Importing Important Libraries

In [6]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.decomposition import PCA
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier, AdaBoostClassifier, RandomForestClassifie
from sklearn.naive_bayes import GaussianNB
from sklearn.pipeline import Pipeline
import warnings
```

In [7]:
```
warnings.filterwarnings('ignore')
```

Load data

In [8]:
```
df = pd.read_csv(r"C:\Users\Pradyumn Sharma\Downloads\kaam\thoda\ml\heat_d_model\heart-disease.csv
```

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

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

In [10]:
```
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   trestbps  303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   restecg   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
```

In [11]:
```
df.describe()
```

Out[11]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	o
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.0
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.1
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.0
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.0
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.8
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.6
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.2

In [14]:
```
df.duplicated().sum()
```

Out[14]: 1

In [15]:
```
df.corr()
```

Out[15]:

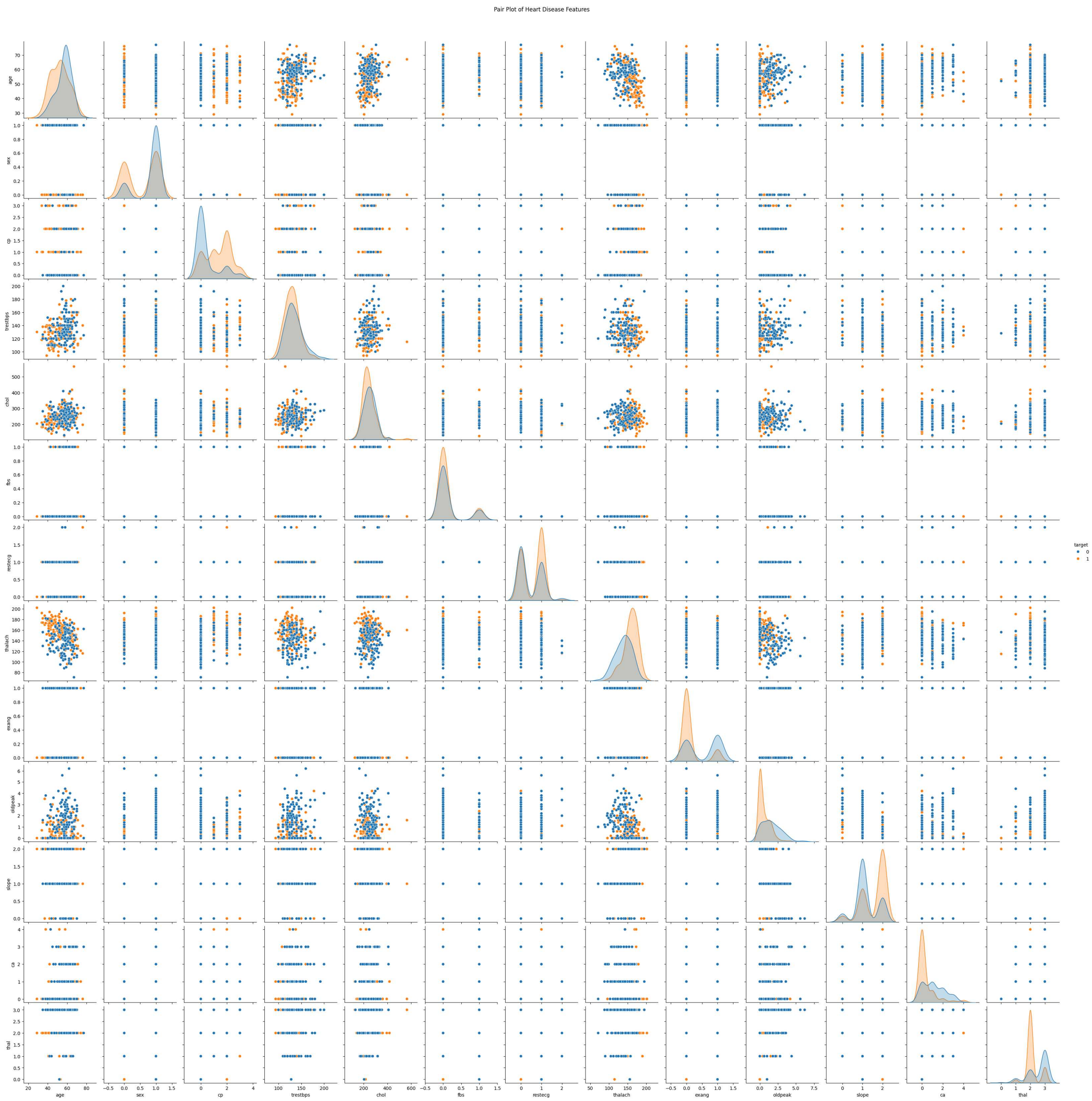
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	s
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522	0.096801	0.210013	-0.168
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020	0.141664	0.096093	-0.03
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762	-0.394280	-0.149230	0.11
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698	0.067616	0.193216	-0.12
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940	0.067023	0.053952	-0.00
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567	0.025665	0.005747	-0.05
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123	-0.070733	-0.058770	0.09
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000	-0.378812	-0.344187	0.38
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812	1.000000	0.288223	-0.25
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187	0.288223	1.000000	-0.57
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784	-0.257748	-0.577537	1.00
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177	0.115739	0.222682	-0.08
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439	0.206754	0.210244	-0.10
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.421741	-0.436757	-0.430696	0.34

In [16]:
```
df.shape
```

Out[16]:
```
(303, 14)
```

Pair plot of all features

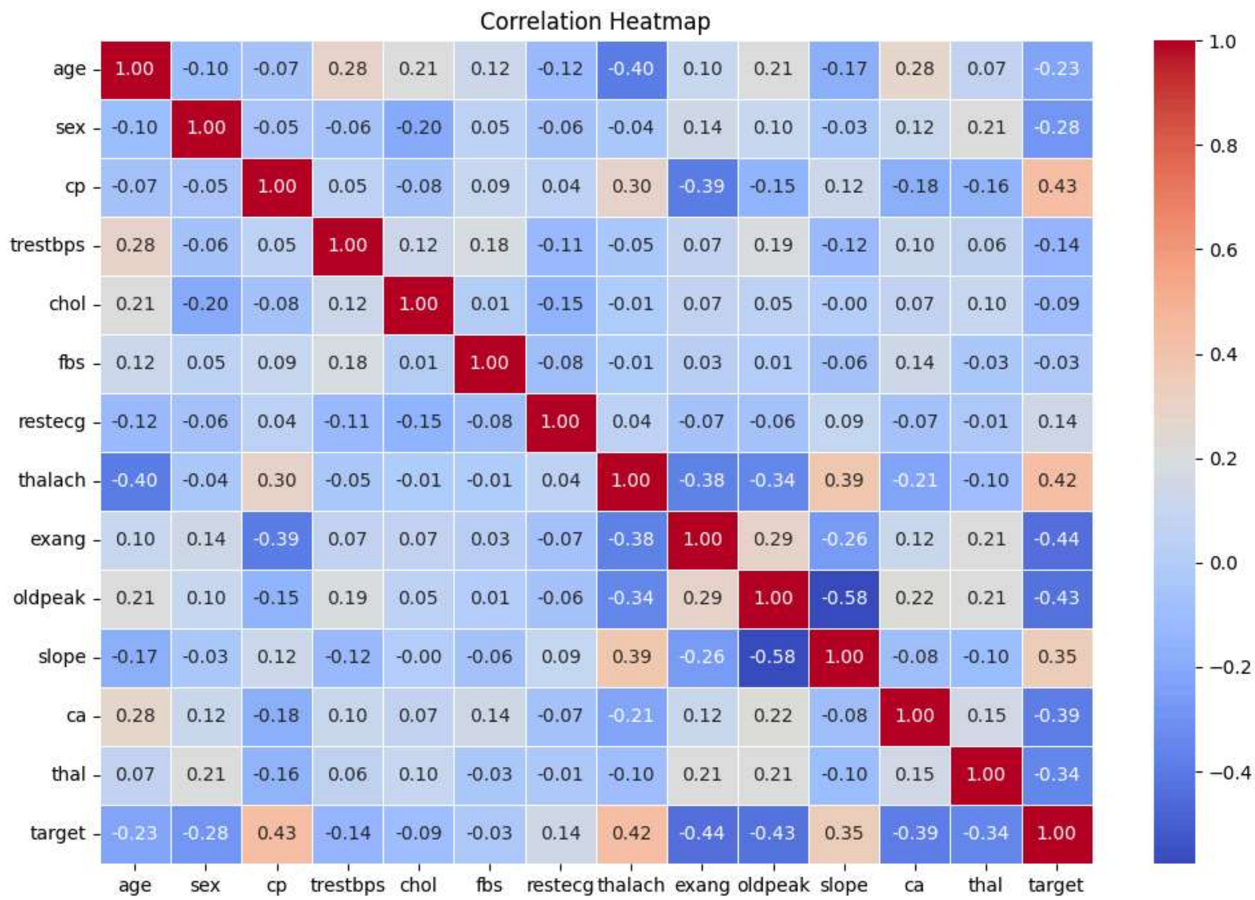
In [17]:
```
sns.pairplot(df, diag_kind='kde', hue='target')
plt.suptitle('Pair Plot of Heart Disease Features', y=1.02)
plt.show()
```



In [18]:
```
correlation_matrix = df.corr()
```

Plotting the heatmap of correlations

In [20]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5, fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



Feature engineering based on correlation

In [21]:
```
corr_threshold = 0.3
target_corr = correlation_matrix['target'].abs()
strong_features = target_corr[target_corr > corr_threshold].index.tolist()

df = df[strong_features]
```

Check for multicollinearity among the strong features

In [22]:
```
high_corr_pairs = set()
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > 0.5:
            high_corr_pairs.add(correlation_matrix.columns[i])

features_to_drop = list(high_corr_pairs - {'target'})
df = df.drop(columns=features_to_drop)
```

Convert categorical variables to dummy/indicator variables

In [23]:
```
categorical_features = ['cp']
df = pd.get_dummies(df, columns=categorical_features, drop_first=True)

X = df.drop(columns=['target'])
y = df['target']
```

Scale the features

In [24]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Split into training and test sets

In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

Define the models and their parameter grids

In [26]:
```
classifiers = {
    'LogisticRegression': (LogisticRegression(), {
        'classifier__penalty': ['l1', 'l2'],
        'classifier__C': [0.01, 0.1, 1, 10, 100],
        'classifier__solver': ['liblinear', 'saga'],
        'classifier__max_iter': [100, 200, 300]
    }),

    'SVM': (SVC(), {
        'classifier__C': [1, 10, 100],
        'classifier__kernel': ['linear', 'rbf'],
        'classifier__gamma': ['scale', 'auto'],
        'classifier__degree': [2, 3, 4]
    }),

    'GradientBoosting': (GradientBoostingClassifier(), {
        'classifier__n_estimators': [50, 100, 200],
        'classifier__learning_rate': [0.01, 0.1, 0.2],
        'classifier__max_depth': [3, 4, 5]
    }),

    'NaiveBayes': (GaussianNB(), {
        'classifier__var_smoothing': [1e-9, 1e-8, 1e-7]
    })
}
```

In [27]:

```
best_estimators = {}
for clf_name, (clf, params) in classifiers.items():
    print(f"Running Grid Search for {clf_name}...")

    # Define pipeline with StandardScaler and the classifier
    pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('classifier', clf)
    ])

    # Use GridSearchCV to find the best model
    grid_search = GridSearchCV(pipeline, params, cv=5, scoring='accuracy', n_jobs=-1)

    # Fit the model
    grid_search.fit(X_train, y_train)

    # Store the best estimator
    best_estimators[clf_name] = grid_search.best_estimator_

    # Print the best parameters and score for each model
    print(f"Best parameters for {clf_name}: {grid_search.best_params_}")
    print(f"Best cross-validated accuracy for {clf_name}: {grid_search.best_score_:.2f}")
```

```
Running Grid Search for LogisticRegression...
Best parameters for LogisticRegression: {'classifier__C': 0.01, 'classifier__max_iter': 100, 'cla
ssifier__penalty': 'l2', 'classifier__solver': 'liblinear'}
Best cross-validated accuracy for LogisticRegression: 0.81
Running Grid Search for SVM...
Best parameters for SVM: {'classifier__C': 1, 'classifier__degree': 2, 'classifier__gamma': 'scal
e', 'classifier__kernel': 'linear'}
Best cross-validated accuracy for SVM: 0.79
Running Grid Search for GradientBoosting...
Best parameters for GradientBoosting: {'classifier__learning_rate': 0.1, 'classifier__max_depth':
3, 'classifier__n_estimators': 100}
Best cross-validated accuracy for GradientBoosting: 0.81
Running Grid Search for NaiveBayes...
Best parameters for NaiveBayes: {'classifier__var_smoothing': 1e-09}
Best cross-validated accuracy for NaiveBayes: 0.78
```

Evaluate all best models on the test set

In [28]:
```
for clf_name, best_model in best_estimators.items():
    y_pred = best_model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"\nTest Accuracy for {clf_name}: {accuracy:.2f}")
    print(classification_report(y_test, y_pred))
```

```

Test Accuracy for LogisticRegression: 0.85
              precision    recall  f1-score   support

           0       0.83      0.86      0.85        29
           1       0.87      0.84      0.86        32

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.85      0.85      0.85        61


Test Accuracy for SVM: 0.89
              precision    recall  f1-score   support

           0       0.89      0.86      0.88        29
           1       0.88      0.91      0.89        32

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.89        61


Test Accuracy for GradientBoosting: 0.75
              precision    recall  f1-score   support

           0       0.72      0.79      0.75        29
           1       0.79      0.72      0.75        32

    accuracy                           0.75        61
   macro avg       0.76      0.76      0.75        61
weighted avg       0.76      0.75      0.75        61


Test Accuracy for NaiveBayes: 0.85
              precision    recall  f1-score   support

           0       0.81      0.90      0.85        29
           1       0.90      0.81      0.85        32

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.86      0.85      0.85        61
```

In [30]:
```
import plotly.graph_objs as go
import plotly.express as px
```

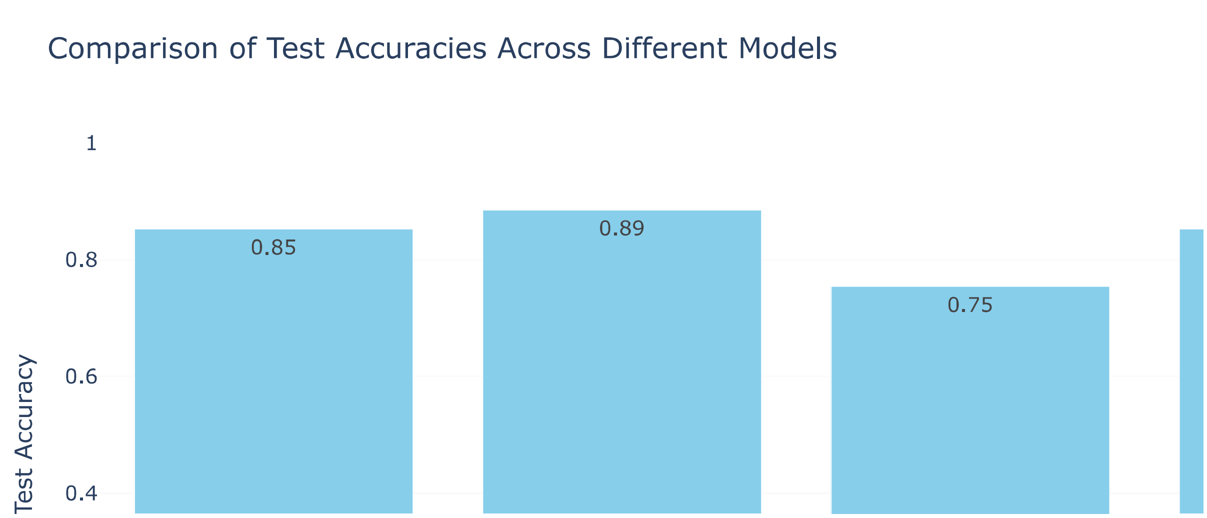
In [31]:

```
# Data for the plot
classifiers = list(test_accuracies.keys())
accuracies = list(test_accuracies.values())

# Creating a bar plot with hover functionality
fig = go.Figure(data=[go.Bar(
    x=classifiers,
    y=accuracies,
    text=[f'{acc:.2f}' for acc in accuracies],  # Display accuracy on hover
    hoverinfo='text',
    marker=dict(color='skyblue')
)])

# Updating layout for better readability
fig.update_layout(
    title='Comparison of Test Accuracies Across Different Models',
    xaxis=dict(title='Classifier'),
    yaxis=dict(title='Test Accuracy', range=[0, 1]),
    template='plotly_white'
)

# Show the plot
fig.show()
```



In [ ]: