1. Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_curve, roc_auc_score
warnings.filterwarnings('ignore')
```

2. Loading the dataset

In [2]:
```
df = pd.read_csv('heart.csv')
```

3. Exploratory Data Analysis

```
Variable definitions in the Dataset

Age: Age of the patient
Sex: Sex of the patient
exang: exercise induced angina (1 = yes; 0 = no)
ca: number of major vessels (0-3)
cp: Chest Pain type chest pain type
Value 1: typical angina
Value 2: atypical angina
Value 3: non-anginal pain
Value 4: asymptomatic
trtbps: resting blood pressure (in mm Hg)
chol: cholestoral in mg/dl fetched via BMI sensor
fbs: (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
_restecg: resting electrocardiographic results
Value 0: normal
Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05
mV)
Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
```

```
thalach: maximum heart rate achieved
target: 0= less chance of heart attack 1= more chance of heart attack
```

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

Out[3]:

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

In [4]:
```
new_columns = ['age', 'sex', 'cp', 'trtbps', 'chol', 'fbs', 'rest_ecg', 'thalach', 'exang',
               'oldpeak', 'slope', 'ca', 'thal', 'target']
```

In [5]:
```
df.columns = new_columns
```

In [6]:
```
df.head()
```

Out[6]:

	age	sex	cp	trtbps	chol	fbs	rest_ecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

In [7]:
```
df.shape
```

Out[7]: (303, 14)

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    int64  
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 3   trtbps    303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   rest_ecg  303 non-null    int64  
 7   thalach   303 non-null    int64  
 8   exang     303 non-null    int64  
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64  
 11  ca        303 non-null    int64  
 12  thal      303 non-null    int64  
 13  target    303 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

3.1 Checking for null values

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
age         0
sex         0
cp          0
trtbps      0
chol        0
fbs         0
rest_ecg    0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

3.2 Checking for unique values

In [10]:
```
unique_number = []

for i in df.columns:
    x = df[i].value_counts().count()
    unique_number.append(x)

pd.DataFrame(unique_number, index = df.columns, columns=['Unique Values'])
```

Out[10]:

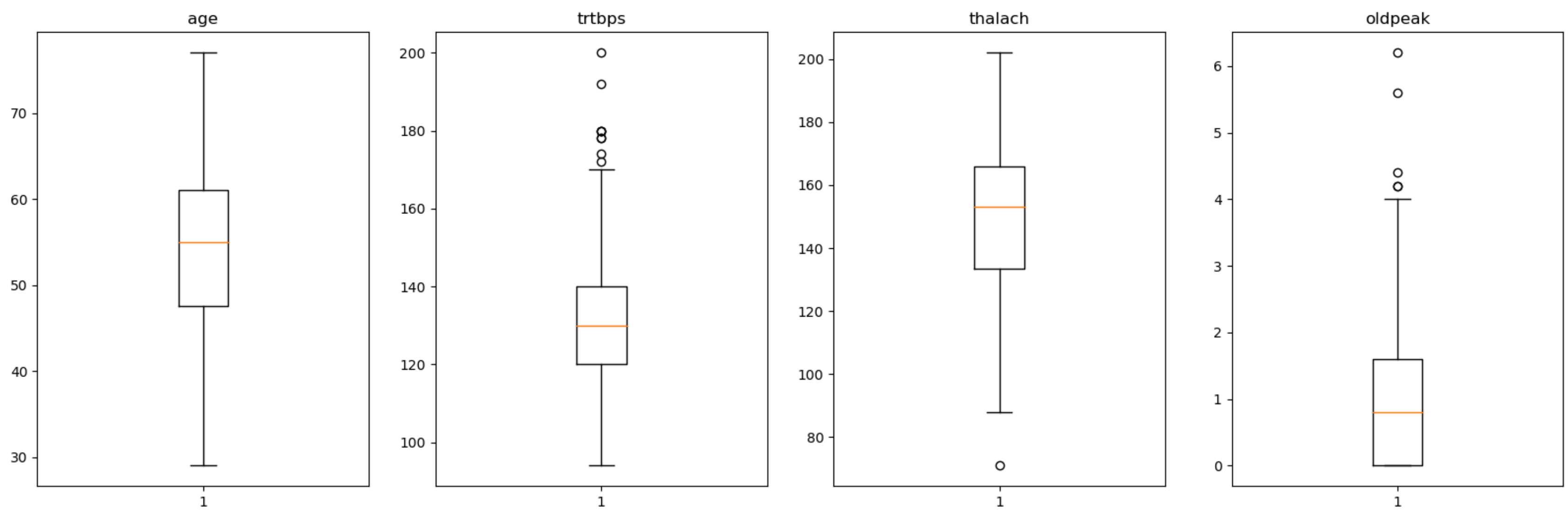
	Unique Values
age	41
sex	2
cp	4
trtbps	49
chol	152
fbs	2
rest_ecg	3
thalach	91
exang	2
oldpeak	40
slope	3
ca	5
thal	4
target	2

- According to the result from the unique value dataframe;
- We determined the variables with few unique values as categorical variables, and the variables with high unique values as numeric variables.
- In this context, Numeric Variables: “age”, “trtbps”, “chol”, “thalach” and “oldpeak ”

- Categorical Variables: "sex", "cp", "fbs", "rest_ecg", "exang", "slope", "ca", "thal", "target"

3.3 Outliers

In [11]:
```
fig, (ax1, ax2, ax3, ax4) = plt.subplots(1, 4, figsize = (20, 6))

ax1.boxplot(df["age"])
ax1.set_title("age")

ax2.boxplot(df["trtbps"])
ax2.set_title("trtbps")

ax3.boxplot(df["thalach"])
ax3.set_title("thalach")

ax4.boxplot(df["oldpeak"])
ax4.set_title("oldpeak")

plt.show()
```



In [12]:
```
numeric_var = ["age", "trtbps", "chol", "thalach", "oldpeak"]
categoric_var = ["sex", "cp", "fbs", "rest_ecg", "exang", "slope", "ca", "thal", "target"]
```

3.4 Examining Statistics of Variables

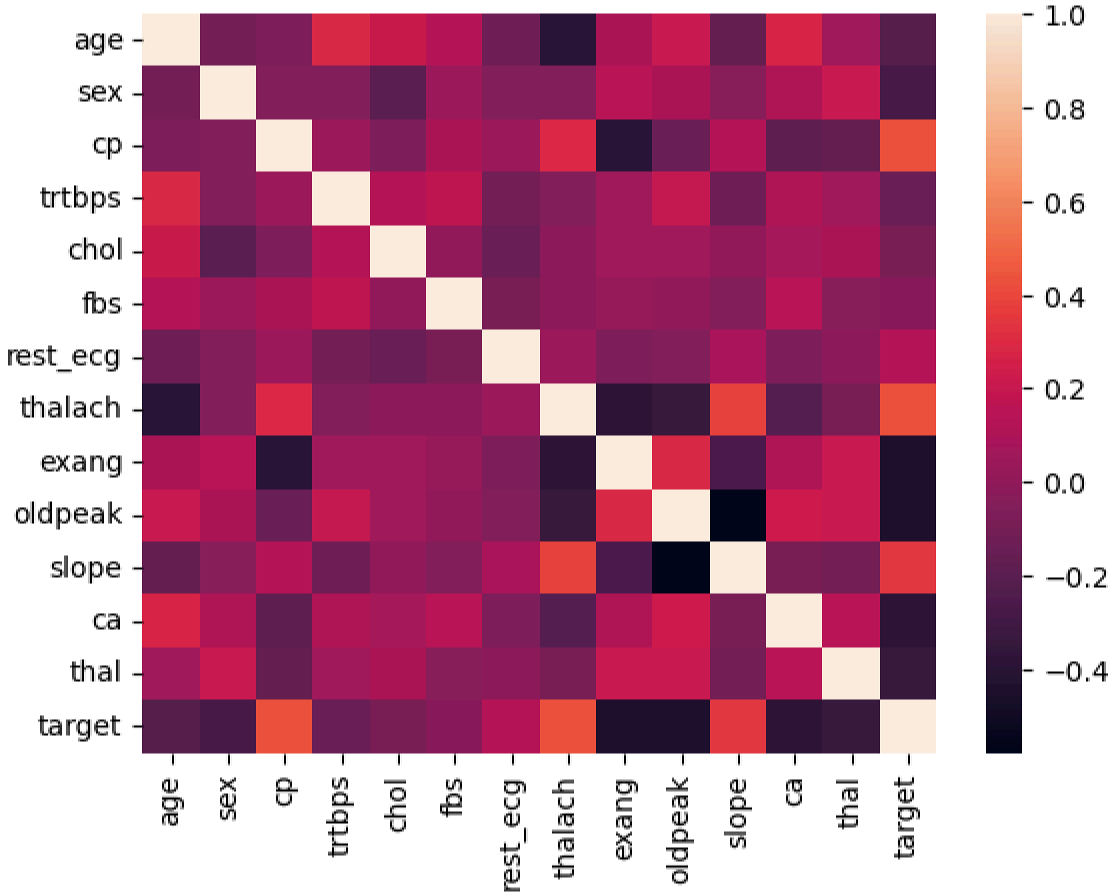
In [13]:
```
df.describe()
```

Out[13]:

	age	sex	cp	trtbps	chol	fbs	rest_ecg	thalach	exang	oldpeak	sl
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.039604	1.399
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000

In [14]:
```
sns.heatmap(df.corr())
```

Out[14]: <Axes: >

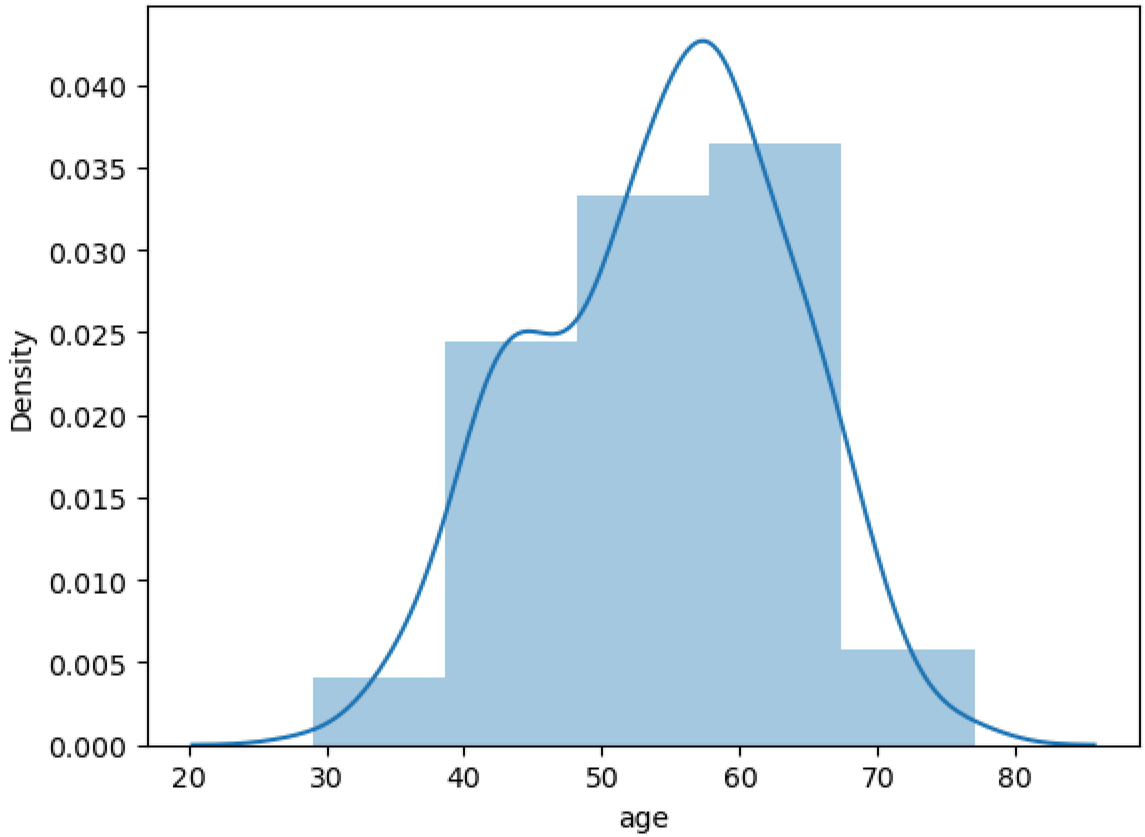


3.5 Let's Check the skewness of Numeric Features

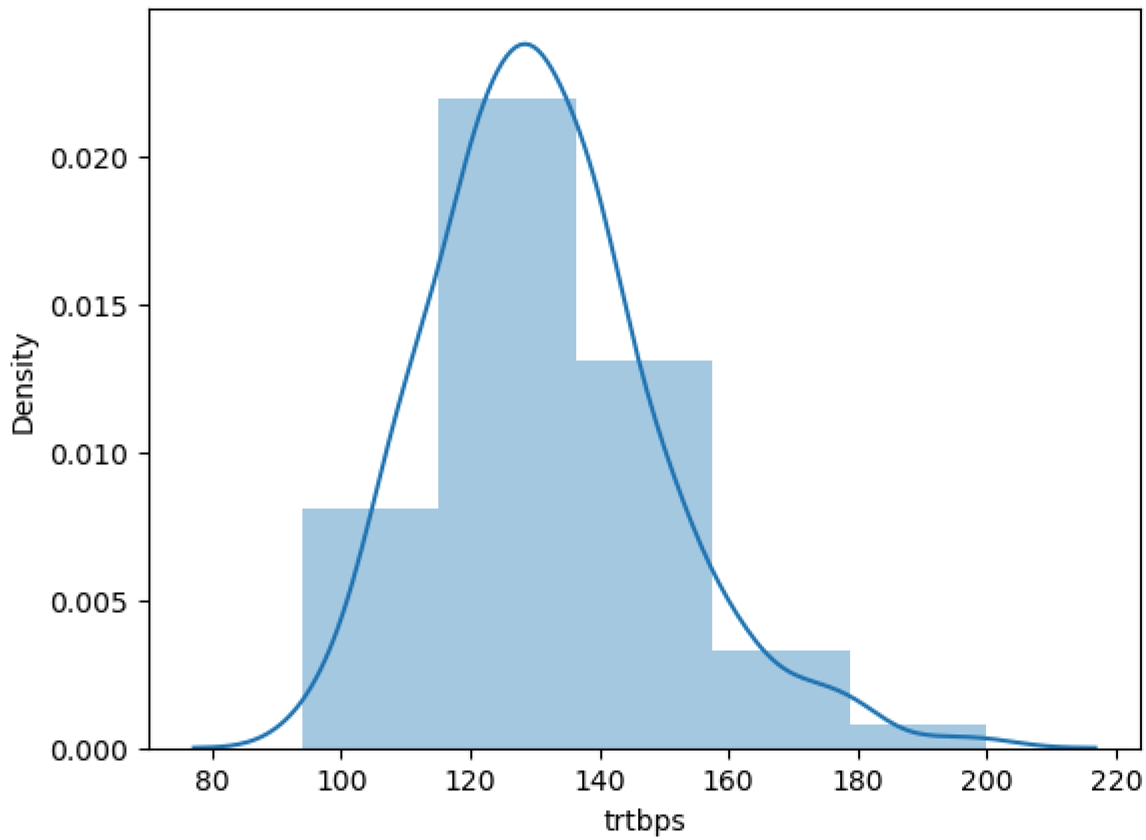
In [15]:
```
stats = df[numeric_var].max() - df[numeric_var].min()
(df[numeric_var].mean() - stats)
```

Out[15]:
```
age           6.366337
trtbps       25.623762
chol       -191.735974
thalach      18.646865
oldpeak      -5.160396
dtype: float64
```

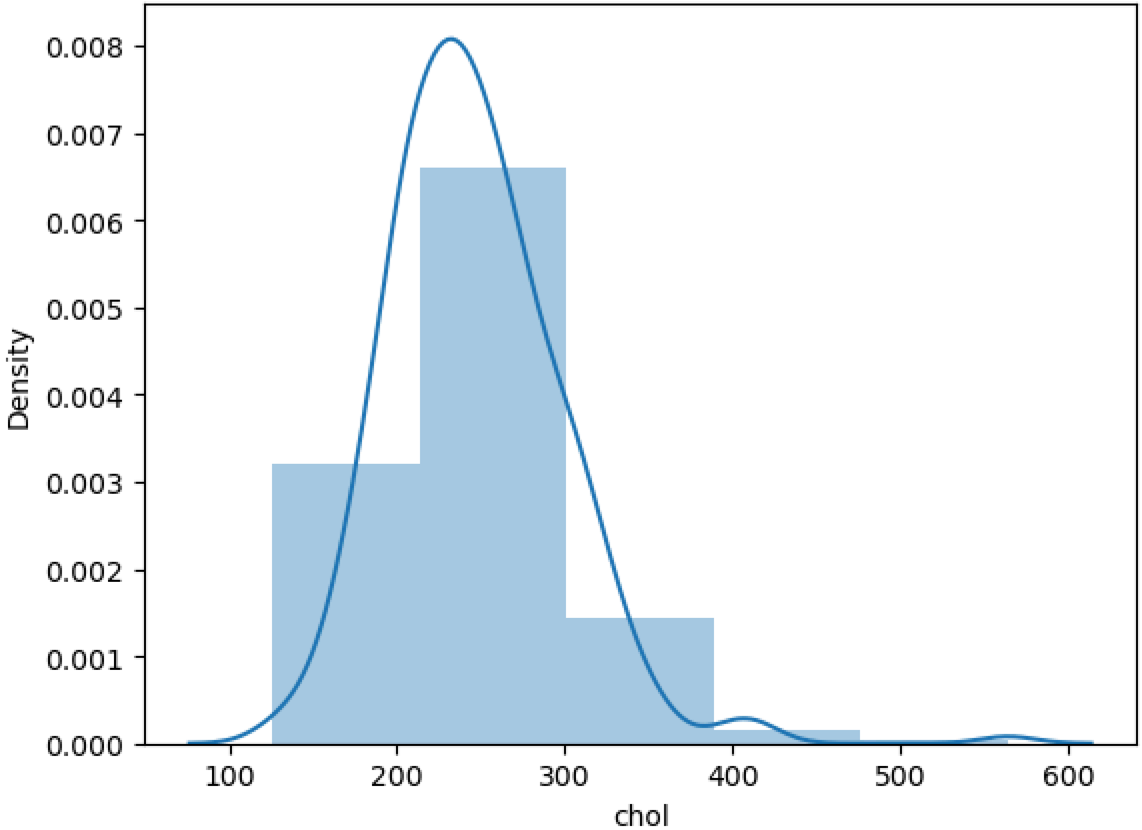
In [16]:
```
sns.distplot(df["age"], bins = 5);
```



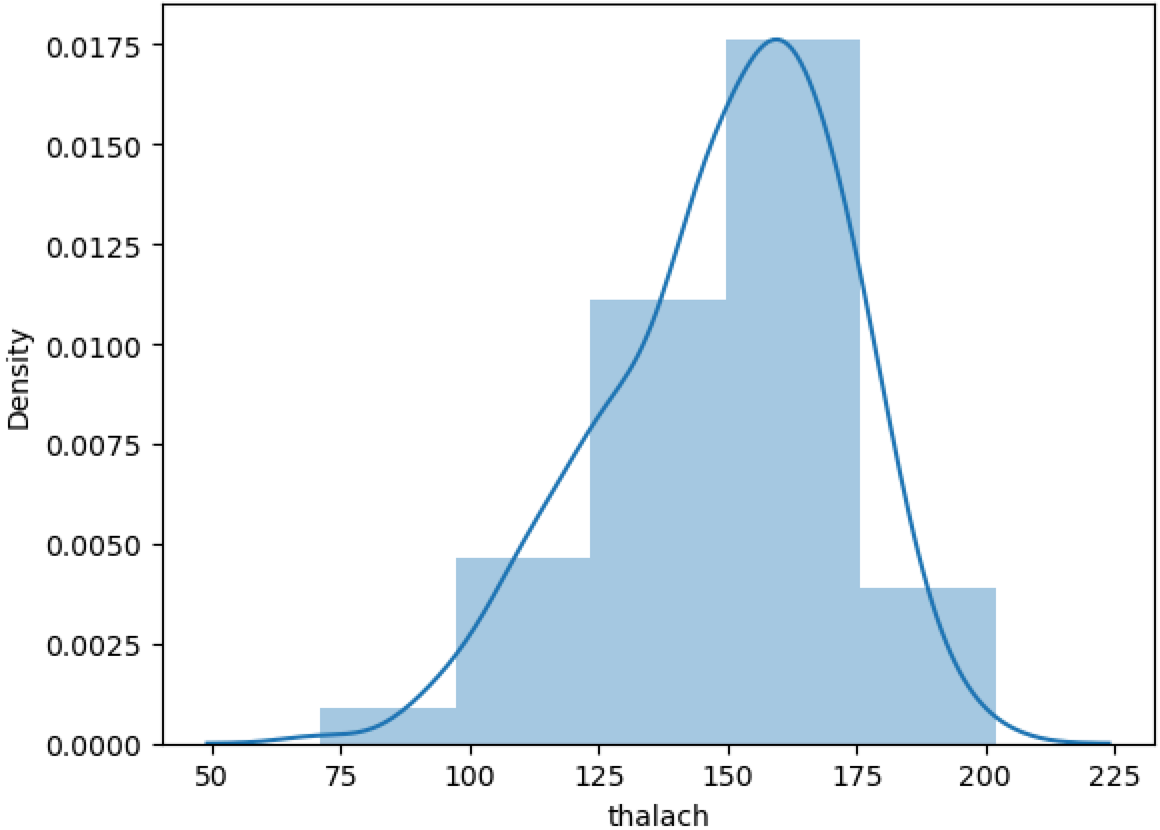
In [17]:
```
sns.distplot(df["trtbps"], bins = 5);
```



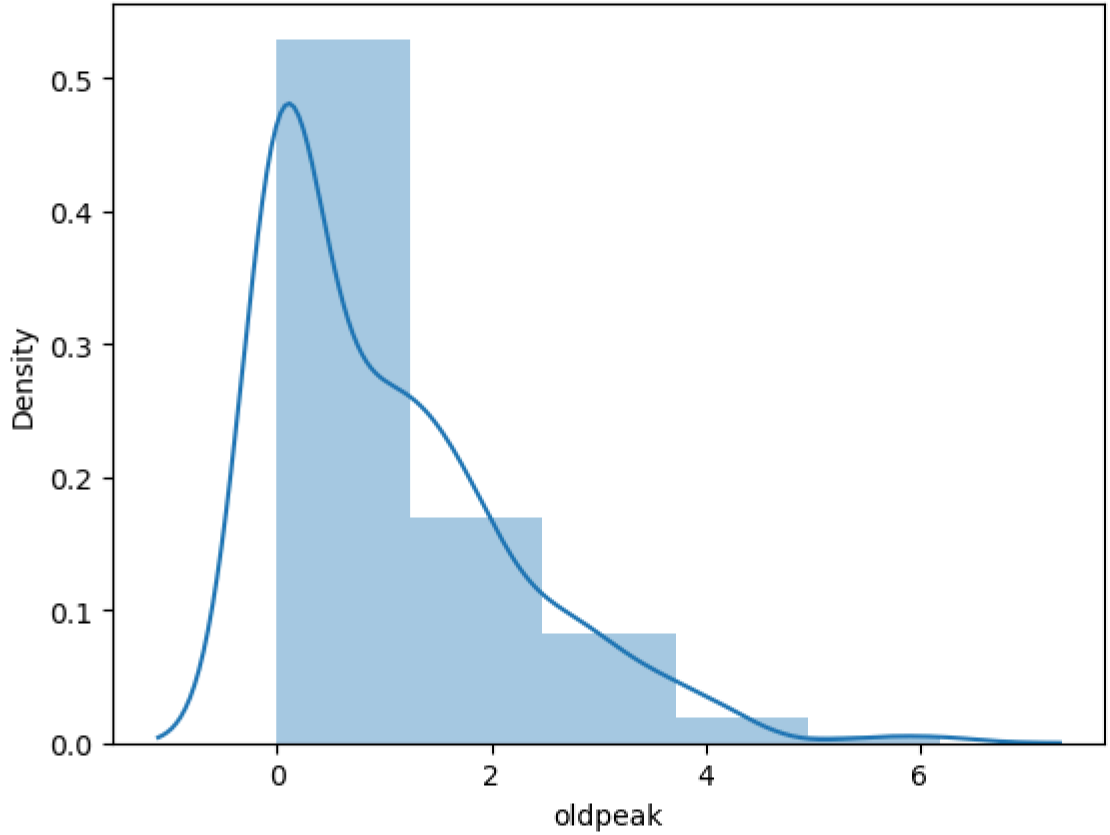
In [18]:
```
sns.distplot(df["chol"], bins = 5);
```



In [19]:
```
sns.distplot(df["thalach"], bins = 5);
```



In [20]:
```
sns.distplot(df["oldpeak"], bins = 5);
```



3.6 Column age, chol, trtbps, thalach, oldpeak are skewed hence we will take log of these columns

In [21]:
```
df['age'] = np.log(df['age'])
```

In [22]:
```
df['chol'] = np.log(df['chol'])
```

In [23]:
```
df['trtbps'] = np.log(df['trtbps'])
```

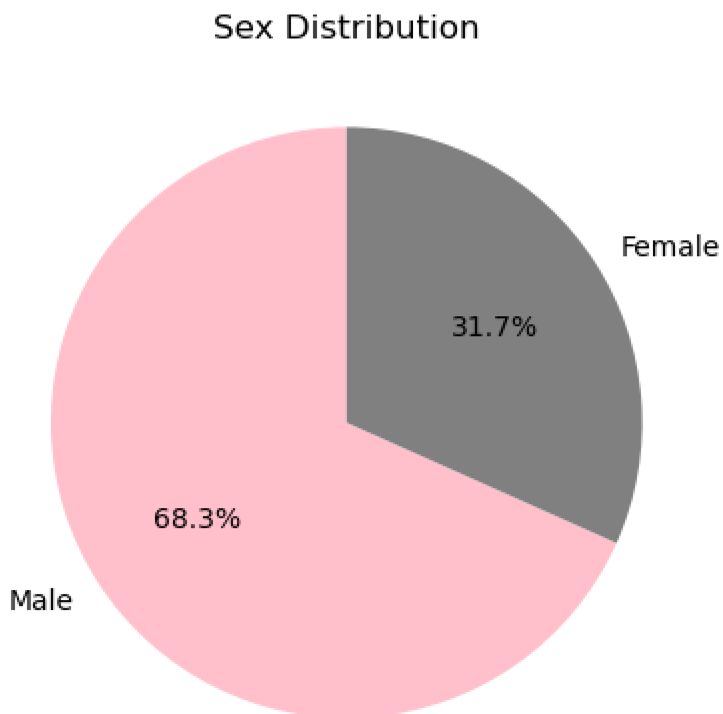
In [24]:
```
df['thalach'] = np.log(df['thalach'])
```

In [25]:
```
categoric_axis_name = ["Gender", "Chest Pain Type", "Fasting Blood sugar", "Resting Electrocardiograp
                       "Exercise Induced Angina", "The Slope of ST Segment", "Number of Major Vessels"
```

In [26]:
```
# Define colors
colors_sex = ['#FFC0CB', '#808080']  # Light pink, grey
colors_cp = ['#FFC0CB', '#D3D3D3', '#808080', '#A9A9A9']  # Light pink, light grey, grey, dark grey
```

In [27]:
```
# Calculate counts for 'sex' column
sex_counts = df['sex'].value_counts()
plt.pie(sex_counts, labels=['Male', 'Female'], autopct='%1.1f%%', startangle=90, colors=colors_sex)
plt.title('Sex Distribution')
```

Out[27]:
```
Text(0.5, 1.0, 'Sex Distribution')
```

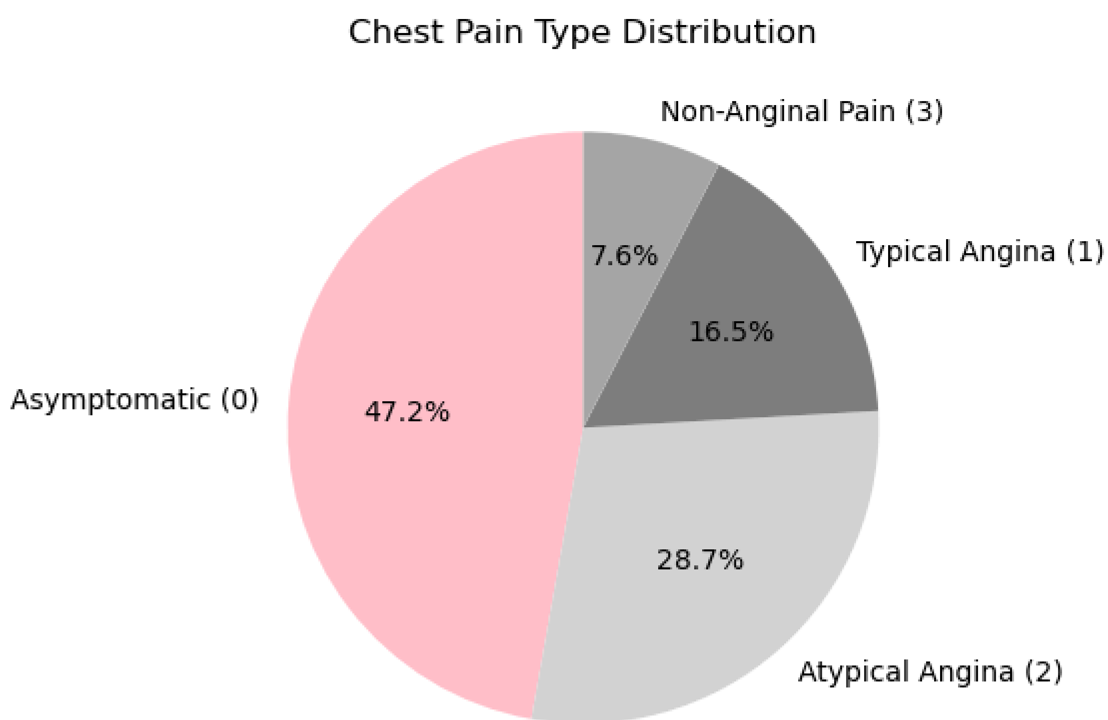


In [28]:
```
# Calculate counts for 'cp' column
cp_counts = df['cp'].value_counts()
```

In [29]:
```
# Map chest pain types to their descriptions
cp_mapping = {
    0: 'Asymptomatic',
    1: 'Typical Angina',
    2: 'Atypical Angina',
    3: 'Non-Anginal Pain'
}
```

In [30]:
```
cp_labels = [f'{cp_mapping[key]} ({key})' for key in cp_counts.index]
plt.pie(cp_counts, labels=cp_labels, autopct='%1.1f%%', startangle=90, colors=colors_cp)
plt.title('Chest Pain Type Distribution')
```

Out[30]:
```
Text(0.5, 1.0, 'Chest Pain Type Distribution')
```

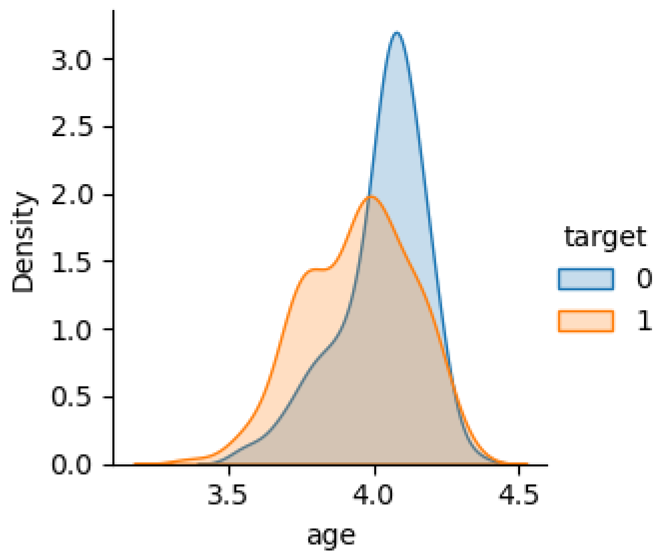


In [31]:
```
numeric_var
```

Out[31]:
```
['age', 'trtbps', 'chol', 'thalach', 'oldpeak']
```

In [32]:
```
numeric_var.append("target")
```

In [33]:
```
g = sns.FacetGrid(df, hue="target")
g.map(sns.kdeplot, "age", shade = True)
g.add_legend()
# Show the plot
plt.show()
```



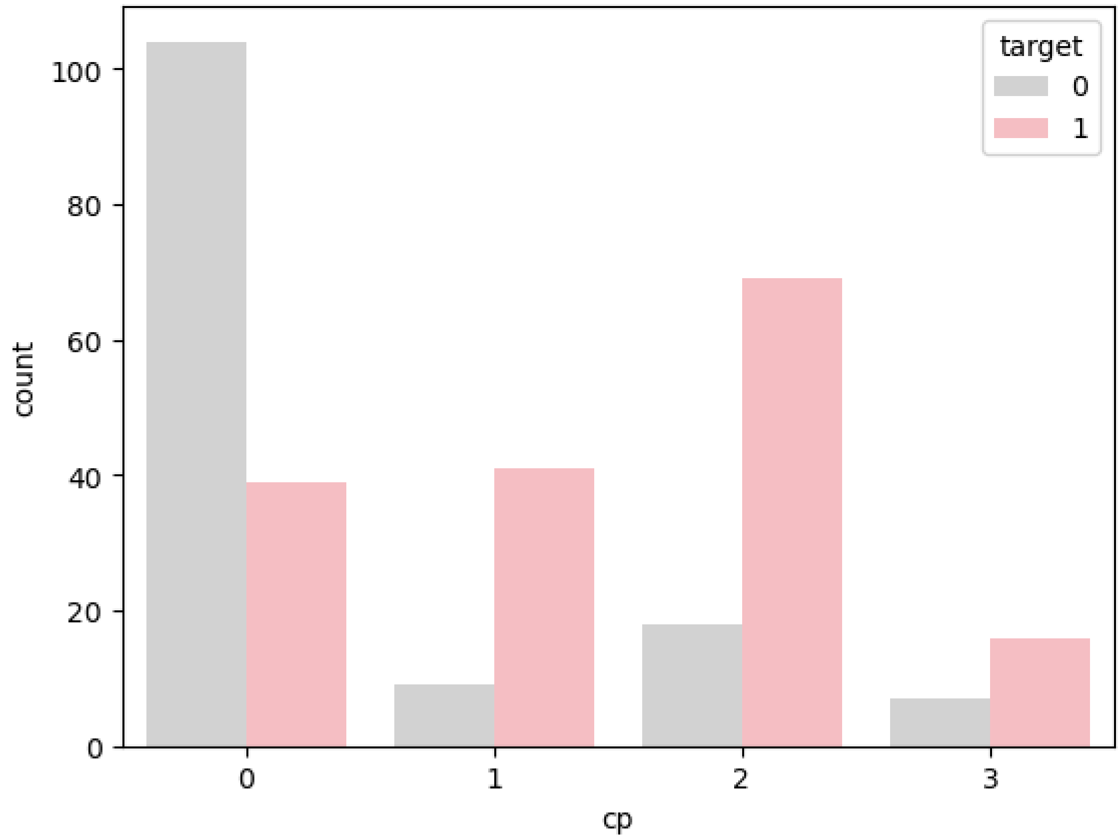
In [34]:
```
df.head()
```

Out[34]:

	age	sex	cp	trtbps	chol	fbs	rest_ecg	thalach	exang	oldpeak	slope	ca	thal	target
0	4.143135	1	3	4.976734	5.451038	1	0	5.010635	0	2.3	0	0	1	1
1	3.610918	1	2	4.867534	5.521461	0	1	5.231109	0	3.5	0	0	2	1
2	3.713572	0	1	4.867534	5.318120	0	0	5.147494	0	1.4	2	0	2	1
3	4.025352	1	1	4.787492	5.463832	0	1	5.181784	0	0.8	2	0	2	1
4	4.043051	0	0	4.787492	5.869297	0	1	5.093750	1	0.6	2	0	2	1

In [35]:
```
sns.countplot(x="cp", data=df, hue="target", palette=['lightgrey', 'lightpink'])
```

Out[35]: <Axes: xlabel='cp', ylabel='count'>



3.6 Extracting features and target

In [36]:
```
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

4. Training and testing dataset

In [37]:
```
from sklearn.model_selection import train_test_split
```

In [38]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [39]:
```
X_train.head()
```

Out[39]:

	age	sex	cp	trtbps	chol	fbs	rest_ecg	thalach	exang	oldpeak	slope	ca	thal
124	3.663562	0	2	4.543295	5.293305	0	1	5.187386	0	0.0	2	0	2
72	3.367296	1	1	4.867534	5.318120	0	0	5.308268	0	0.0	2	0	2
15	3.912023	0	2	4.787492	5.389072	0	1	5.062595	0	1.6	1	0	2
10	3.988984	1	0	4.941642	5.476464	0	1	5.075174	0	1.2	2	0	2
163	3.637586	1	2	4.927254	5.164786	0	1	5.153292	0	0.0	2	4	2

In [40]:
```
y_train.head()
```

Out[40]:
```
124    1
72     1
15     1
10     1
163    1
Name: target, dtype: int64
```

4.1 Standardizing the features

In [41]:
```
from sklearn.preprocessing import StandardScaler
```

In [42]:
```
scaler = StandardScaler()
```

In [43]:
```
X_train = scaler.fit_transform(X_train)
```

In [44]:
```
X_test = scaler.transform(X_test)
```

5. Model building

5.1 building logistics-regression model

In [45]:
```
from sklearn.linear_model import LogisticRegression
```

In [46]:
```
lr = LogisticRegression()
```

In [47]:
```
lr.fit(X_train, y_train)
```

Out[47]:
```
▾ LogisticRegression
LogisticRegression()
```

In [48]:
```
y_pred_lr = lr.predict(X_test)
```

5.1.1 checking the accuracy of the model

In [49]:
```
from sklearn.metrics import accuracy_score
```

In [50]:
```
print(round(accuracy_score(y_test, y_pred_lr)*100,2),'%')
```

```
80.22 %
```

5.1.2 Fine tuning model

In [51]:
```
from sklearn.model_selection import GridSearchCV
```

In [52]:
```
parameters = {
                "penalty":["l1","l2"],
                "solver" : ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
            }
```

In [53]:
```
log_reg_grid = GridSearchCV(lr, param_grid = parameters)
```

In [54]:
```
log_reg_grid.fit(X_train, y_train)
```

Out[54]:
```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [55]:
```
print("Best Parameters: ", log_reg_grid.best_params_)
```

```
Best Parameters:  {'penalty': 'l1', 'solver': 'saga'}
```

In [56]:
```
lr_best = LogisticRegression(penalty = "l1", solver = "saga")
lr_best
```

Out[56]:
```
▾ LogisticRegression
LogisticRegression(penalty='l1', solver='saga')
```

In [57]:
```
lr_best.fit(X_train, y_train)
```

Out[57]:
```
▾ LogisticRegression
LogisticRegression(penalty='l1', solver='saga')
```

In [58]:
```
y_pred_lr_best = lr_best.predict(X_test)
```

In [59]:
```
accuracy_L= accuracy_score(y_test, y_pred_lr_best)
print(round(accuracy_L*100,2),'%')
```

```
81.32 %
```

In [60]:
```
precision_L= precision_score(y_test, y_pred_lr_best)
precision_L
```

Out[60]:
```
0.8235294117647058
```

In [61]:
```
recall_L=recall_score(y_test, y_pred_lr_best)
recall_L
```

Out[61]:
```
0.84
```

5.2 Building decision tree classifier

In [62]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [63]:
```
dec_tree = DecisionTreeClassifier(random_state = 5)
```

In [64]:
```
dec_tree.fit(X_train, y_train)
```

Out[64]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=5)
```

In [65]:
```
y_pred_dt = dec_tree.predict(X_test)
```

5.2.1 Checking the accuracy

In [66]:
```
print(round(accuracy_score(y_test, y_pred_dt)*100,2),'%')
```

```
73.63 %
```

5.2.2 Fine tuning model

In [67]:
```
param_grid = {
    'max_depth': [None, 5, 6, 7, 8, 9, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy']
}
```

In [68]:
```
dec_tree_ft = GridSearchCV(dec_tree, param_grid=param_grid, cv=5, verbose=1, scoring='accuracy')
```

In [69]:
```
dec_tree_ft.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 126 candidates, totalling 630 fits
```

Out[69]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [85]:
```
print('Best Parameters: ',dec_tree_ft.best_params_)
```

```
Best Parameters:  {'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 4, 'min_samples_spli
t': 2}
```

In [86]:
```
dec_tree_best = DecisionTreeClassifier(criterion='gini', max_depth=None, min_samples_leaf=4, min_samp
```

In [87]:
```
dec_tree_best.fit(X_train, y_train)
```

Out[87]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(min_samples_leaf=4)
```

In [88]:
```
y_pred_dt_best = dec_tree_best.predict(X_test)
```

In [89]:
```
accuracy_DT = accuracy_score(y_test, y_pred_dt_best)
print(round((accuracy_DT)*100,2),'%')
```

```
75.82 %
```

In [90]:
```
precision_DT=precision_score(y_test, y_pred_dt_best)
precision_DT
```

Out[90]:
```
0.8043478260869565
```

In [91]:
```
recall_DT= recall_score(y_test, y_pred_dt_best)
recall_DT
```

Out[91]:
```
0.74
```

5.3 Building Random Forest model

In [92]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [93]:
```
random_forest = RandomForestClassifier(random_state = 5)
```

In [94]:
```
random_forest.fit(X_train, y_train)
```

Out[94]:
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=5)
```

In [95]:
```
y_pred_rf = random_forest.predict(X_test)
```

5.3.1 Checking the accuracy

In [96]:
```
print(round(accuracy_score(y_test, y_pred_rf)*100,2),'%')
```

```
80.22 %
```

5.3.2 Fine tuning

In [97]:
```
parameters = {"n_estimators" : [50, 100, 150, 200],
              "criterion" : ["gini", "entropy"],
              'max_features': ['auto', 'sqrt', 'log2'],
              'bootstrap': [True, False]}
```

In [98]:
```
random_forest_grid = GridSearchCV(random_forest, param_grid = parameters)
```

In [99]:
```
random_forest_grid.fit(X_train, y_train)
```

Out[99]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [100]:
```
print("Best Parameters:", random_forest_grid.best_params_)
```

```
Best Parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_features': 'sqrt', 'n_estimators':
50}
```

In [101]:
```
random_forest_best = RandomForestClassifier(bootstrap = True, criterion = "entropy", max_features = "
```

In [102]:
```
random_forest_best.fit(X_train, y_train)
```

Out[102]:
```
▾ RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=50, random_state=5)
```

In [103]:
```
y_pred_rf_best = random_forest_best.predict(X_test)
```

In [104]:
```
accuracy_RF=accuracy_score(y_test, y_pred_rf_best)
accuracy_RF
```

Out[104]: 0.7912087912087912

In [105]:
```
precision_RF=precision_score(y_test, y_pred_rf_best)
precision_RF
```

Out[105]: 0.8163265306122449

In [106]:
```
recall_RF= recall_score(y_test, y_pred_rf_best)
recall_RF
```

Out[106]: 0.8

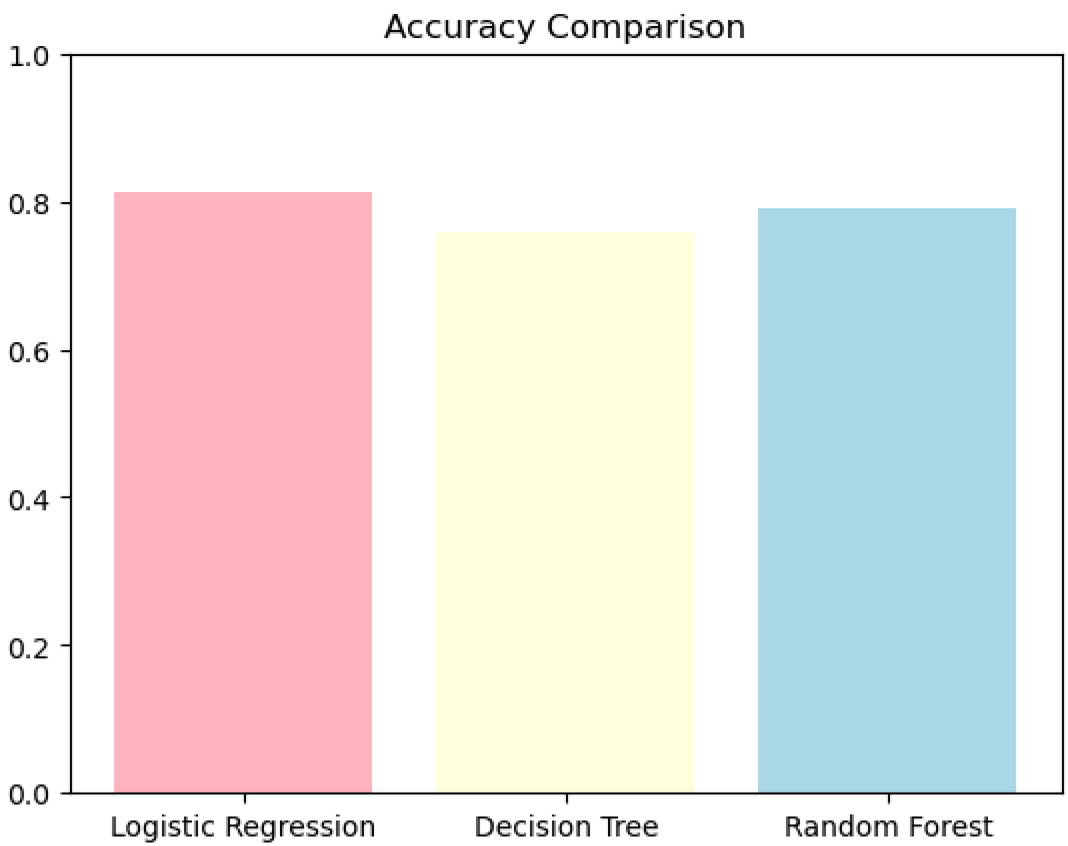
6. Model Comparision

6.1 Comparing accuracy

In [107]:
```
models = ['Logistic Regression', 'Decision Tree', 'Random Forest']
accuracy_scores = [accuracy_L,
                   accuracy_DT,
                   accuracy_RF]
```

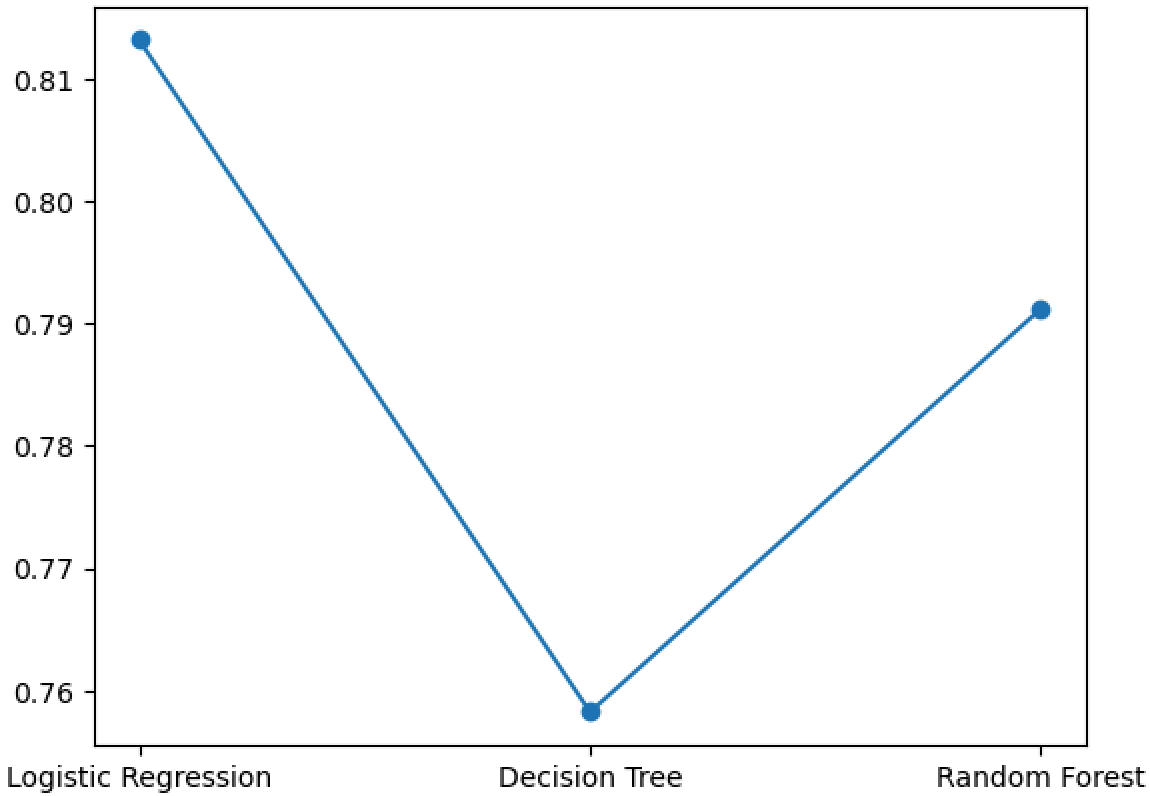
In [108]:
```
# Accuracy comparison
plt.bar(models, accuracy_scores, color=['lightpink', 'lightyellow', 'lightblue'])
plt.title('Accuracy Comparison')
plt.ylim([0, 1])
```

Out[108]: (0.0, 1.0)



In [109]:
```
# Accuracy comparison
plt.plot(models, accuracy_scores, marker='o', label='Accuracy')
```

Out[109]: [<matplotlib.lines.Line2D at 0x15f33a310>]

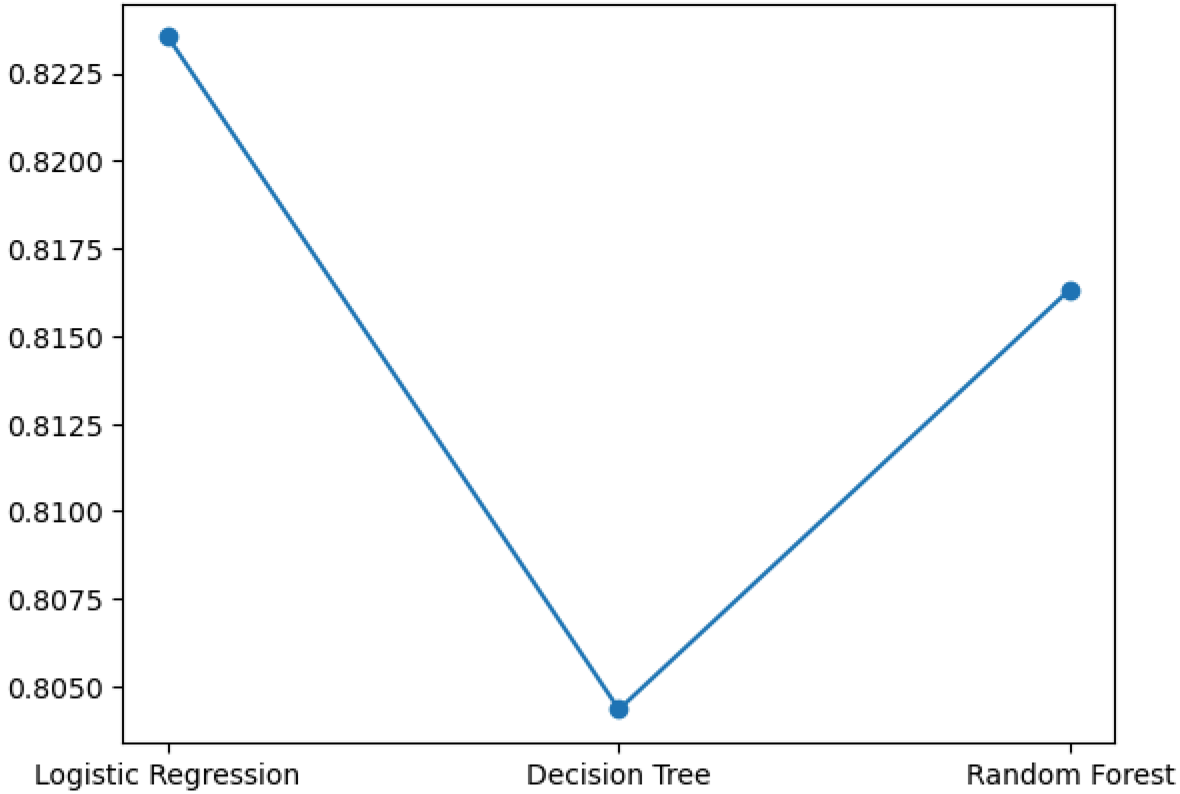


6.2 Comparing precision score

In [110]:
```
precision_scores = [precision_L,
                    precision_DT,
                    precision_RF]
```

In [112]:
```
# Precision comparison
plt.plot(models, precision_scores, marker='o', label='Precision')
```

Out[112]:
```
[<matplotlib.lines.Line2D at 0x15f8ffa10>]
```

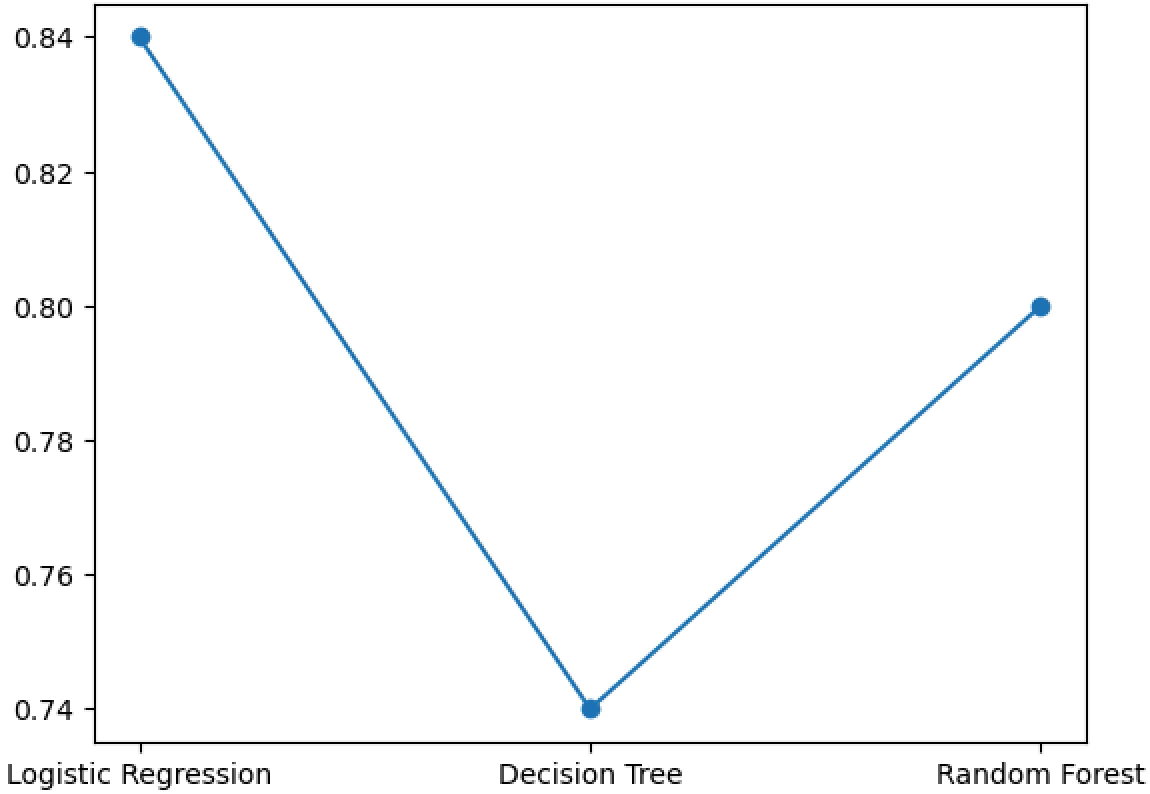


6.3 Comparing recall score

In [113]:
```
recall_scores = [recall_L,
                 recall_DT,
                 recall_RF]
```

In [114]:
```
# Recall comparison
plt.plot(models, recall_scores, marker='o', label='Recall')
```

Out[114]:
```
[<matplotlib.lines.Line2D at 0x15fb315d0>]
```



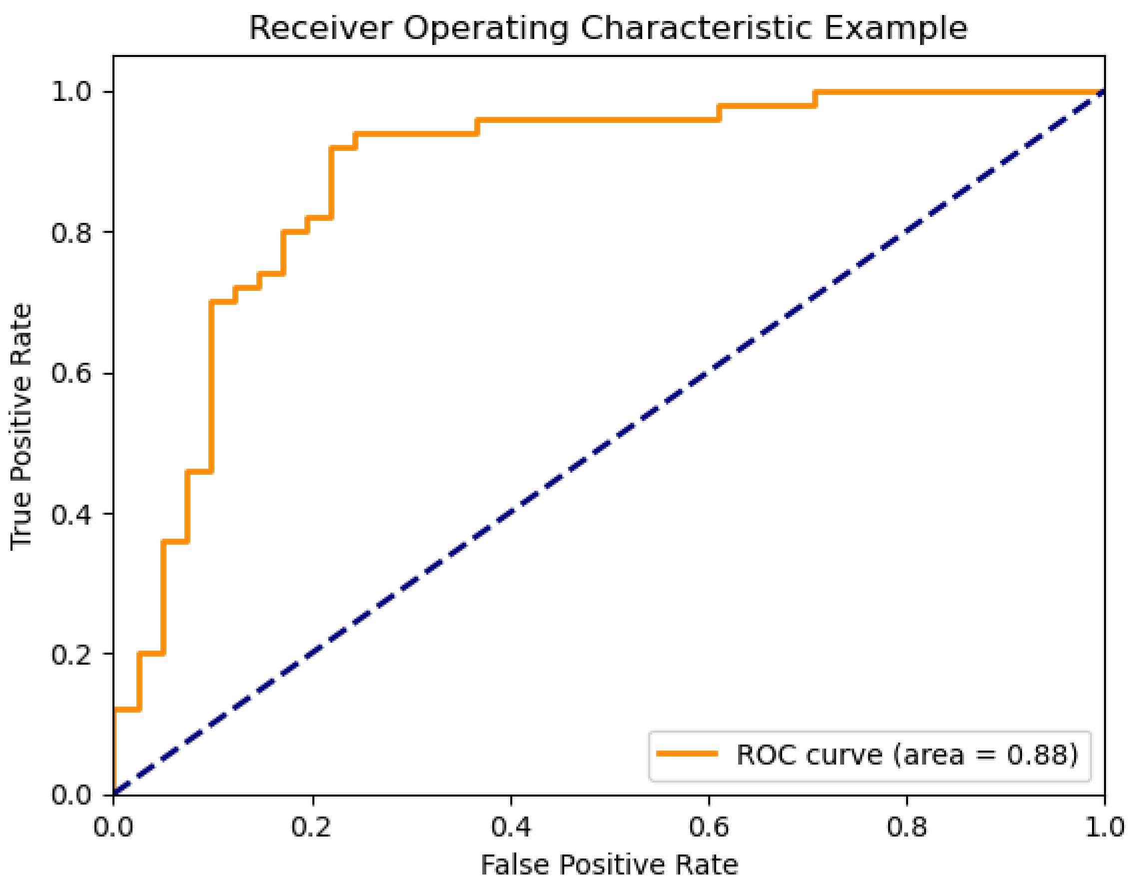
6.4 ROC curve

6.4.1 ROC for Logistics Regression

In [115]:
```
## Probability for positive class

y_prob_lr = lr_best.predict_proba(X_test)[:,1]
```

In [116]:
```
# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob_lr)
```

In [117]:
```
# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc_score(y_test,
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Example')
plt.legend(loc="lower right")
plt.show()
```

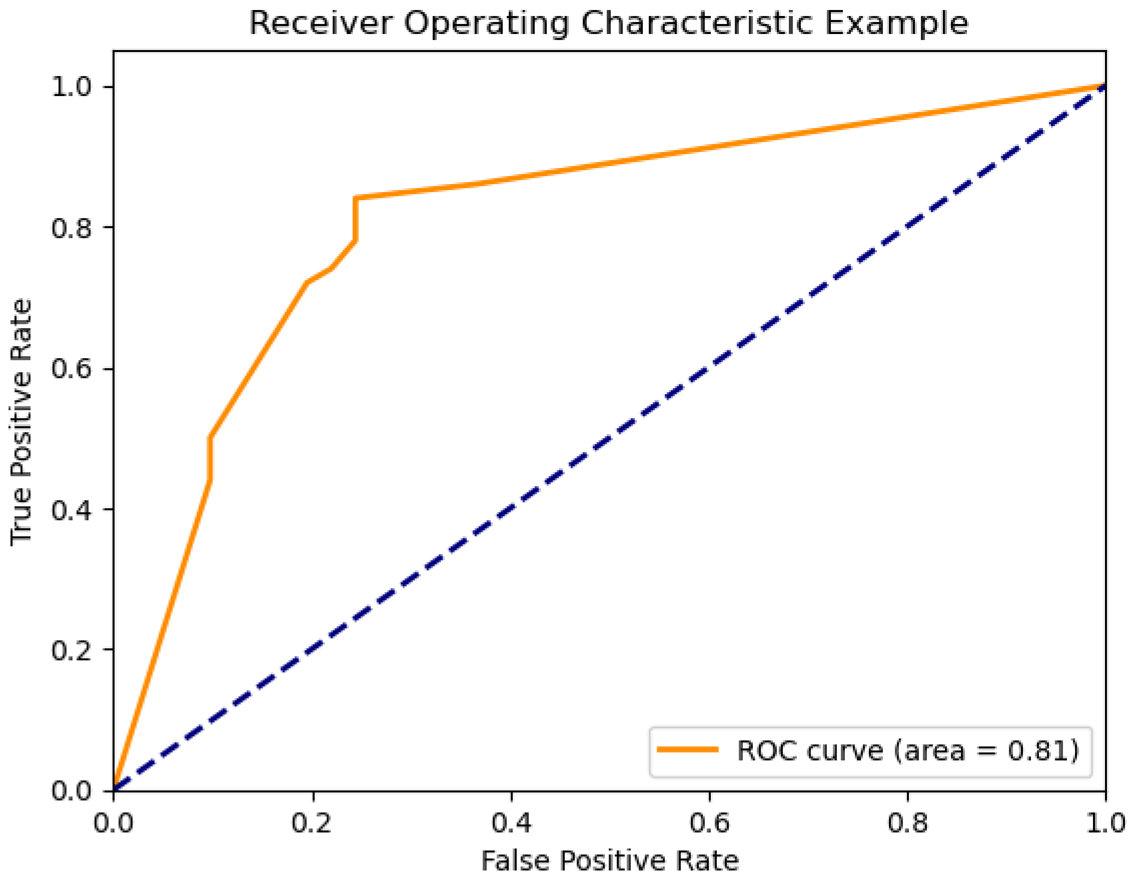


6.4.2 ROC for Decision Tree

In [118]:
```
## Probability for positive class

y_prob_dt = dec_tree_best.predict_proba(X_test)[:,1]
```

In [119]:
```
# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob_dt)
```

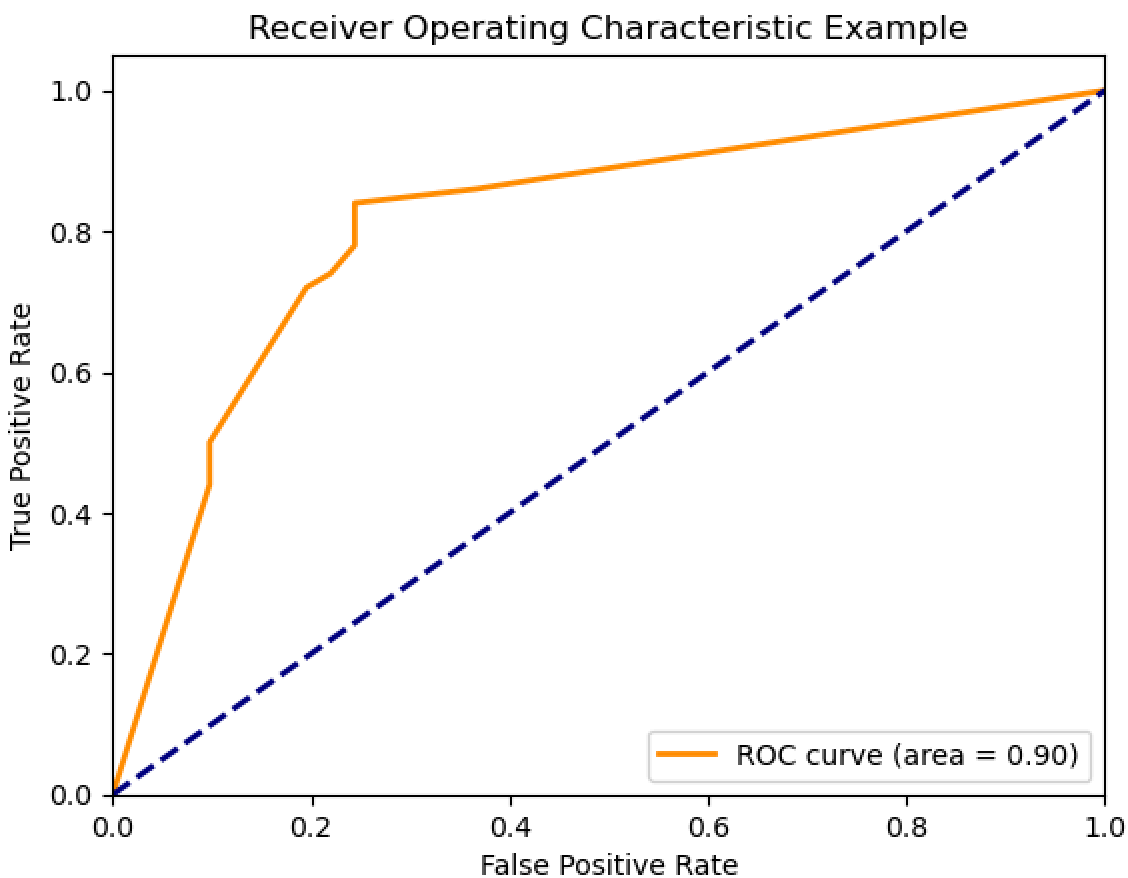
In [120]:
```
# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc_score(y_test,
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Example')
plt.legend(loc="lower right")
plt.show()
```



6.4.3 ROC for Random Forest

In [121]:
```
## Probability for positive class

y_prob_rf = random_forest_best.predict_proba(X_test)[:,1]
```

In [122]:
```
# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc_score(y_test,
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Example')
plt.legend(loc="lower right")
plt.show()
```



In [ ]:

```

```