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("HR_Analytics.csv")
```

In [4]:
```
df.head()
```

Out[4]:

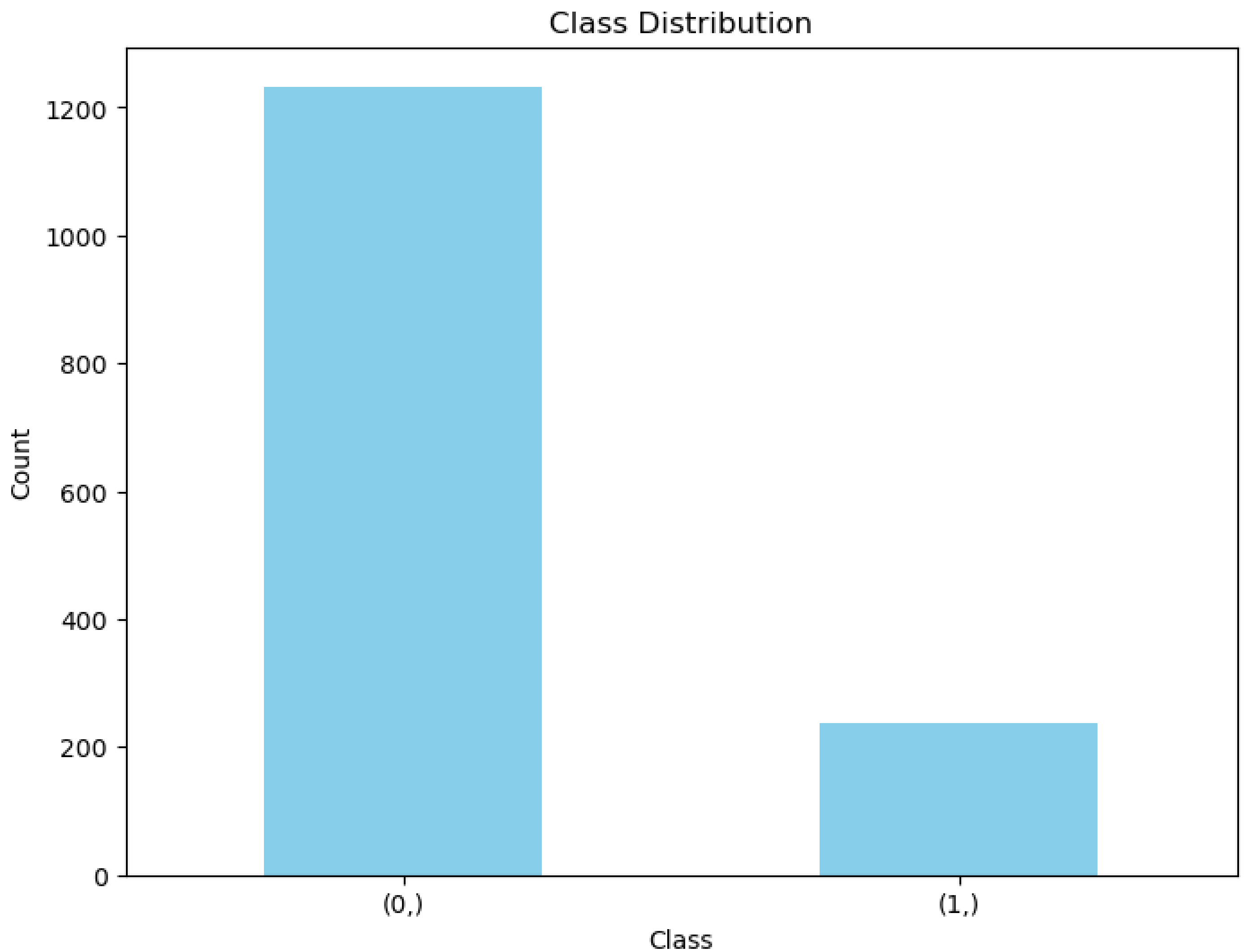
	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	StockOptior
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	1	80	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	4	80	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	2	80	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	...	3	80	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	...	4	80	

5 rows × 35 columns

In [5]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

In [6]:
```
y["Attrition"] = [1 if i == "Yes" else 0 for i in y["Attrition"]]
```

In [7]:
```
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 [8]:
```
# Step 1: Identify string columns
string_columns = X.columns[X.dtypes == 'object']

# Step 2: Convert string columns to categorical
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 [9]:
```
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 [10]:
```
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_pred=clf.predict(x_test)
acc=accuracy_score(y_test,y_pred)
print("OUT OF SAMPLE ACCURACY : " , round(acc,2))
```

```
IN SAMPLE ACCURACY :  1.0
OUT OF SAMPLE ACCURACY :  0.77
```

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]:

```python
# 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')

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
```

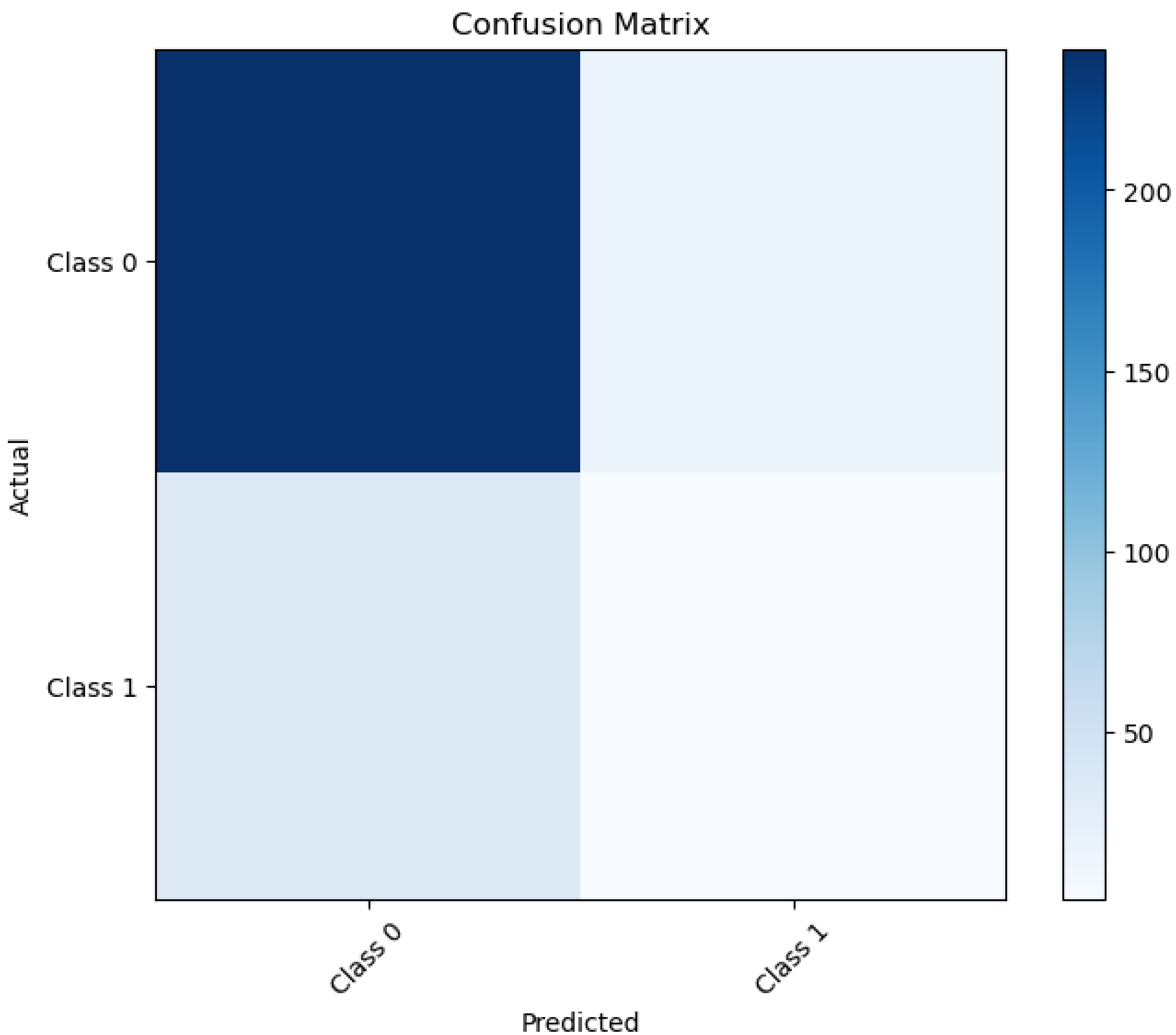
In [12]:

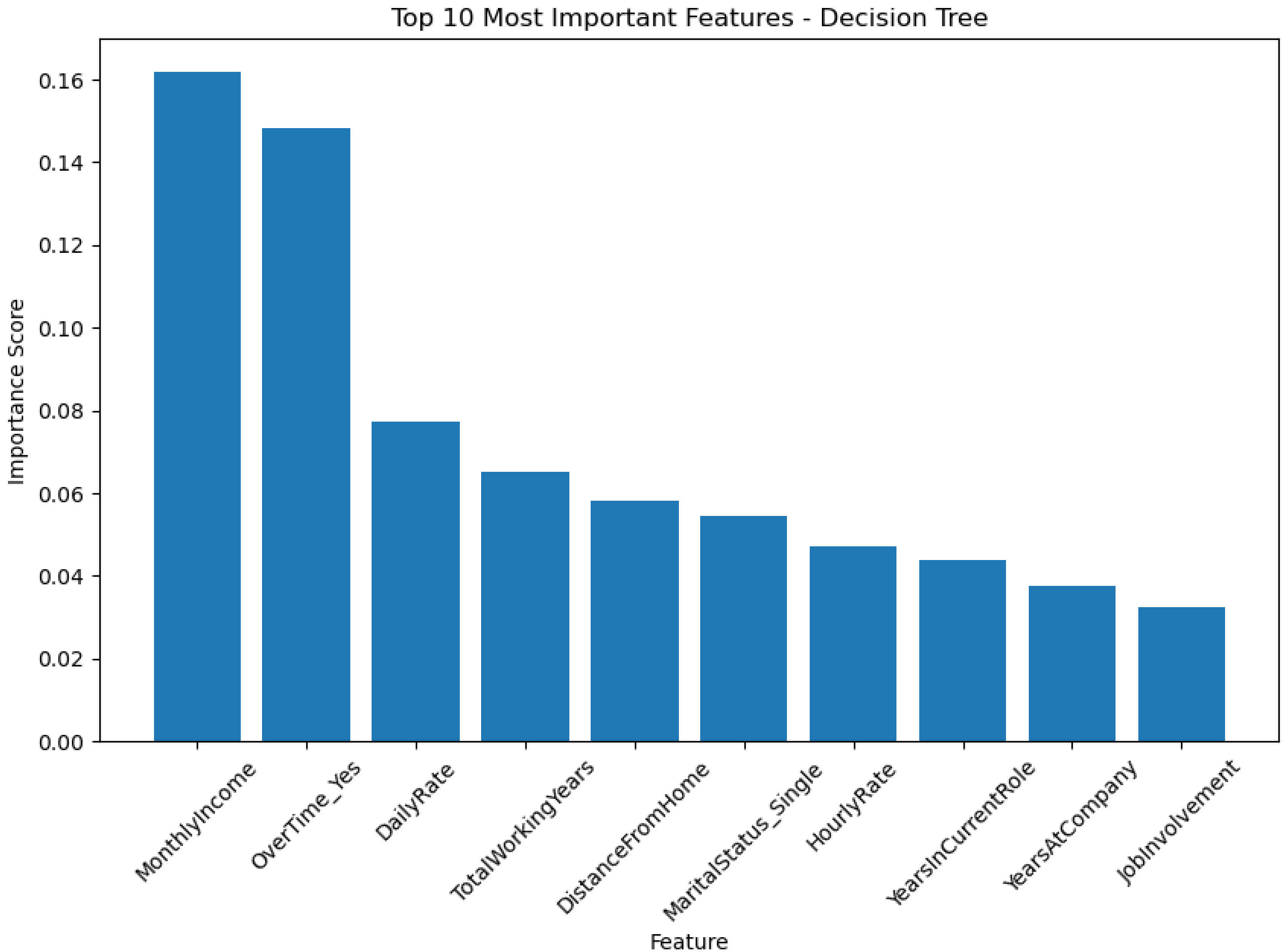
```python
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

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

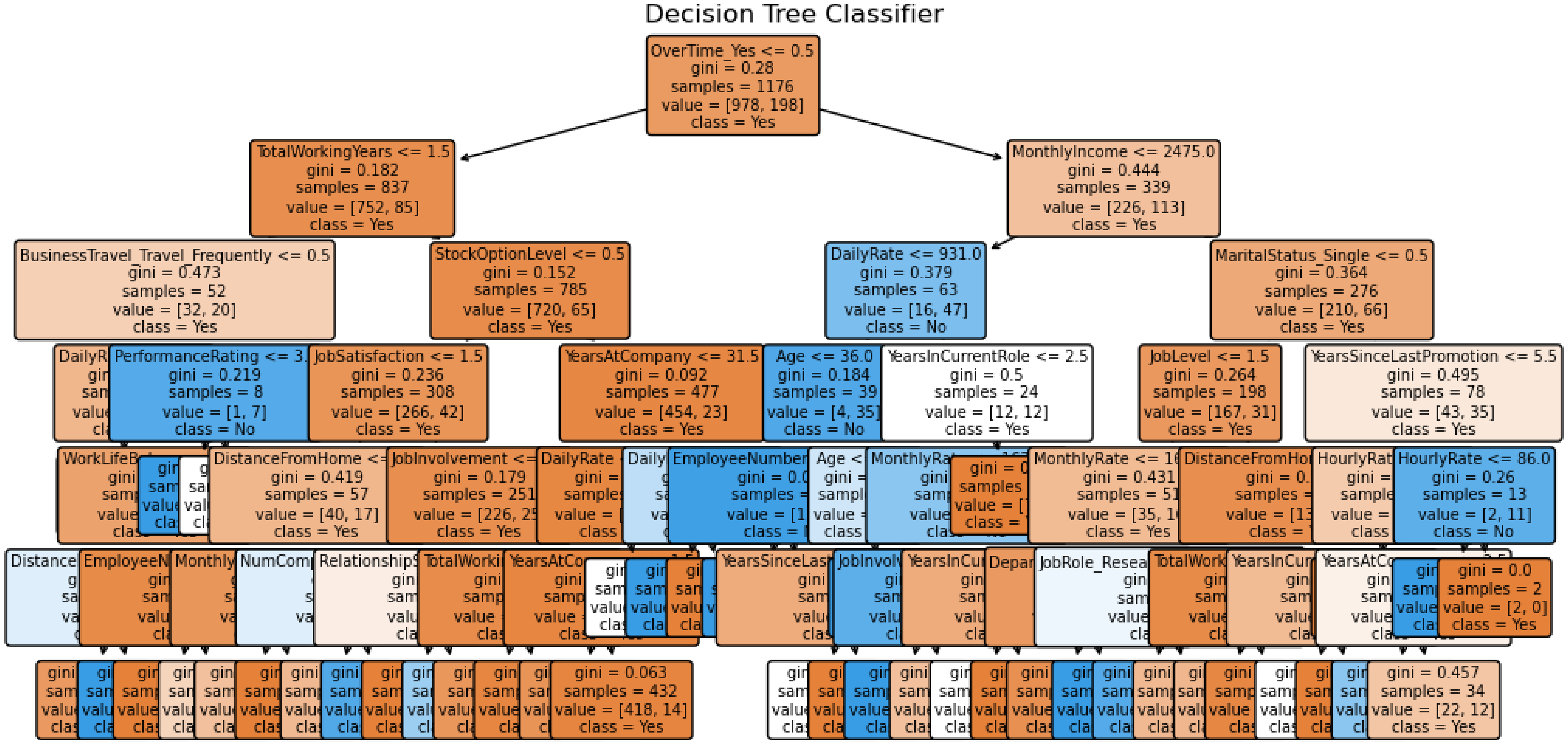
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

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()

plt.figure(figsize=(12, 6))
plot_tree(clf, filled=True, feature_names=X.columns.tolist(), class_names=["Yes", "No"], rounded=True, fontsize=7)
plt.title('Decision Tree Classifier')
plt.show()
```


Confusion Matrix
Actual
Class 0
Class 1
Predicted
Class 0
Class 1
200
150
100
50


Top 10 Most Important Features - Decision Tree
Importance Score
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
MonthlyIncome
OverTime_Yes
DailyRate
TotalWorkingYears
DistanceFromHome
MaritalStatus_Single
HourlyRate
YearsInCurrentRole
YearsAtCompany
JobInvolvement
Feature



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

ANSWER :

We should pay more to let employees stay based the most important feature, MonthlyIncome.

For the second most important feature ,OverTime_Yes, we see a small positive relationship between working overtime and retention. So we should offer more overtime working opportunities to improve retention rate. The following calculation is the prove.

In [14]:
```
np.corrcoef(np.array(X["OverTime_Yes"]),y["Attrition"])
```

Out[14]:
```
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 employee retention?

In [15]:
```
x_train_experiment = x_train.copy()
x_train_experiment["OverTime_Yes"] = 0.
y_pred_experiment = clf.predict(x_train_experiment)
y_pred = clf.predict(x_train)
print("Stopping overtime work would have prevented people from leaving : ", sum(y_pred - y_pred_experiment))
```

```
Stopping overtime work would have prevented people from leaving :  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 [16]:
```
x_train_experiment["Y"] = y_pred
x_train_experiment["Y_exp"] = y_pred_experiment
x_train_experiment["Ret_change"] = x_train_experiment["Y"] - x_train_experiment["Y_exp"]
```

In [17]:
```
# Saving : Change In Training Cost
sav = sum(x_train_experiment["Ret_change"] * 2.8 * x_train_experiment["MonthlyIncome"] )
```

In [18]:
```
# Cost of lost Overtime
cost = 2000* len(x_train[x_train["OverTime_Yes"] == 1.])
```

In [19]:
```
print("Profit from this experiment : ", sav-cost)
```

```
Profit from this experiment :  -117593.99999999977
```

ANSWER : Company should not prioritize overtime and attrition as significant issues, as the experiment suggests a negative profit when eliminating overtime.

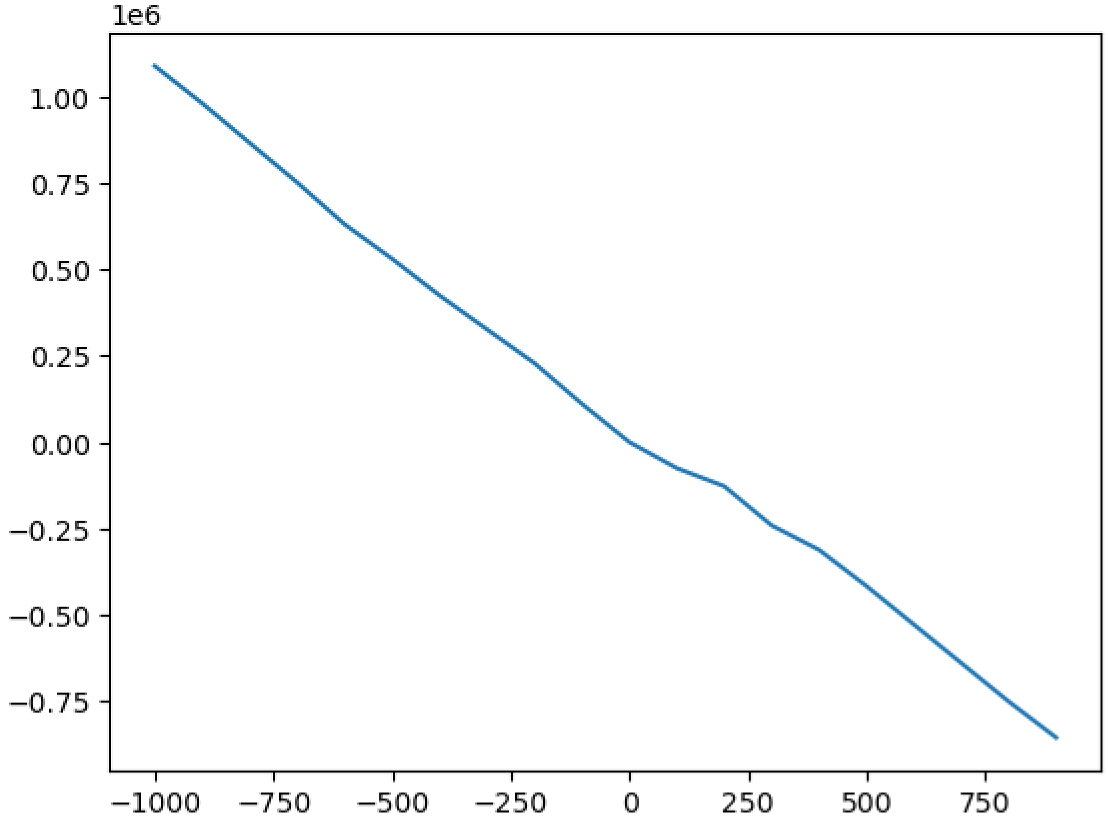
8.) Use your model and get the expected change in retention for raising and lowering peoples income. Plot the outcome of the experiment. Comment on the outcome of the experiment and your suggestions to maximize profit.

In [20]:
```
raise_amount = 500
```

In [21]:
```
profits = []
for raise_amount in range (-1000,1000,100):
    x_train_experiment = x_train.copy()
    x_train_experiment["MonthlyIncome"] =  x_train_experiment["MonthlyIncome"] + raise_amount
    y_pred_experiment = clf.predict(x_train_experiment)
    y_pred = clf.predict(x_train)
    x_train_experiment["Y"] = y_pred
    x_train_experiment["Y_exp"] = y_pred_experiment
    x_train_experiment["Ret_change"] = x_train_experiment["Y"] - x_train_experiment["Y_exp"]
    # Saving : Change In Training Cost
    print("Retention difference ", sum(x_train_experiment["Ret_change"]))
    sav = sum(x_train_experiment["Ret_change"] * 2.8 * x_train_experiment["MonthlyIncome"])

    # Cost of lost Overtime
    cost = raise_amount * len(x_train)

    print("Profit is , ", sav-cost)
    profits.append(sav-cost)
```

```
Retention difference  -16
Profit is ,  1087584.4
Retention difference  -14
Profit is ,  979524.0
Retention difference  -13
Profit is ,  864992.8
Retention difference  -12
Profit is ,  750738.8
Retention difference  -12
Profit is ,  629778.8
Retention difference  -9
Profit is ,  530138.0
Retention difference  -7
Profit is ,  424200.0
Retention difference  -4
Profit is ,  326096.4
Retention difference  -1
Profit is ,  228440.8
Retention difference  -1
Profit is ,  110714.8
Retention difference  0
Profit is ,  0.0
Retention difference  6
Profit is ,  -75328.40000000001
Retention difference  15
Profit is ,  -127503.60000000002
Retention difference  15
Profit is ,  -240914.8
Retention difference  21
Profit is ,  -311586.80000000005
Retention difference  22
Profit is ,  -416449.6000000001
Retention difference  22
Profit is ,  -527889.6000000001
Retention difference  22
Profit is ,  -639329.6000000001
Retention difference  22
Profit is ,  -750769.6000000001
Retention difference  23
Profit is ,  -854999.6000000001
```

In [22]:
```
plt.plot(range (-1000,1000,100),profits)
plt.show()
```



ANSWER : We should lower worker monthly income to maximize profit.