HR ATTRIBUTION

In [1]:
```
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, a
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 [2]:
```
df = pd.read_csv("HR_Analytics.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Educatio
0	41	Yes	Travel_Rarely	1102	Sales	1	
1	49	No	Travel_Frequently	279	Research & Development	8	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	
4	27	No	Travel_Rarely	591	Research & Development	2	

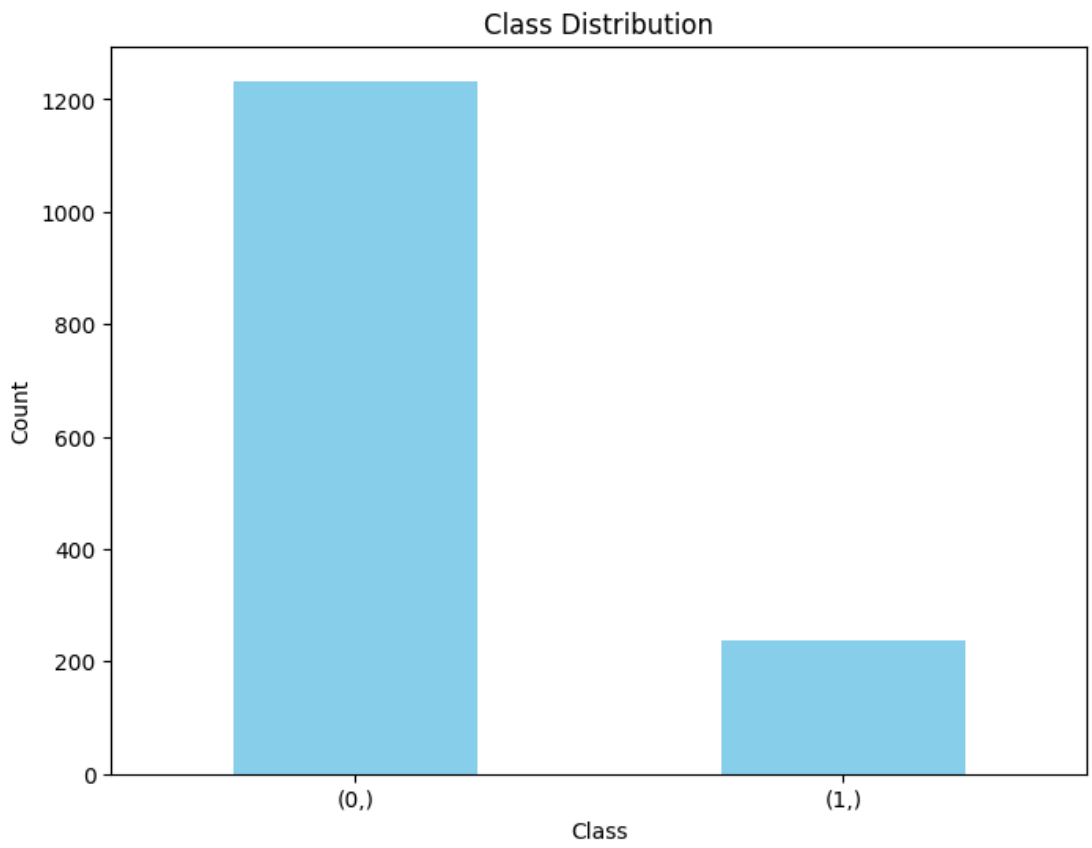
5 rows × 35 columns

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
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_
```

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 [9]:
```
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 :  0.76
```

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 [10]:
```
# 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

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
```

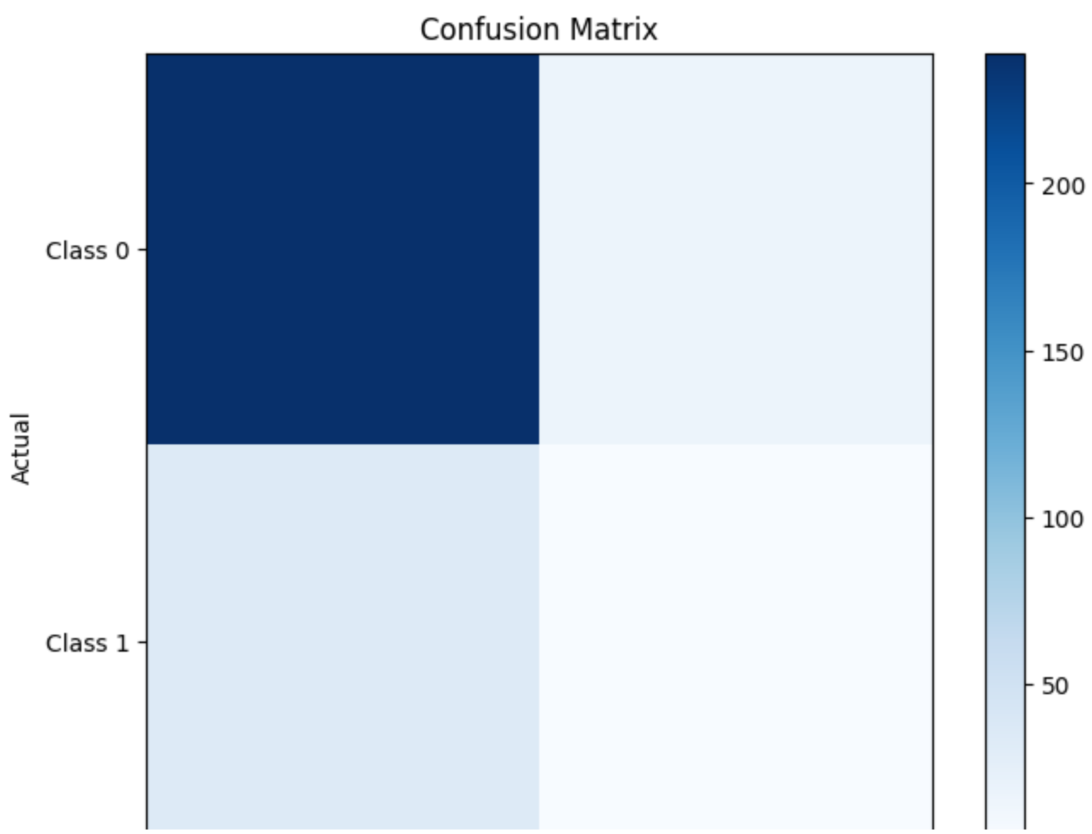
In [11]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

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

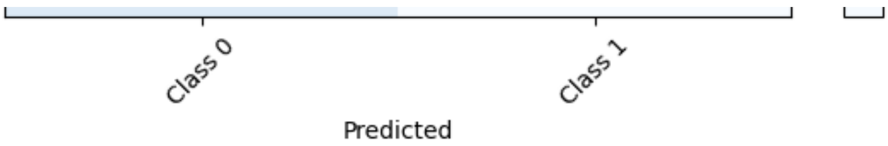
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

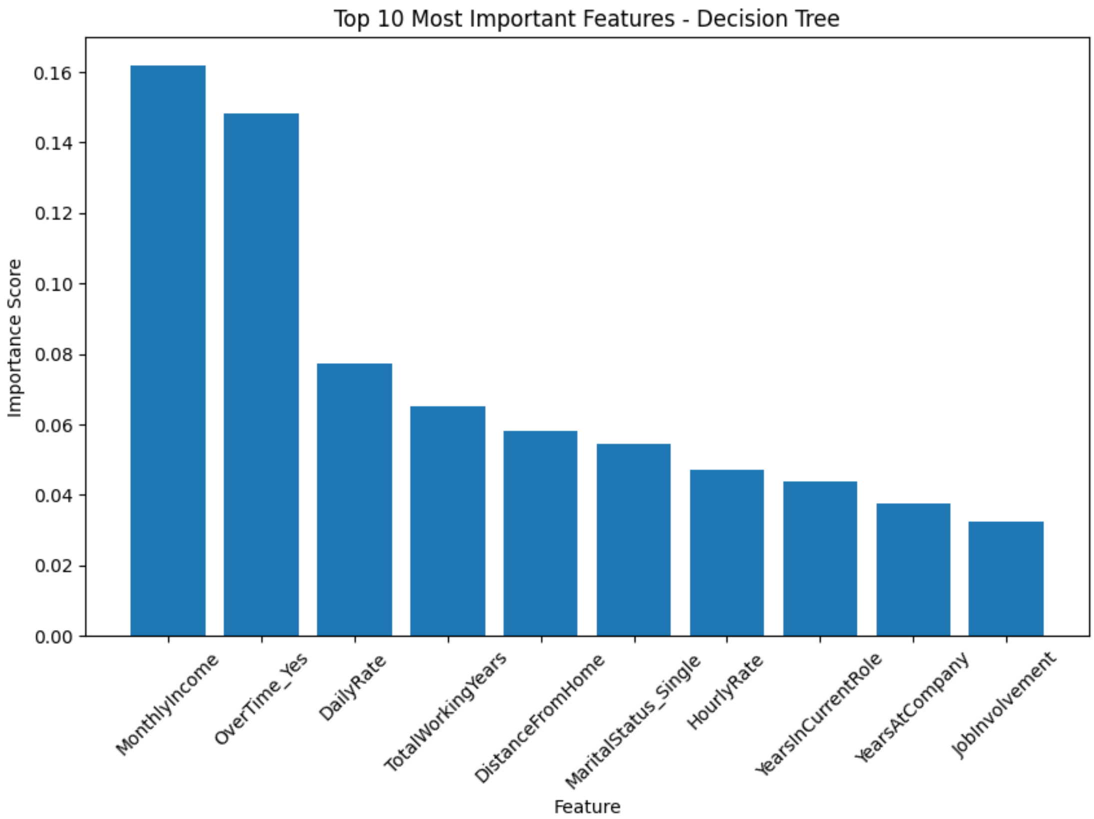
4.) Plot ......

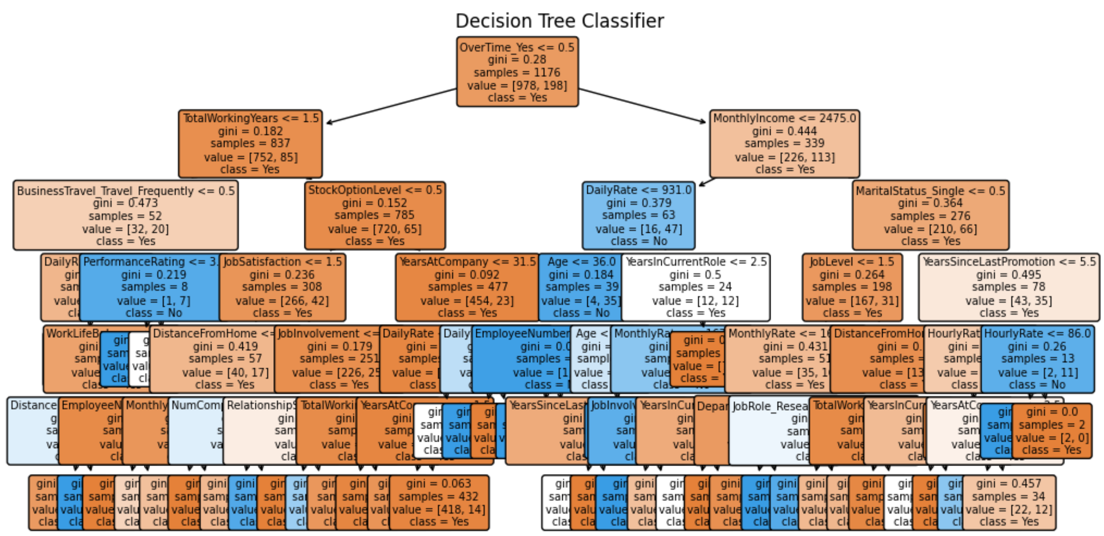
In [12]:
```
# Make predictions on the test data
y_pred = clf.predict(x_test)
y_prob = clf.predict_proba(x_test)[:, 1]

# 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 feature
plt.figure(figsize=(12, 6))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=["Yes",
plt.title('Decision Tree Classifier')
plt.show()
```









In [ ]:

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

- Analyzing the confusion matrix reveals that the model performs well in predicting employees who are likely to stay (class 0), but it struggles in accurately predicting employee attrition.
- Examining the graph of feature importance scores, we observe that monthly income, overtime work, and daily rate are the top three factors influencing attrition.
- The decision tree supports our findings, indicating that overtime work, monthly income, and total working years play relatively more crucial roles in influencing attrition.

In summary, the graphical analyses suggest that employees with lower monthly income, higher overtime work hours, and fewer total working years are more prone to leave the company. To mitigate attrition, I suggest the company consider increasing monthly income, reducing overtime work, and fostering a stronger sense of belonging among employees.

In [13]:
```
np.corrcoef(np.array(X["MonthlyIncome"]),y["Attrition"])
```

Out[13]:
```
array([[ 1.        , -0.15983958],
       [-0.15983958,  1.        ]])
```

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

Out[14]:
```
array([[1.        , 0.24611799],
       [0.24611799, 1.        ]])
```

In [15]:
```
np.corrcoef(np.array(X["TotalWorkingYears"]),y["Attrition"])
```

Out[15]:
```
array([[ 1.        , -0.17106325],
       [-0.17106325,  1.        ]])
```

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

In [16]:
```
x_train_experiment = x_train.copy()
```

In [17]:
```
x_train_experiment["OverTime_Yes"] = 0.
```

In [18]:
```
y_pred_experiment = clf.predict(x_train_experiment)
y_pred = clf.predict(x_train)
```

In [19]:
```
print("Stopping overtime work would have prevented people from leaving:",
```

```
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 [20]:
```
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_expe
```

In [21]:
```
# Savings
savings = sum(x_train_experiment["Ret_Change"] * 2.8 * x_train_experiment
```

In [22]:
```
cost = 2000 * len(x_train[x_train["OverTime_Yes"] == 1.])
```

In [23]:
```
print("profit form this experiment: ", savings - cost)
```

```
profit form this experiment:  -117593.99999999977
```

Based on the results, remove overtime work may not be financially advantageous, as the expected loss from the above experiment is approximately 117,594. To optimize company profits, an alternative approach would be to invest in training new employees instead of removing overtime work. However, the company may also consider exploring options to reduce overtime work, as this could potentially enhance profits without completely eliminating overtime opportunities.

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 [24]:
```
raise_amount = 500
```

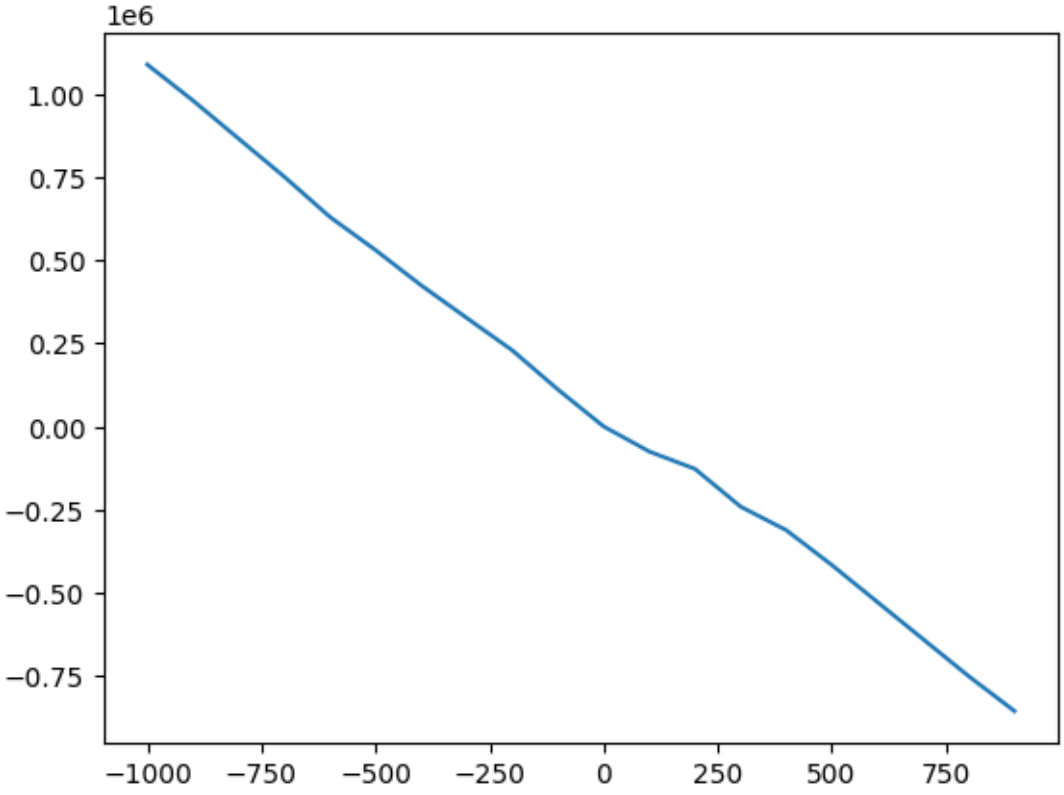
In [25]:
```
profits = []
for raise_amount in range(-1000,1000,100):
    x_train_experiment = x_train.copy()
    x_train_experiment["MonthlyIncome"] = x_train_experiment["MonthlyInco
    y_pred_experiment = clf.predict(x_train_experiment)
    y_pred = clf.predict(x_train)
    x_train_experiment["Y"] = y_pred
    x_train_experiment["Y_exp"] = y_pred_experiment
    x_train_experiment["Ret_Change"] = x_train_experiment["Y"] - x_train_

    # Savings
    print("Retention different: ", sum(x_train_experiment["Ret_Change"]))
```

```
    savings = sum(x_train_experiment["Ret_Change"] * 2.8 * x_train_experi

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

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

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

In [26]:

```
plt.plot(range(-1000,1000,100), profits)
plt.show()
```



The results depicted in the graph indicate that as the raise amount given to employees increases, the company's profit decreases due to a negative correlation between profit and raise amount, forming an almost straight declining line. Conversely, when the company lowers wages, the profit increases. Hence, to maximize profits, my recommendation is to maintain the current wage without providing additional amounts or reducing compensation. This approach is essential for retaining profits while fostering employee commitment and loyalty to the company.