILC	111110	TITTIC	TITLIC
154	Mine	Rock	Rock	Mine	Rock
Rock	D 1	D	D 1	D .	D .
68 Rock	Rock	Rock	Rock	Rock	Rock
66	Rock	Rock	Rock	Rock	Rock
Rock					
120	Mine	Mine	Rock	Mine	Mine
Rock	M	Mina	Daal	M	M
147 Mine	Mine	Mine	Rock	Mine	Mine
	Mine	Mine	Mine	Mine	Mine
Mine					
98 Mine	Mine	Mine	Mine	Mine	Mine

138	Mine	Mine	Mine	Mine	Mine
Mine 167	Mine	Mine	Rock	Rock	Rock
Rock 45	Rock	Rock	Rock	Rock	Rock
Rock 113	Mine	Rock	Mine	Mine	Mine
Rock 65	Rock	Rock	Rock	Rock	Rock
Rock 178	Mine	Rock	Rock	Rock	Mine
Rock					
161 15 73 96 166 9 100 135 18 148 171 30 155 180 125 197 164 190 84 75 124 170 104 101 69 25 95 16 168 66 120 147	SVM Mine Rock Rock Rock Mine Rock Mine Mine Mine Rock Mine Mine Mine Mine Mine Mine Mine Mine				

```
98 Mine
138 Mine
167 Rock
45 Rock
113 Mine
65 Rock
178 Rock
```

Create and print the Confusion Matrix and the accuracy scores for each model.

```
def print evaluation(model_name, y_true, y_pred):
    print(f"===== {model name} =====")
    cm = confusion matrix(y true, y pred)
    print(f"Confusion Matrix:\n{cm}")
    acc_score = accuracy_score(y_true, y_pred)
    print(f"Accuracy Score: {acc score:.4f}\n")
print evaluation("Logistic Regression", y test,
y pred logistic regression)
print_evaluation("Decision Tree", y_test, y_pred_decision_tree)
print_evaluation("Random Forest", y_test, y_pred_random_forest)
print_evaluation("K-NN", y_test, y_pred_knn)
print_evaluation("Naive Bayes", y_test, y_pred_naive_bayes)
print evaluation("SVM", y test, y pred svm)
==== Logistic Regression =====
Confusion Matrix:
[[20 6]
[ 2 14]]
Accuracy Score: 0.8095
==== Decision Tree =====
Confusion Matrix:
[[19 7]
[ 5 11]]
Accuracy Score: 0.7143
==== Random Forest =====
Confusion Matrix:
[[22 4]
[ 3 13]]
Accuracy Score: 0.8333
==== K-NN =====
Confusion Matrix:
[[23 3]
[ 1 15]]
Accuracy Score: 0.9048
```

For each model, use the K-fold cross-validation (use K=10; in python - cv=10).

```
def cross val and print(model, model name):
    scores = cross_val_score(model, X_train_scaled, y_train, cv=10,
scoring='accuracy')
    print(f"===== {model name} (K-fold Cross-Validation) =====")
    print(f"Accuracy Scores: {scores}")
    print(f"Mean Accuracy: {scores.mean():.4f}")
    print(f"Standard Deviation: {scores.std():.4f}\n")
cross_val_and_print(logistic regression, "Logistic Regression")
cross_val_and_print(decision_tree, "Decision Tree")
cross_val_and_print(random_forest, "Random Forest")
cross val and print(knn, "K-NN")
cross_val_and_print(naive bayes, "Naive Bayes")
cross_val_and_print(svm, "SVM")
==== Logistic Regression (K-fold Cross-Validation) =====
Accuracy Scores: [0.76470588 0.52941176 1. 0.82352941
0.76470588 0.70588235
           0.5625
                      0.875 0.8125 1
 0.8125
Mean Accuracy: 0.7651
Standard Deviation: 0.1324
==== Decision Tree (K-fold Cross-Validation) =====
Accuracy Scores: [0.88235294 0.70588235 0.64705882 0.70588235
0.76470588 0.70588235
                                 0.8125
 0.875
           0.6875
                      0.75
Mean Accuracy: 0.7537
Standard Deviation: 0.0758
==== Random Forest (K-fold Cross-Validation) =====
Accuracy Scores: [0.82352941 0.76470588 0.70588235 0.82352941
0.88235294 0.76470588
                                 0.8125
 0.6875
           0.8125
                      0.75
Mean Accuracy: 0.7827
```

```
Standard Deviation: 0.0563
==== K-NN (K-fold Cross-Validation) =====
Accuracy Scores: [0.94117647 0.58823529 0.70588235 0.82352941
0.64705882 0.76470588
0.8125
           0.8125
                      0.875
                                 0.75
Mean Accuracy: 0.7721
Standard Deviation: 0.0997
==== Naive Bayes (K-fold Cross-Validation) =====
Accuracy Scores: [0.82352941 0.64705882 0.88235294 0.58823529
0.58823529 0.76470588
0.625
           0.625
                      0.8125 0.5625 1
Mean Accuracy: 0.6919
Standard Deviation: 0.1107
==== SVM (K-fold Cross-Validation) =====
Accuracy Scores: [0.94117647 0.76470588 0.94117647 0.82352941
0.82352941 0.88235294
0.8125
           0.8125
                      0.8125 0.8125 1
Mean Accuracy: 0.8426
Standard Deviation: 0.0561
```

For the chosen best performing model select two hyperparameters you would like to tune.

```
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2, random_state=42)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

gnb = GaussianNB()

param_grid = {
    'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5]}

grid_search = GridSearchCV(estimator=gnb, param_grid=param_grid, cv=5, scoring='accuracy')

grid_search.fit(X_train, y_train)

print("Best Parameters: ", grid_search.best_params_)
    print("Best Accuracy: {:.2f}".format(grid_search.best_score_))

Best Parameters: {'var_smoothing': 1e-09}
Best Accuracy: 0.85
```

After tuning the hyperparameter, we can see that the model performed slightly better, however the value of var_smoothing is the same as the default one used - 1e-09