HR ATTRIBUTION

In [2]:
```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, f1_score
import numpy as np
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, auc
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, roc_auc_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import accuracy_score
```

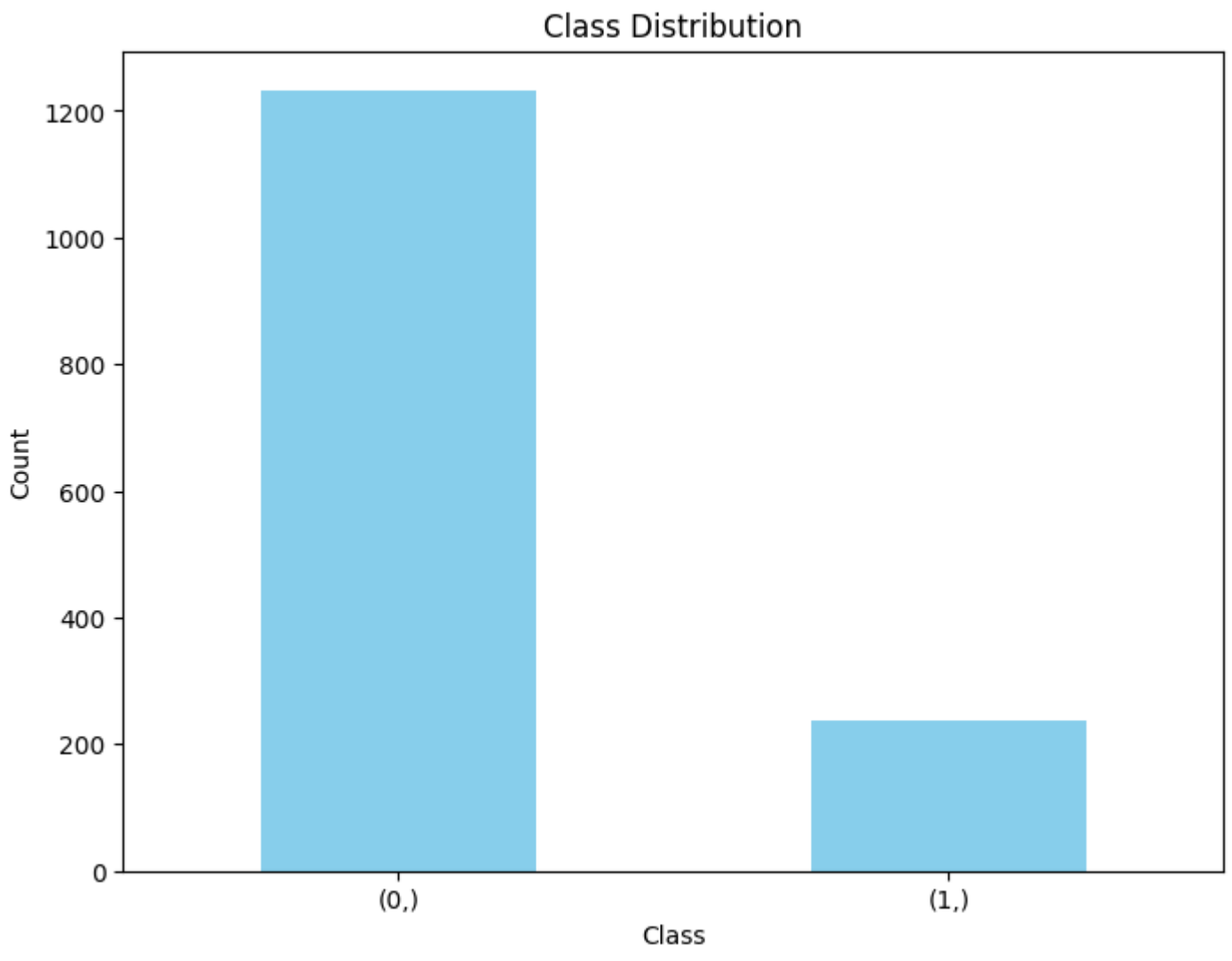
1.) Import, split data into X/y, plot y data as bar charts, turn X categorical variables binary and tts.

In [3]:
```
df = pd.read_csv("/Users/yuanhang/Desktop/UCLA/2024 spring/441 lab /w4/CLASSWORKWEEK4/HR_Analytics.csv")
```

In [4]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

In [5]:
```
y["Attrition"] = [1 if i == "Yes" else 0 for i in y["Attrition"]]
```

In [6]:
```
class_counts = y.value_counts()


plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar', color='skyblue')
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Class Distribution')
plt.xticks(rotation=0)  # Remove rotation of x-axis labels
plt.show()
```



In [7]:
```
# Step 1: Identify string columns
string_columns = X.columns[X.dtypes == 'object']

# Step 2: Convert string columns to categorical
# 很多机器学习算法（包括决策树）在处理非数值数据时会更高效或者只能处理数值数据
for col in string_columns:
    X[col] = pd.Categorical(X[col])

# Step 3: Create dummy columns
X = pd.get_dummies(X, columns=string_columns, prefix=string_columns,drop_first=True)
```

In [8]:
```
x_train,x_test,y_train,y_test=train_test_split(X,
 y, test_size=0.20, random_state=42)
```

2.) Using the default Decision Tree. What is the IN/Out of Sample accuracy?

In [28]:
```
clf = DecisionTreeClassifier()
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

y_pred1=clf.predict(x_test)
acc=accuracy_score(y_test,y_pred1)
print("OUT OF SAMPLE ACCURACY : " , round(acc,2))
```

```
IN SAMPLE ACCURACY :  1.0
OUT OF SAMPLE ACCURACY :  0.78
```

3.) Run a grid search cross validation using F1 score to find the best metrics. What is the In and Out of Sample now?

In [11]:
```
# Define the hyperparameter grid to search through
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': np.arange(1, 11),  # Range of max_depth values to try
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}


dt_classifier = DecisionTreeClassifier(random_state=42)

scoring = make_scorer(f1_score, average='weighted')
#精确度（Precision）和召回率（Recall）的调和平均值

grid_search = GridSearchCV(estimator=dt_classifier, param_grid=param_grid, scoring=scoring, cv=5)


grid_search.fit(x_train, y_train)

# Get the best parameters and the best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best F1-Score:", best_score)
```

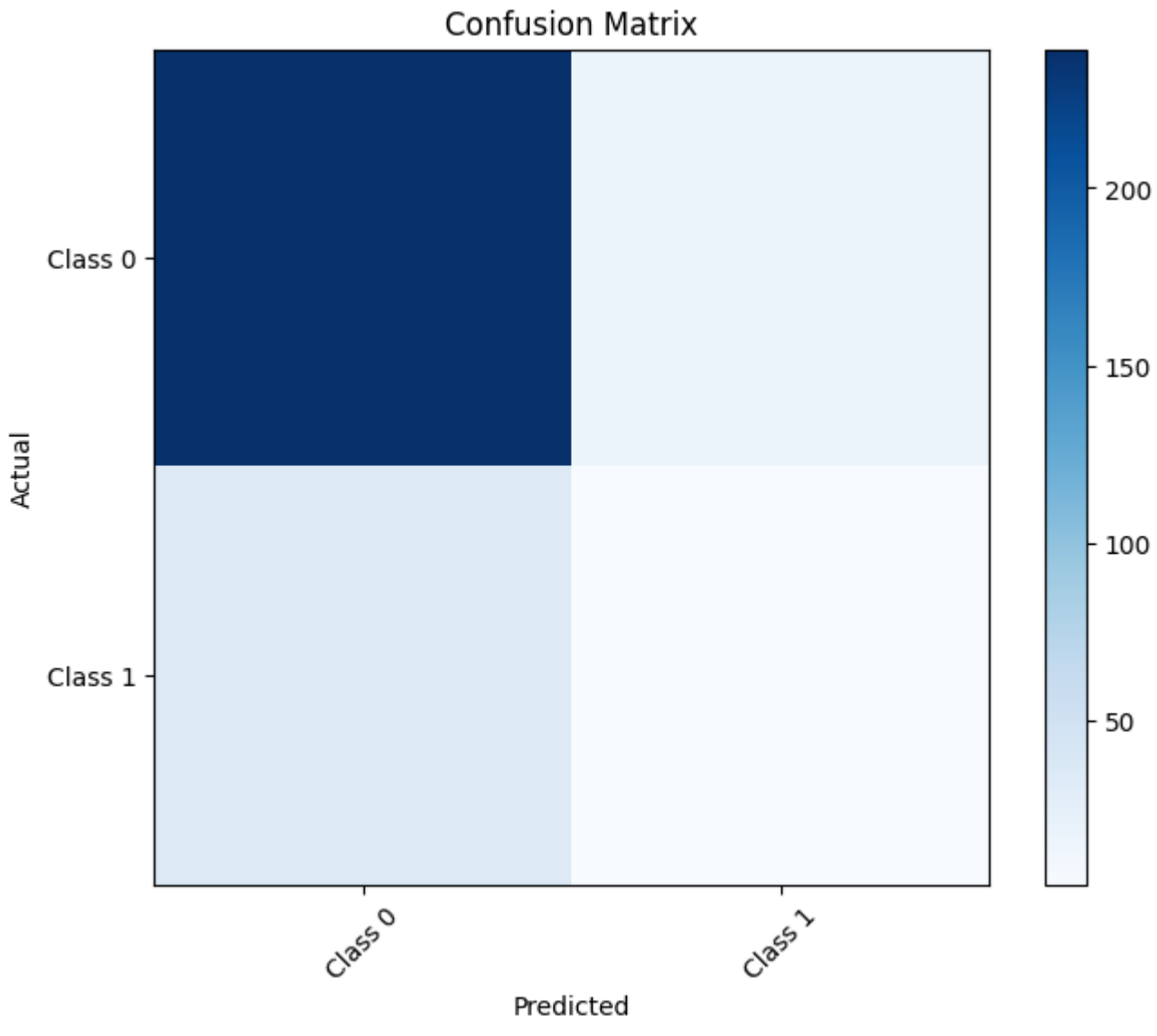
```
Best Parameters: {'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 2}
Best F1-Score: 0.8214764475510983
```

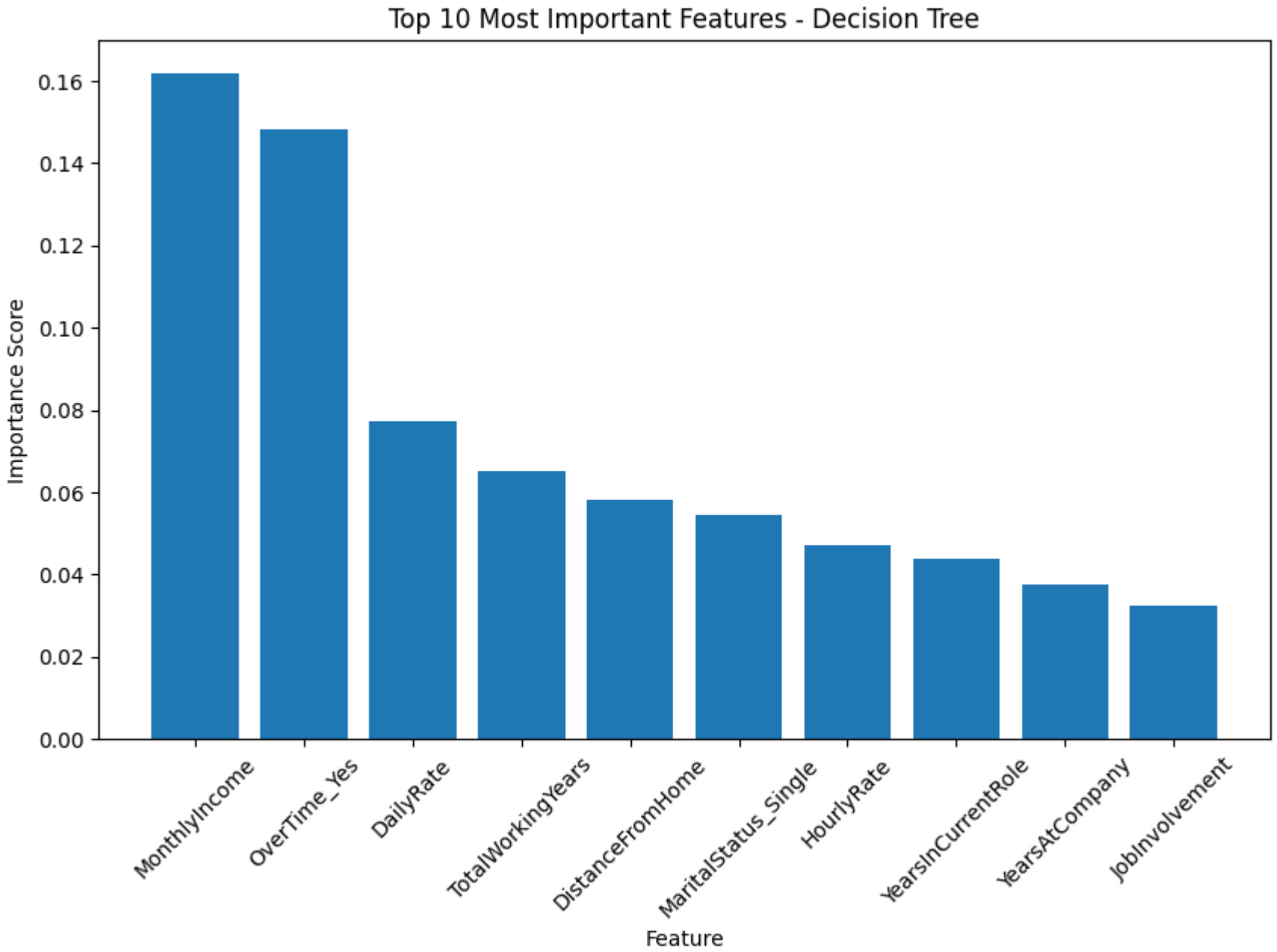
In [12]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

y_pred=clf.predict(x_test)
acc=accuracy_score(y_test,y_pred)
print("OUT OF SAMPLE ACCURACY : " , round(acc,2))
```

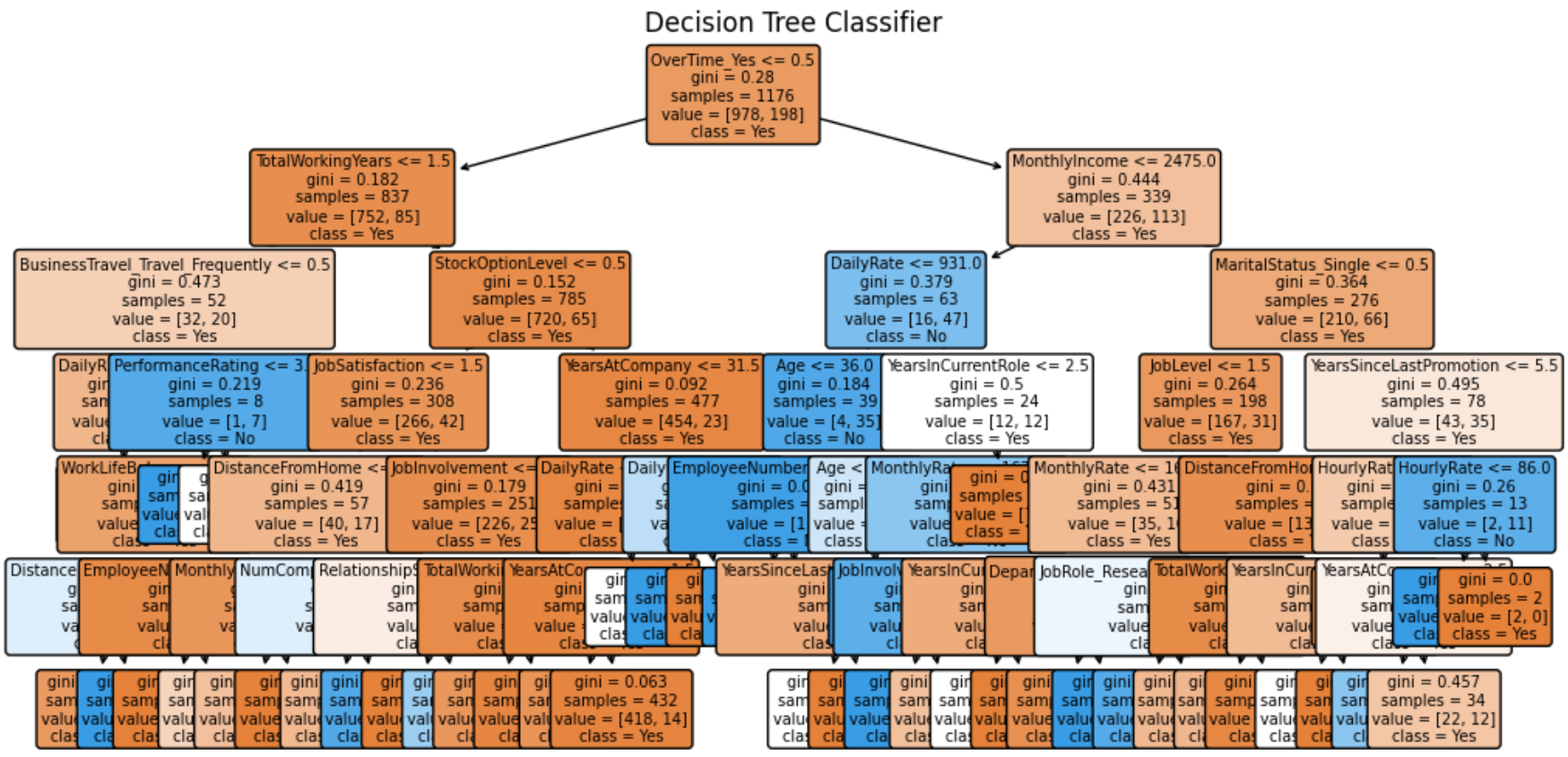
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

4.) Plot .....

In [13]:
```
# Make predictions on the test data
y_pred = clf.predict(x_test)
y_prob = clf.predict_proba(x_test)[:, 1]

# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
plt.imshow(conf_matrix, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(conf_matrix))
plt.xticks(tick_marks, ['Class 0', 'Class 1'], rotation=45)
plt.yticks(tick_marks, ['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()



feature_importance = clf.feature_importances_

# Sort features by importance and select the top 10
top_n = 10
top_feature_indices = np.argsort(feature_importance)[::-1][:top_n]
top_feature_names = X.columns[top_feature_indices]
top_feature_importance = feature_importance[top_feature_indices]

# Plot the top 10 most important features
plt.figure(figsize=(10, 6))
plt.bar(top_feature_names, top_feature_importance)
plt.xlabel('Feature')
plt.ylabel('Importance Score')
plt.title('Top 10 Most Important Features - Decision Tree')
plt.xticks(rotation=45)
plt.show()

# Plot the Decision Tree for better visualization of the selected features
plt.figure(figsize=(12, 6))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=["Yes", "No"], rounded=True, fontsize=7)
plt.title('Decision Tree Classifier')
plt.show()
#特征重要性衡量的是整个数据集中一个特征的整体重要性，而决策树的第一行所表示的是在树的顶部分裂点上的最佳特征。
#这两者之间并不总是一致的
```







5.) Looking at the graphs. what would be your suggestions to try to improve customer retention? What additional information would you need for a better plan. Plot anything you think would assist in your assessment.

ANSWER :

Observing the graph, to curb employee turnover, the company could increase monthly wages. However, it's crucial to determine the impact of adjusting overtime compensation on this strategy.

In [15]:
```
from scipy.stats import pearsonr
```

In [16]:
```
def calculate_correlation(X, feature_name, y):
    feature = X[feature_name]

    coef, _= pearsonr(feature, y)

    return(coef)
```

In [17]:
```
np.corrcoef(np.array(X['OverTime_Yes']), np.array(y['Attrition']))
```

Out[17]:
```
array([[1.        , 0.24611799],
       [0.24611799, 1.        ]])
```

6.) Using the Training Data, if they made everyone work overtime. What would have been the expected difference in client retention?

we keep extra 59 employees from leaving

In [18]:
```
x_train_experiment = x_train.copy()
```

In [19]:
```
x_train_experiment['OverTime_Yes'] = 0
```

In [20]:
```
y_pred = clf.predict(x_train)
y_pred_experiment = clf.predict(x_train_experiment)
```

In [21]:
```
diff = sum(y_pred - y_pred_experiment)
print('Change from...', diff)
```

```
Change from... 59
```

7.) If they company loses an employee, there is a cost to train a new employee for a role ~2.8 * their monthly income.

To make someone not work overtime costs the company 2K per person.

Is it profitable for the company to remove overtime? If so/not by how much?

What do you suggest to maximize company profits?

In [22]:
```
x_train_experiment['Y'] = y_pred
x_train_experiment['Y_exp'] = y_pred_experiment
```

In [23]:
```
x_train_experiment['Ret_Change'] = x_train_experiment['Y_exp'] - x_train_experiment['Y']
```

In [24]:
```
sav = sum(-2.8 * x_train_experiment['Ret_Change']* x_train_experiment['MonthlyIncome'])
cost = len(x_train[x_train['OverTime_Yes'] == 1])*2000
```

In [25]:
```
sav - cost
```

Out[25]:
```
-117593.99999999977
```

ANSWER :

When employees work overtime, it incurs additional costs for the company. Maintaining their active engagement during regular hours is more cost-effective and profitable.

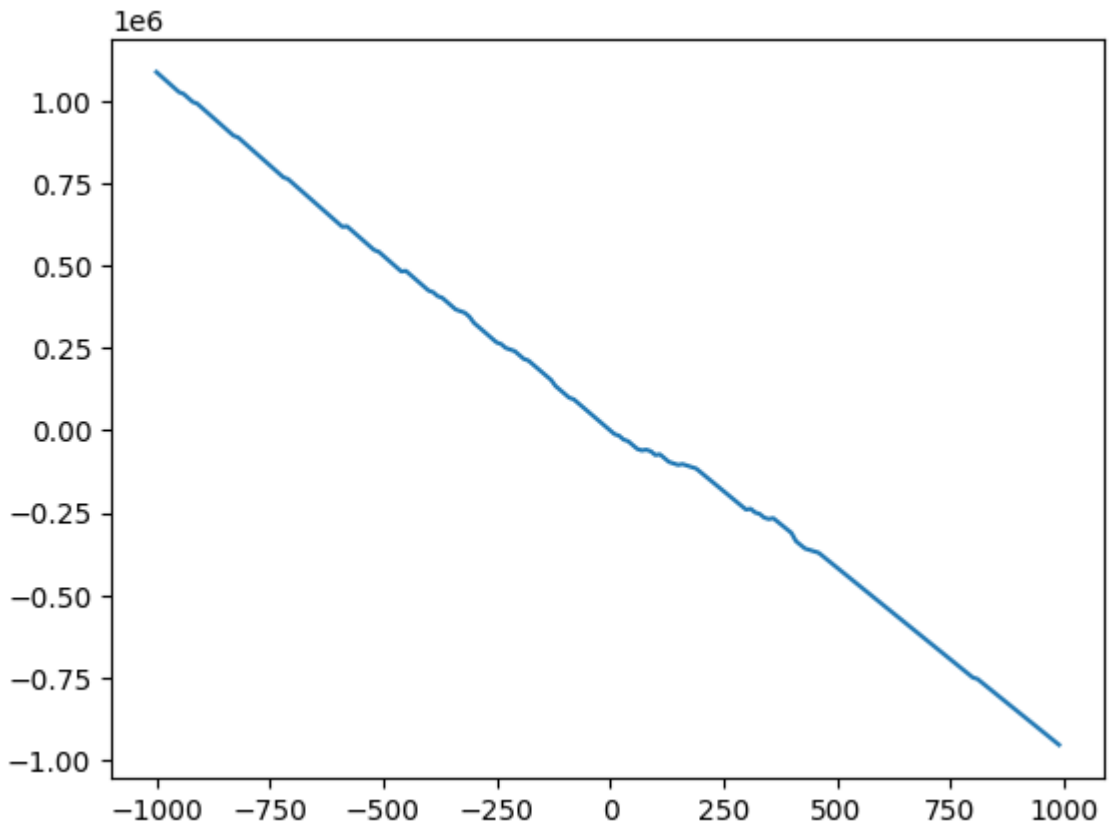
8.) Use your model and get the expected change in retention for raising and lowering peoples income. Plot the outcome of the experiment. Comment on the outcome of the experiment and your suggestions to maximize profit.

In [ ]:
```
raise_amount = 100
```

In [26]:
```
profit = []
for raise_amount in range(-1000, 1000, 10):
    x_train_experiment = x_train.copy()
    x_train_experiment['MonthlyIncome'] = x_train_experiment['MonthlyIncome'] + raise_amount
    y_pred = clf.predict(x_train)
    y_pred_experiment = clf.predict(x_train_experiment)
    diff = sum(y_pred - y_pred_experiment)
    print('Change from attrition', diff)
    x_train_experiment['Y'] = y_pred
    x_train_experiment['Y_exp'] = y_pred_experiment
    x_train_experiment['Ret_Change'] = x_train_experiment['Y_exp'] - x_train_experiment['Y']
    sav = sum(-2.8 * x_train_experiment['Ret_Change']* x_train_experiment['MonthlyIncome'])
    cost = len(x_train)*raise_amount

    print('Profit,', sav-cost)
    profit.append(sav - cost)
```

```
Change from attrition 23
Profit, -854999.6000000001
Change from attrition 23
Profit, -866115.6000000001
Change from attrition 23
Profit, -877231.6000000001
Change from attrition 23
Profit, -888347.6000000001
Change from attrition 23
Profit, -899463.6000000001
Change from attrition 23
Profit, -910579.6000000001
Change from attrition 23
Profit, -921695.6000000001
Change from attrition 23
Profit, -932811.6000000001
Change from attrition 23
Profit, -943927.6000000001
Change from attrition 23
Profit, -955043.6000000001
```

In [27]:
```
plt.plot(range(-1000, 1000, 10), profit)
plt.show()
```



ANSWER :

The more funds you secure, the lower the profit margins for the company become. Therefore, it's essential to ensure employees remain productive while simultaneously decreasing their compensation.