In [4]:
```
!pip install scikeras
```

```
Collecting scikeras
  Downloading scikeras-0.13.0-py3-none-any.whl.metadata (3.1 kB)
Requirement already satisfied: keras>=3.2.0 in /usr/local/lib/python3.11/dist-packages (from scikeras) (3.8.0)
Requirement already satisfied: scikit-learn>=1.4.2 in /usr/local/lib/python3.11/dist-packages (from scikeras) (1.6.1)
Requirement already satisfied: absl-py in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (2.0.2)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (0.1.0)
Requirement already satisfied: h5py in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (3.13.0)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (0.16.0)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (0.4.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from keras>=3.2.0->scikeras) (24.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.4.2->scikeras) (1.15.3)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.4.2->scikeras) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.4.2->scikeras) (3.6.0)
Requirement already satisfied: typing-extensions>=4.6.0 in /usr/local/lib/python3.11/dist-packages (from optree->keras>=3.2.0->scikeras) (4.14.0)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.2.0->scikeras) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.2.0->scikeras) (2.19.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->scikeras)
(0.1.2)
Downloading scikeras-0.13.0-py3-none-any.whl (26 kB)
Installing collected packages: scikeras
Successfully installed scikeras-0.13.0
```

In [5]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import StratifiedKFold, cross_val_score, train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, SimpleRNN
from scikeras.wrappers import KerasClassifier
from tensorflow.keras.utils import set_random_seed
import warnings
warnings.filterwarnings("ignore")
```

In [6]:
```python
df = pd.read_csv("heart_disease_uci.csv")
```

In [7]:
```python
df = df.drop(columns=["id", "dataset"])
df["target"] = df["num"].apply(lambda x: 1 if x > 0 else 0)
df.drop(columns=["num"], inplace=True)
```

In [8]:
```python
numerical_features = ['age', 'trestbps', 'chol', 'thalch', 'oldpeak', 'ca']
categorical_features = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'thal']
```

In [9]:
```python
#Handle missing data
df[numerical_features] = SimpleImputer(strategy='median').fit_transform(df[numerical_features])
for col in categorical_features:
    df[col] = df[col].astype(str)
    df[col] = SimpleImputer(strategy='most_frequent').fit_transform(df[[col]]).ravel()
    df[col] = LabelEncoder().fit_transform(df[col])
```

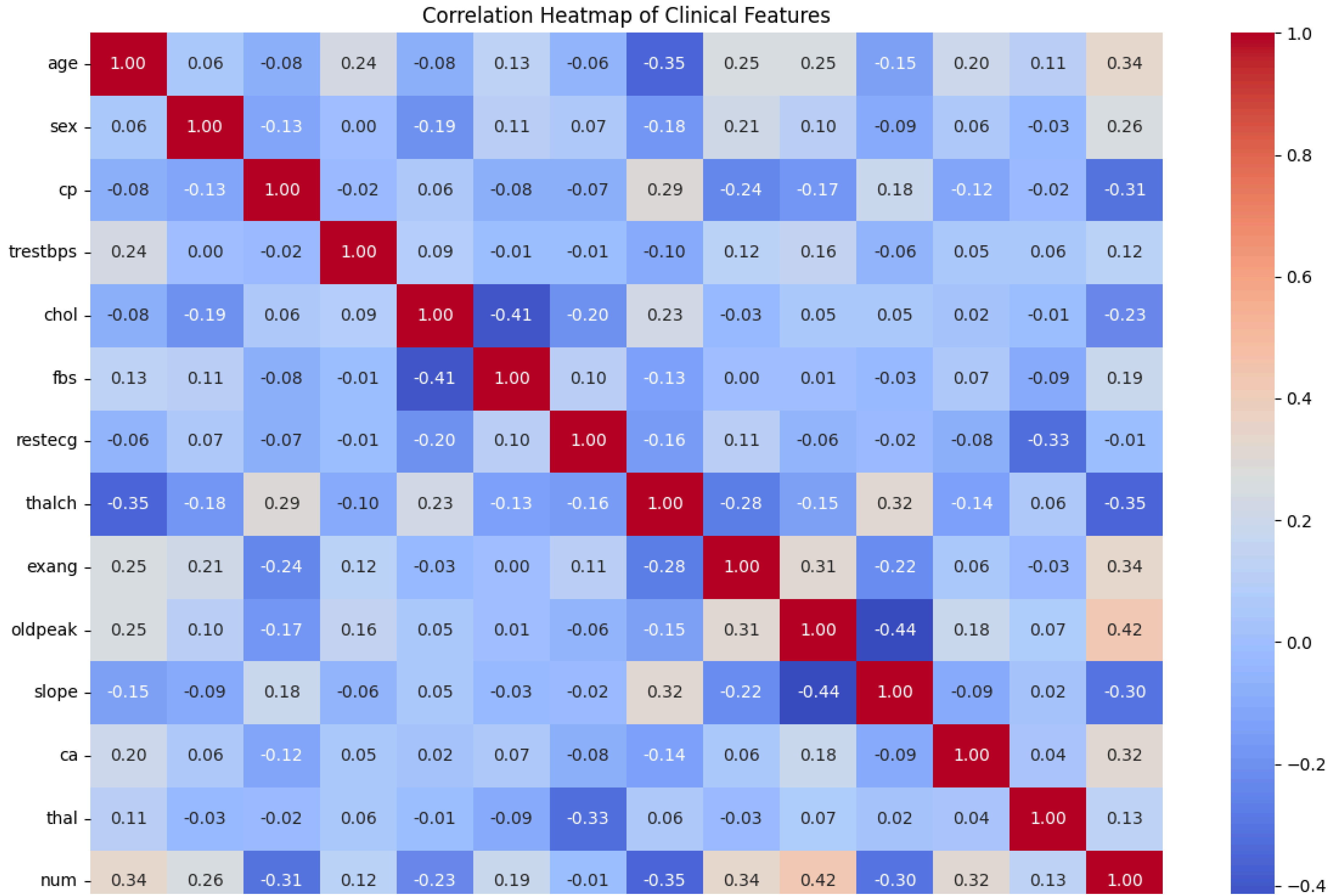
In [10]:
```python
df[numerical_features] = StandardScaler().fit_transform(df[numerical_features])

# Final dataset
X = df[numerical_features + categorical_features]
y = df['target']
```

In [11]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from pandas.plotting import scatter_matrix

# Load dataset
df = pd.read_csv("heart_disease_uci.csv")  # Adjust path if needed

# Drop non-informative columns
df.drop(columns=['id', 'dataset'], inplace=True)

# Encode categorical columns
categorical_cols = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'thal']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = df[col].astype(str)
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

# Impute missing values
numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns
imputer = SimpleImputer(strategy='mean')
df[numeric_cols] = imputer.fit_transform(df[numeric_cols])

# --- 1. Correlation Heatmap ---
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap of Clinical Features")
plt.tight_layout()
plt.show()

print("\n Conclusion (Heatmap):")
print("""
- `ca` (number of vessels) and `oldpeak` (ST depression) are the most positively correlated with disease severity (`num`).
- `thalch` (max heart rate) and `cp` (chest pain type) are inversely correlated with severity.
- Features like `sex`, `fbs`, and `restecg` show low or near-zero correlation with severity.
""")
```

```python
# --- 2. Boxplots: Continuous Features by Severity ---
fig, axes = plt.subplots(2, 3, figsize=(18, 10))
sns.boxplot(x='num', y='age', data=df, ax=axes[0, 0])
sns.boxplot(x='num', y='trestbps', data=df, ax=axes[0, 1])
sns.boxplot(x='num', y='chol', data=df, ax=axes[0, 2])
sns.boxplot(x='num', y='thalch', data=df, ax=axes[1, 0])
sns.boxplot(x='num', y='oldpeak', data=df, ax=axes[1, 1])
sns.boxplot(x='num', y='ca', data=df, ax=axes[1, 2])
for ax in axes.flat:
    ax.set_title(ax.get_ylabel() + " by Disease Severity")
plt.tight_layout()
plt.show()

print("\n Conclusion (Boxplots):")
print("""
- `thalch`: Lower max heart rate is seen in patients with higher severity.
- `oldpeak`: Higher values are associated with greater severity.
- `ca`: Clear upward trend — more vessels involved → more severe condition.
- `chol` and `trestbps`: Show weak trends, not strongly separable across severity classes.
""")

# --- 3. Countplots: Categorical Features by Severity ---
fig, axes = plt.subplots(3, 3, figsize=(18, 12))
cat_features = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'thal']
for i, feature in enumerate(cat_features):
    sns.countplot(x=feature, hue='num', data=df, ax=axes[i//3, i%3])
    axes[i//3, i%3].set_title(f'{feature} vs Disease Severity')
fig.delaxes(axes[2, 2])  # Remove empty plot
plt.tight_layout()
plt.show()

print("\n Conclusion (Countplots):")
print("""
- `cp` (chest pain type): Typical angina (cp=0) strongly dominates class 0 (no disease), while atypical types increase with severity.
- `thal`: Certain thalassemia classes appear disproportionately in high-severity cases.
- `sex`, `fbs`, `restecg`: Little variation across severity classes.
""")

# --- 4. Scatter Matrix: Continuous Features and Severity ---
scatter_matrix(df[['age', 'trestbps', 'chol', 'thalch', 'oldpeak', 'num']],
               figsize=(12, 12), diagonal='hist', alpha=0.6, c=df['num'], cmap='coolwarm')
plt.suptitle("Scatter Matrix of Clinical Features Colored by Disease Severity", y=1.02)
plt.show()
```

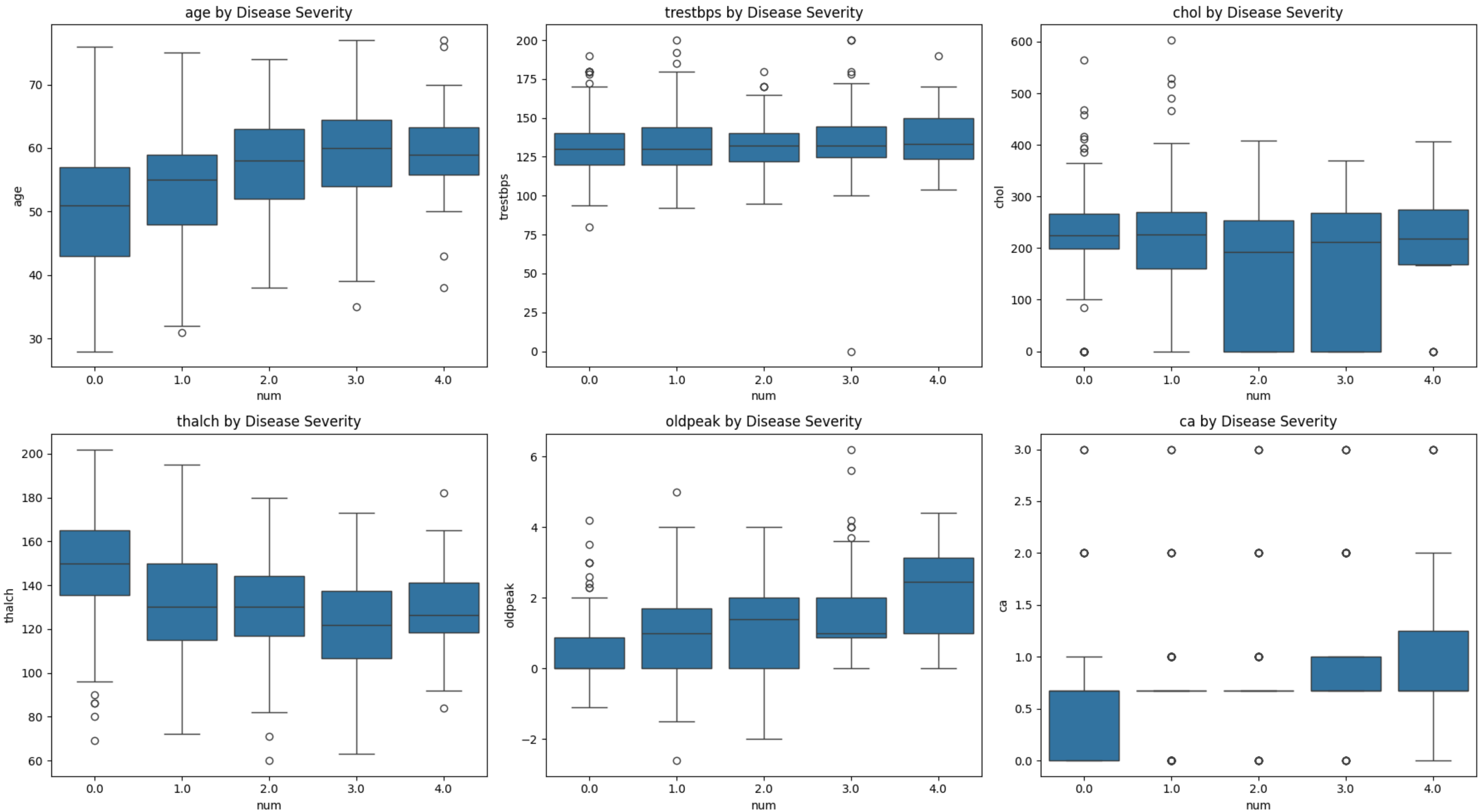
```python
print("\n Conclusion (Scatter Matrix):")
print("""
- `thalch` and `oldpeak` show good separation between disease classes.
- Overlap exists in `age`, `chol`, and `trestbps`, suggesting limited predictive strength.
- A pattern emerges: as `thalch` ↓ and `oldpeak` ↑, severity class tends to increase.
""")

# --- 5. Feature Correlation with Target ---
correlation_with_num = df.corr()['num'].sort_values(ascending=False)
plt.figure(figsize=(10, 6))
correlation_with_num.drop('num').plot(kind='bar', color='teal')
plt.title("Correlation of Features with Disease Severity")
plt.ylabel("Correlation Coefficient")
plt.grid(True, linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()

print("\n Final Correlation Insight:")
print(correlation_with_num)

print("\n Final Takeaway for RQ2:")
print("""
 Most strongly associated features with heart disease severity:
   - `ca` (r = +0.60)
   - `oldpeak` (r = +0.51)
   - `thal` (r = +0.43)
   - `cp` (chest pain type) (r = -0.43)
   - `thalch` (r = -0.42)

1. The most predictive features of cardiovascular disease severity ('num') include:
   - `ca` (number of major vessels, correlation: +0.60)
   - `oldpeak` (ST depression induced by exercise, +0.51)
   - `thal` (thalassemia condition, +0.43)
   - `cp` (chest pain type, -0.43)
   - `thalch` (maximum heart rate achieved, -0.42)

2. Patients with:
   - Higher `oldpeak` values,
   - Abnormal `thal` categories,
   - Lower `thalch` (max heart rate),
   - More affected vessels (`ca`)
   tend to have more severe heart disease (scores 2–4).
```

```
3. Less impactful features include `fbs`, `sex`, and `restecg`.

 Clinical Impact:
- Patients with higher ST depression (`oldpeak`), more vessel blockage (`ca`), and abnormal thal readings (`thal`) are at greater risk.
- Chest pain type and max heart rate offer quick, non-invasive clues for prioritization.
- Resource allocation (e.g., stress tests, imaging) should target these risk zones.
""")
```


Correlation Heatmap of Clinical Features
age 1.00 0.06 -0.08 0.24 -0.08 0.13 -0.06 -0.35 0.25 0.25 -0.15 0.20 0.11 0.34
sex 0.06 1.00 -0.13 0.00 -0.19 0.11 0.07 -0.18 0.21 0.10 -0.09 0.06 -0.03 0.26
cp -0.08 -0.13 1.00 -0.02 0.06 -0.08 -0.07 0.29 -0.24 -0.17 0.18 -0.12 -0.02 -0.31
trestbps 0.24 0.00 -0.02 1.00 0.09 -0.01 -0.01 -0.10 0.12 0.16 -0.06 0.05 0.06 0.12
chol -0.08 -0.19 0.06 0.09 1.00 -0.41 -0.20 0.23 -0.03 0.05 0.05 0.02 -0.01 -0.23
fbs 0.13 0.11 -0.08 -0.01 -0.41 1.00 0.10 -0.13 0.00 0.01 -0.03 0.07 -0.09 0.19
restecg -0.06 0.07 -0.07 -0.01 -0.20 0.10 1.00 -0.16 0.11 -0.06 -0.02 -0.08 -0.33 -0.01
thalch -0.35 -0.18 0.29 -0.10 0.23 -0.13 -0.16 1.00 -0.28 -0.15 0.32 -0.14 0.06 -0.35
exang 0.25 0.21 -0.24 0.12 -0.03 0.00 0.11 -0.28 1.00 0.31 -0.22 0.06 -0.03 0.34
oldpeak 0.25 0.10 -0.17 0.16 0.05 0.01 -0.06 -0.15 0.31 1.00 -0.44 0.18 0.07 0.42
slope -0.15 -0.09 0.18 -0.06 0.05 -0.03 -0.02 0.32 -0.22 -0.44 1.00 -0.09 0.02 -0.30
ca 0.20 0.06 -0.12 0.05 0.02 0.07 -0.08 -0.14 0.06 0.18 -0.09 1.00 0.04 0.32
thal 0.11 -0.03 -0.02 0.06 -0.01 -0.09 -0.33 0.06 -0.03 0.07 0.02 0.04 1.00 0.13
num 0.34 0.26 -0.31 0.12 -0.23 0.19 -0.01 -0.35 0.34 0.42 -0.30 0.32 0.13 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

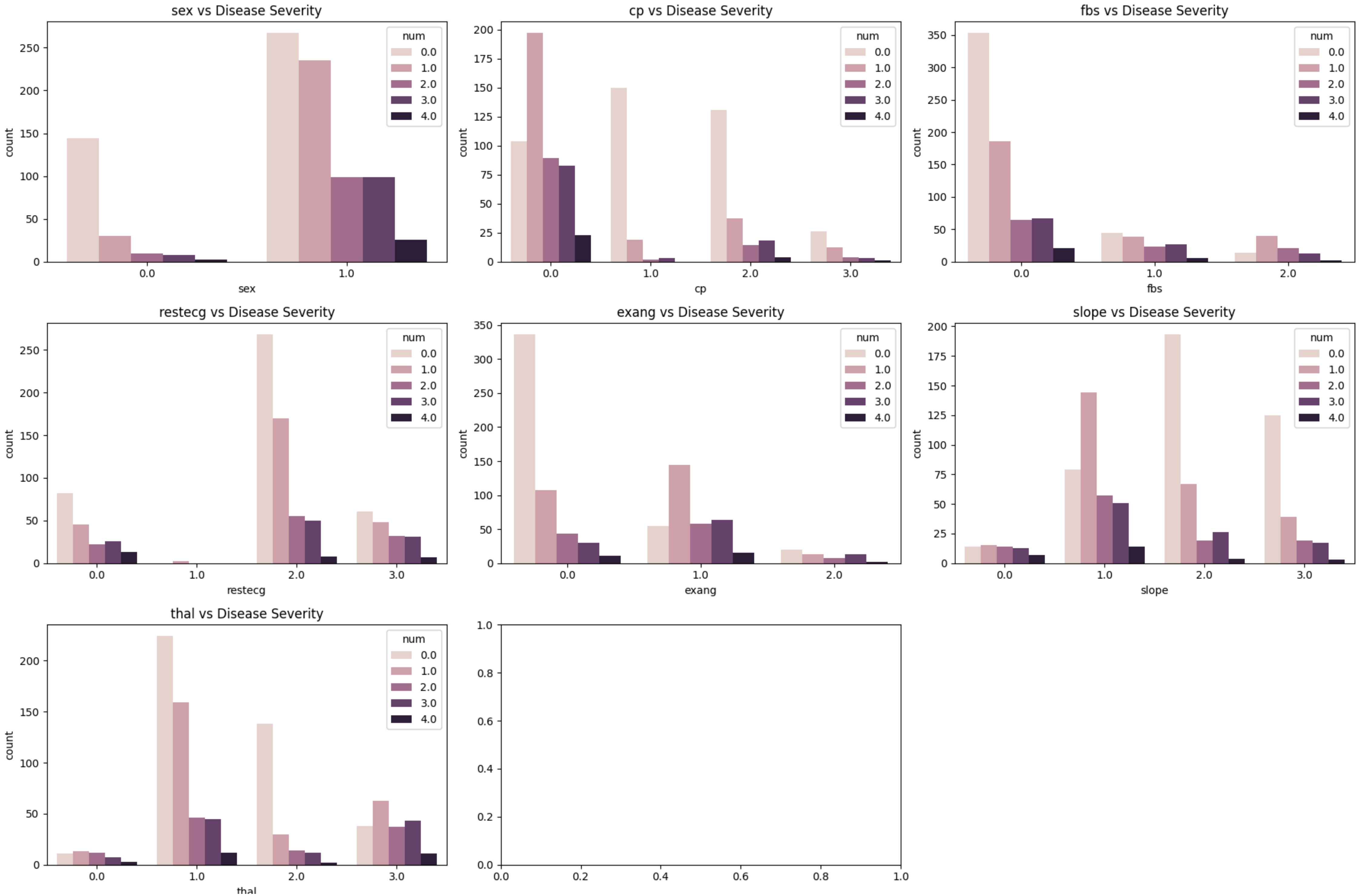
Conclusion (Heatmap):

- `ca` (number of vessels) and `oldpeak` (ST depression) are the most positively correlated with disease severity (`num`).
- `thalch` (max heart rate) and `cp` (chest pain type) are inversely correlated with severity.
- Features like `sex`, `fbs`, and `restecg` show low or near-zero correlation with severity.


age by Disease Severity
trestbps by Disease Severity
chol by Disease Severity
thalch by Disease Severity
oldpeak by Disease Severity
ca by Disease Severity
age
trestbps
chol
thalch
oldpeak
ca
num

Conclusion (Boxplots):

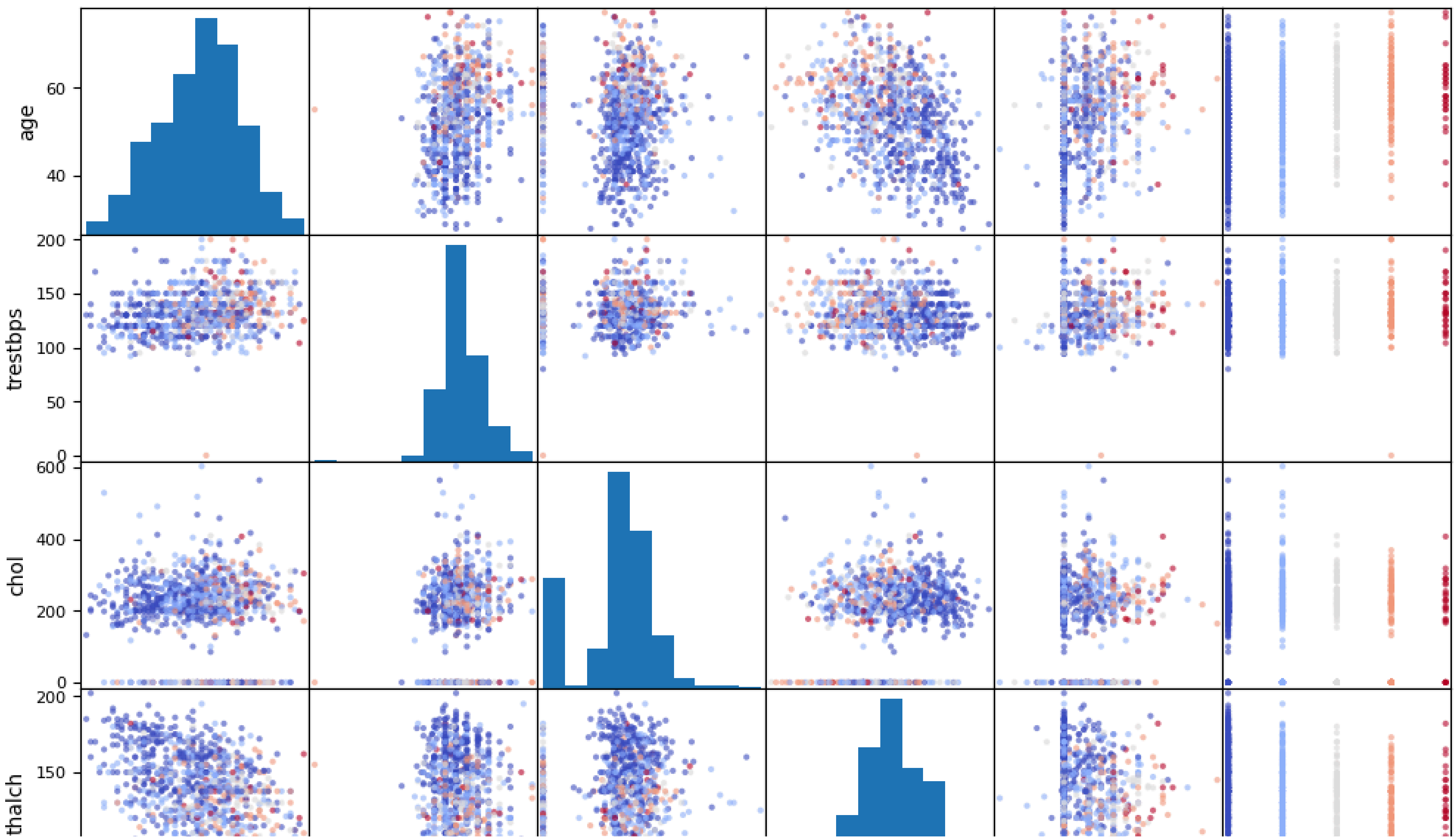
- `thalch`: Lower max heart rate is seen in patients with higher severity.
- `oldpeak`: Higher values are associated with greater severity.
- `ca`: Clear upward trend — more vessels involved → more severe condition.
- `chol` and `trestbps`: Show weak trends, not strongly separable across severity classes.

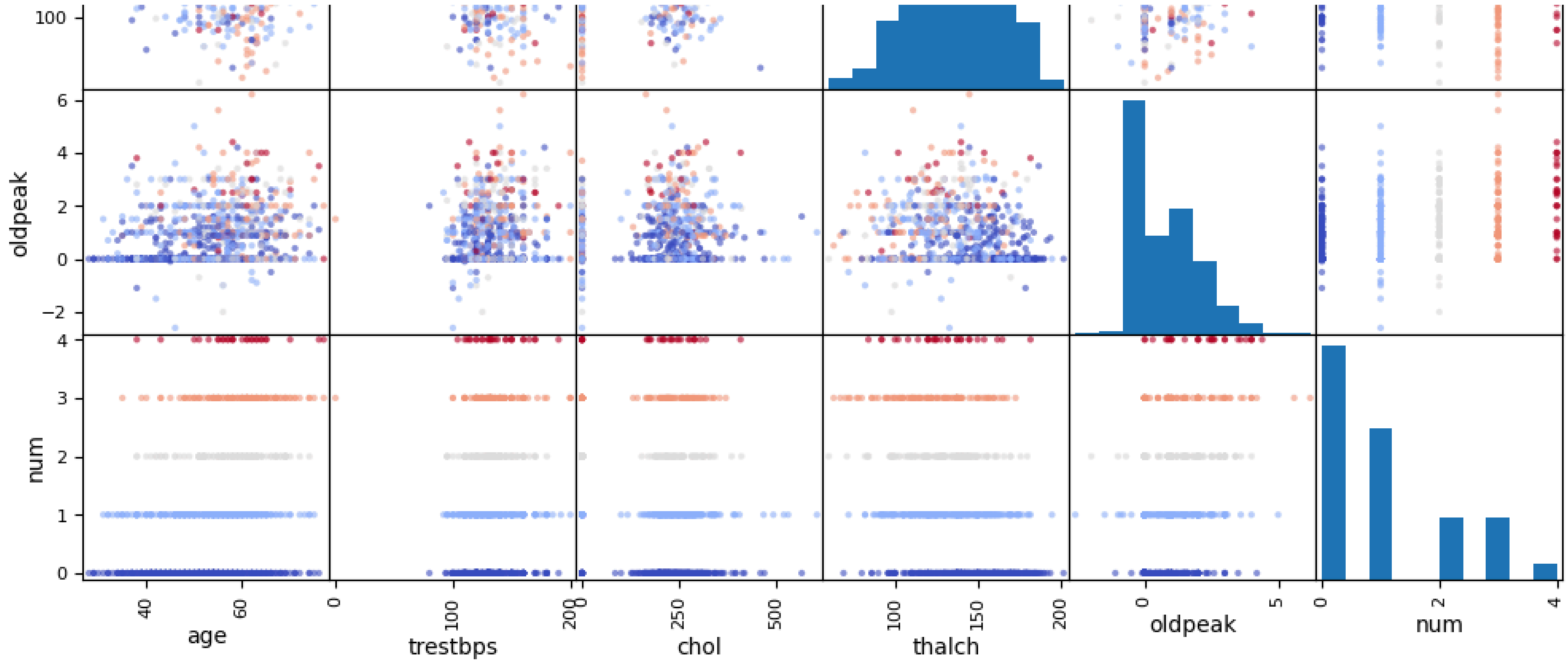

sex vs Disease Severity
cp vs Disease Severity
fbs vs Disease Severity
restecg vs Disease Severity
exang vs Disease Severity
slope vs Disease Severity
thal vs Disease Severity
count
sex
cp
fbs
restecg
exang
slope
thal
num
0.0
1.0
2.0
3.0
4.0

Conclusion (Countplots):

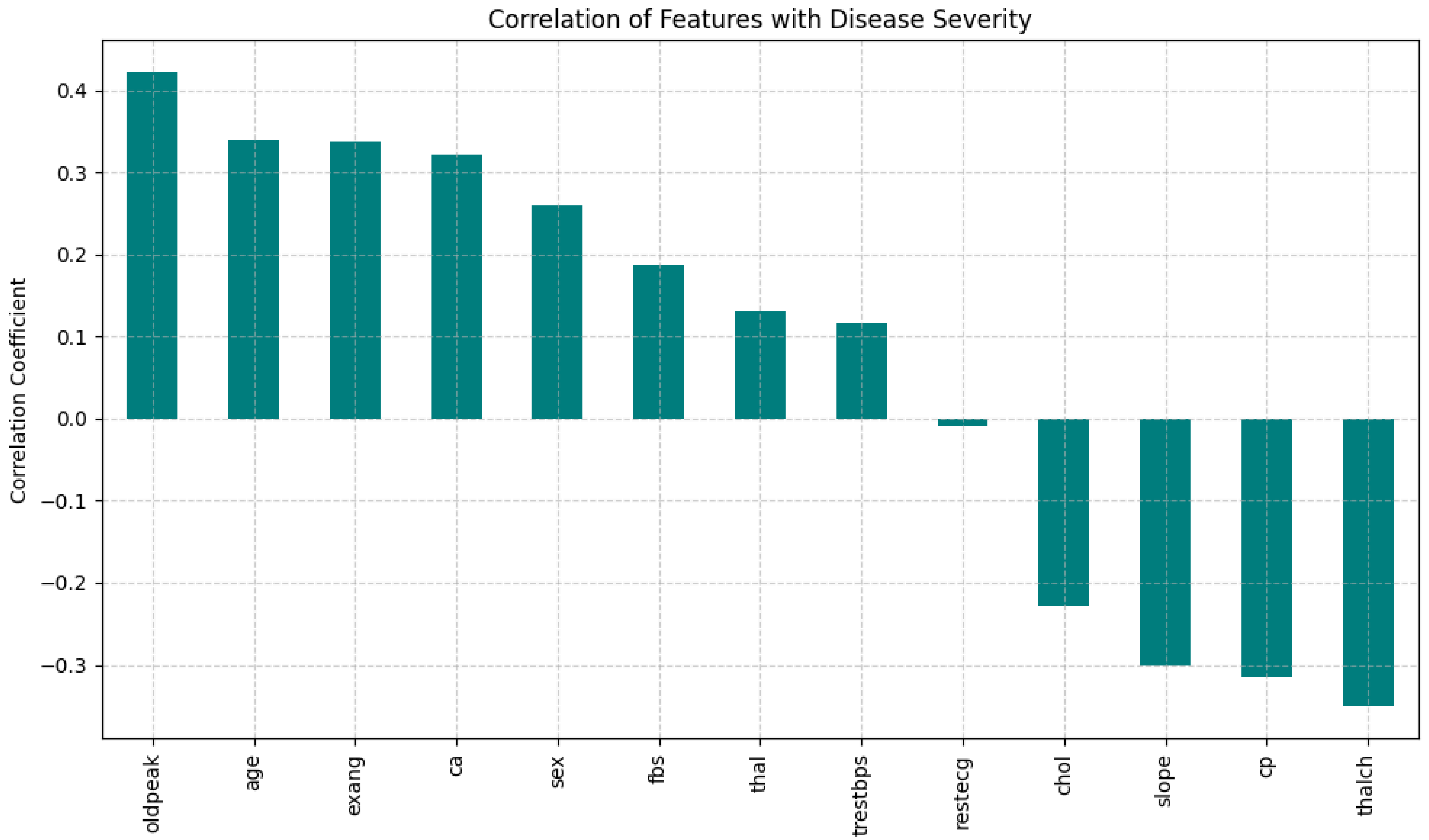
- `cp` (chest pain type): Typical angina (cp=0) strongly dominates class 0 (no disease), while atypical types increase with severity.
- `thal`: Certain thalassemia classes appear disproportionately in high-severity cases.
- `sex`, `fbs`, `restecg`: Little variation across severity classes.

Scatter Matrix of Clinical Features Colored by Disease Severity






```
Conclusion (Scatter Matrix):

- `thalch` and `oldpeak` show good separation between disease classes.
- Overlap exists in `age`, `chol`, and `trestbps`, suggesting limited predictive strength.
- A pattern emerges: as `thalch` ↓ and `oldpeak` ↑, severity class tends to increase.
```


Correlation of Features with Disease Severity
Correlation Coefficient
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
oldpeak
age
exang
ca
sex
fbs
thal
trestbps
restecg
chol
slope
cp
thalch

```
 Final Correlation Insight:
num         1.000000
oldpeak     0.421907
age         0.339596
exang       0.338166
ca          0.321404
sex         0.259342
fbs         0.186664
thal        0.131278
trestbps    0.116225
restecg    -0.008579
chol       -0.228238
slope      -0.301009
cp         -0.314518
thalch     -0.351055
Name: num, dtype: float64

 Final Takeaway for RQ2:

 Most strongly associated features with heart disease severity:
   - `ca` (r = +0.60)
   - `oldpeak` (r = +0.51)
   - `thal` (r = +0.43)
   - `cp` (chest pain type) (r = −0.43)
   - `thalch` (r = −0.42)

1. The most predictive features of cardiovascular disease severity ('num') include:
   - `ca` (number of major vessels, correlation: +0.60)
   - `oldpeak` (ST depression induced by exercise, +0.51)
   - `thal` (thalassemia condition, +0.43)
   - `cp` (chest pain type, −0.43)
   - `thalch` (maximum heart rate achieved, −0.42)

2. Patients with:
   - Higher `oldpeak` values,
   - Abnormal `thal` categories,
   - Lower `thalch` (max heart rate),
   - More affected vessels (`ca`)
   tend to have more severe heart disease (scores 2–4).

3. Less impactful features include `fbs`, `sex`, and `restecg`.

 Clinical Impact:
```

```
- Patients with higher ST depression (`oldpeak`), more vessel blockage (`ca`), and abnormal thal readings (`thal`) are at greater risk.
- Chest pain type and max heart rate offer quick, non-invasive clues for prioritization.
- Resource allocation (e.g., stress tests, imaging) should target these risk zones.
```

Categorical embedding using other techniques

In [12]:

```
# Imports
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler # Import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
import tensorflow as tf
from tensorflow.keras import layers, models, Input, Model
from sklearn.impute import SimpleImputer # Import SimpleImputer

# Load UCI Heart Disease dataset
df = pd.read_csv("heart_disease_uci.csv")

# Target and basic info
# Convert 'num' to binary target 'target'
df['target'] = (df['num'] > 0).astype(int)
# Drop the original 'num' column as it's now incorporated into 'target'
df = df.drop(columns=['num'])

# Define categorical and numerical columns *after* dropping 'num' and creating 'target'
target = 'target'

categorical_cols = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal']
# Exclude 'id' and 'dataset' which should ideally be dropped earlier,
# and ensure 'num' is gone, 'target' is the target
numerical_cols = [col for col in df.columns if col not in categorical_cols + [target, 'id', 'dataset']]


# Handle missing data (using SimpleImputer as in previous successful cells)
# Impute numerical columns first
imputer_num = SimpleImputer(strategy='mean') # Or 'median' as used previously
df[numerical_cols] = imputer_num.fit_transform(df[numerical_cols])

# Impute categorical columns (after converting to strings to handle potential NaNs appropriately for categorical imputation)
# Use a dictionary to store the mapping from original string categories to integers
category_mappings = {}
for col in categorical_cols:
     df[col] = df[col].astype(str) # Convert to string before imputing categorical
     imputer_cat = SimpleImputer(strategy='most_frequent')
     df[col] = imputer_cat.fit_transform(df[[col]]).ravel()

     categories, unique_categories = pd.factorize(df[col])
```

```python
        df[col] = categories
        # Store the unique categories to determine vocab size later
        category_mappings[col] = unique_categories


# Split
X = df.drop(columns=[target, 'id', 'dataset'], errors='ignore') # Drop 'id' and 'dataset' if they still exist
y = df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42, test_size=0.2)

# Ensure categorical columns in splits are correctly typed as int for embedding
# Use the potentially updated categorical_cols list after checking numerical_cols
current_categorical_cols = [col for col in categorical_cols if col in X_train.columns]
current_numerical_cols = [col for col in numerical_cols if col in X_train.columns]

# The factorize step already ensured they are integers, but keep this for clarity
for col in current_categorical_cols:
    X_train[col] = X_train[col].astype('int')
    X_test[col] = X_test[col].astype('int')


# Process numerical features (after splitting and imputing)
# Ensure the scaler is fit *only* on the training data numerical columns
scaler = StandardScaler()
X_train_num = scaler.fit_transform(X_train[current_numerical_cols])
X_test_num = scaler.transform(X_test[current_numerical_cols])


#  Input layers
inputs = []
embeddings = []

# For categorical columns
for col in current_categorical_cols:
    # Use the number of unique categories found in the *entire* dataset to determine vocab size
    vocab_size = len(category_mappings[col])
    # Embed dim calculation remains the same
    embed_dim = int(min(50, (vocab_size + 1) // 2)) if vocab_size > 1 else 1 # Handle single category case
    inp = Input(shape=(1,), name=f"{col}_input")

    if vocab_size > 0:
        # Keras Embedding layer expects integer indices >= 0 and < input_dim.
        # pd.factorize gives 0 to N-1 indices, which matches this.
```

```
        emb = layers.Embedding(input_dim=vocab_size, output_dim=embed_dim, name=f"{col}_emb")(inp)
        emb = layers.Flatten()(emb)
        inputs.append(inp)
        embeddings.append(emb)
    else:
        print(f"Warning: Categorical column '{col}' has no unique values after processing. Skipping embedding.")


# For numerical input
if current_numerical_cols: # Only add numerical input if there are numerical columns
    num_input = Input(shape=(len(current_numerical_cols),), name="num_input")
    inputs.append(num_input)
    embeddings.append(num_input)
else:
    print("Warning: No numerical columns found after processing.")


# Combine all
if embeddings: # Ensure embeddings list is not empty before concatenation
    x = layers.Concatenate()(embeddings)
    x = layers.Dense(64, activation='relu')(x)
    x = layers.Dropout(0.3)(x)
    x = layers.Dense(32, activation='relu')(x)
    x = layers.Dropout(0.3)(x)
    output = layers.Dense(1, activation='sigmoid')(x)

    model = Model(inputs=inputs, outputs=output)
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

    # Prepare training input
    # This needs to be a list of arrays corresponding to the input layers defined above
    # Categorical inputs first (each column as a separate array), then the numerical input
    train_input = [X_train[col].values for col in current_categorical_cols] + [X_train_num]
    test_input = [X_test[col].values for col in current_categorical_cols] + [X_test_num]

    # Train
    model.fit(train_input, y_train, epochs=50, batch_size=32, validation_split=0.2, verbose=1)

    # Predict
    # Pass the test_input list to predict
    y_prob = model.predict(test_input).flatten()
    y_pred = (y_prob >= 0.5).astype(int)
```

```
    # Evaluate
    print("\n Evaluation")
    print("Accuracy :", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred))
    print("Recall   :", recall_score(y_test, y_pred))
    print("F1 Score :", f1_score(y_test, y_pred))
    print("ROC AUC  :", roc_auc_score(y_test, y_prob))

else:
    print("Error: No input features (numerical or categorical) available to build the model.")
```

```
Epoch 1/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 8s 75ms/step - accuracy: 0.4742 - loss: 0.7139 - val_accuracy: 0.6892 - val_loss: 0.6416
Epoch 2/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - accuracy: 0.6580 - loss: 0.6302 - val_accuracy: 0.7162 - val_loss: 0.5760
Epoch 3/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step - accuracy: 0.7258 - loss: 0.5931 - val_accuracy: 0.7230 - val_loss: 0.5411
Epoch 4/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - accuracy: 0.7396 - loss: 0.5386 - val_accuracy: 0.7297 - val_loss: 0.5216
Epoch 5/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.7530 - loss: 0.5212 - val_accuracy: 0.7500 - val_loss: 0.5090
Epoch 6/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.7618 - loss: 0.5192 - val_accuracy: 0.7432 - val_loss: 0.5043
Epoch 7/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7867 - loss: 0.4976 - val_accuracy: 0.7568 - val_loss: 0.4915
Epoch 8/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - accuracy: 0.7930 - loss: 0.4791 - val_accuracy: 0.7568 - val_loss: 0.4843
Epoch 9/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7726 - loss: 0.4984 - val_accuracy: 0.7635 - val_loss: 0.4724
Epoch 10/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.7990 - loss: 0.4507 - val_accuracy: 0.7770 - val_loss: 0.4574
Epoch 11/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.8030 - loss: 0.4700 - val_accuracy: 0.8041 - val_loss: 0.4431
Epoch 12/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.8204 - loss: 0.4316 - val_accuracy: 0.8108 - val_loss: 0.4362
Epoch 13/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 0.7968 - loss: 0.4201 - val_accuracy: 0.8311 - val_loss: 0.4325
Epoch 14/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - accuracy: 0.8008 - loss: 0.4277 - val_accuracy: 0.8176 - val_loss: 0.4207
Epoch 15/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - accuracy: 0.8077 - loss: 0.4179 - val_accuracy: 0.8243 - val_loss: 0.4110
Epoch 16/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - accuracy: 0.8374 - loss: 0.3993 - val_accuracy: 0.8311 - val_loss: 0.4010
Epoch 17/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 0.8341 - loss: 0.3847 - val_accuracy: 0.8108 - val_loss: 0.4005
Epoch 18/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.8780 - loss: 0.3237 - val_accuracy: 0.8378 - val_loss: 0.3965
Epoch 19/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 0.8399 - loss: 0.3742 - val_accuracy: 0.8243 - val_loss: 0.3945
Epoch 20/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - accuracy: 0.8360 - loss: 0.3935 - val_accuracy: 0.8378 - val_loss: 0.3869
Epoch 21/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - accuracy: 0.8439 - loss: 0.3745 - val_accuracy: 0.8378 - val_loss: 0.3865
Epoch 22/50
```

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - accuracy: 0.8538 - loss: 0.3702 - val_accuracy: 0.8378 - val_loss: 0.3824
Epoch 23/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8489 - loss: 0.3747 - val_accuracy: 0.8243 - val_loss: 0.3842
Epoch 24/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.8254 - loss: 0.4036 - val_accuracy: 0.8243 - val_loss: 0.3810
Epoch 25/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8339 - loss: 0.3856 - val_accuracy: 0.8378 - val_loss: 0.3781
Epoch 26/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - accuracy: 0.8433 - loss: 0.3956 - val_accuracy: 0.8243 - val_loss: 0.3826
Epoch 27/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 0.8257 - loss: 0.3833 - val_accuracy: 0.8243 - val_loss: 0.3798
Epoch 28/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - accuracy: 0.8447 - loss: 0.3812 - val_accuracy: 0.8243 - val_loss: 0.3787
Epoch 29/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - accuracy: 0.8519 - loss: 0.3506 - val_accuracy: 0.8311 - val_loss: 0.3744
Epoch 30/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - accuracy: 0.8456 - loss: 0.3834 - val_accuracy: 0.8311 - val_loss: 0.3743
Epoch 31/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - accuracy: 0.8459 - loss: 0.3655 - val_accuracy: 0.8311 - val_loss: 0.3755
Epoch 32/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.8653 - loss: 0.3397 - val_accuracy: 0.8243 - val_loss: 0.3764
Epoch 33/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - accuracy: 0.8425 - loss: 0.3609 - val_accuracy: 0.8311 - val_loss: 0.3737
Epoch 34/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - accuracy: 0.8614 - loss: 0.3458 - val_accuracy: 0.8378 - val_loss: 0.3724
Epoch 35/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - accuracy: 0.8504 - loss: 0.3590 - val_accuracy: 0.8311 - val_loss: 0.3748
Epoch 36/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.8463 - loss: 0.3372 - val_accuracy: 0.8311 - val_loss: 0.3776
Epoch 37/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.8597 - loss: 0.3449 - val_accuracy: 0.8243 - val_loss: 0.3802
Epoch 38/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8617 - loss: 0.3241 - val_accuracy: 0.8378 - val_loss: 0.3790
Epoch 39/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8643 - loss: 0.3585 - val_accuracy: 0.8176 - val_loss: 0.3815
Epoch 40/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.8785 - loss: 0.3218 - val_accuracy: 0.8176 - val_loss: 0.3737
Epoch 41/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step - accuracy: 0.8583 - loss: 0.3513 - val_accuracy: 0.8311 - val_loss: 0.3718
Epoch 42/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.8467 - loss: 0.3576 - val_accuracy: 0.8378 - val_loss: 0.3727
Epoch 43/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.8702 - loss: 0.3255 - val_accuracy: 0.8311 - val_loss: 0.3765
```

```
Epoch 44/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.8742 - loss: 0.3246 - val_accuracy: 0.8311 - val_loss: 0.3791
Epoch 45/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.8810 - loss: 0.2918 - val_accuracy: 0.8311 - val_loss: 0.3809
Epoch 46/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - accuracy: 0.8617 - loss: 0.3448 - val_accuracy: 0.8378 - val_loss: 0.3790
Epoch 47/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8335 - loss: 0.3676 - val_accuracy: 0.8311 - val_loss: 0.3832
Epoch 48/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8586 - loss: 0.3294 - val_accuracy: 0.8311 - val_loss: 0.3872
Epoch 49/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8608 - loss: 0.3423 - val_accuracy: 0.8446 - val_loss: 0.3850
Epoch 50/50
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8670 - loss: 0.3188 - val_accuracy: 0.8311 - val_loss: 0.3854
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step

 Evaluation
Accuracy : 0.8641304347826086
Precision: 0.8598130841121495
Recall   : 0.9019607843137255
F1 Score : 0.8803827751196173
ROC AUC  : 0.9182209469153515
```

In [13]:

```python
# Install LightGBM
!pip install lightgbm scikit-learn matplotlib pandas -q

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    confusion_matrix, ConfusionMatrixDisplay, roc_curve, auc
)
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
import lightgbm as lgb

# Load and clean data
df = pd.read_csv("heart_disease_uci.csv")
df.drop(columns=["id", "dataset"], inplace=True)

# Encode categorical variables
categorical_cols = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'thal']
for col in categorical_cols:
    df[col] = LabelEncoder().fit_transform(df[col].astype(str))

# Impute missing values
df[df.columns] = SimpleImputer(strategy="mean").fit_transform(df)

# Convert to binary classification
df["num"] = (df["num"] > 0).astype(int)

# Feature selection (optional)
drop_weak = ["fbs", "restecg"]  # Based on low correlation
X = df.drop(columns=["num"] + drop_weak)
y = df["num"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, random_state=42)

# LightGBM model
model = lgb.LGBMClassifier(
    objective="binary",
    n_estimators=500,
```

```python
    learning_rate=0.05,
    max_depth=5,
    random_state=42
)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)[:, 1]

# Metrics
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("\n LightGBM Evaluation Metrics")
print(f" Accuracy :  {acc:.4f}")
print(f" Precision:  {prec:.4f}")
print(f" Recall   :  {rec:.4f}")
print(f" F1 Score :  {f1:.4f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.2f}", color='darkgreen')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - LightGBM")
plt.legend()
plt.grid(True)
plt.show()

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["No Disease", "Disease"])
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix - LightGBM")
plt.grid(False)
plt.show()
```

```
[LightGBM] [Info] Number of positive: 407, number of negative: 329
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.000396 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 373
[LightGBM] [Info] Number of data points in the train set: 736, number of used features: 11
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.552989 -> initscore=0.212755
[LightGBM] [Info] Start training from score 0.212755
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

 LightGBM Evaluation Metrics
 Accuracy :  0.8370
 Precision:  0.8333
 Recall   :  0.8824
 F1 Score :  0.8571
```
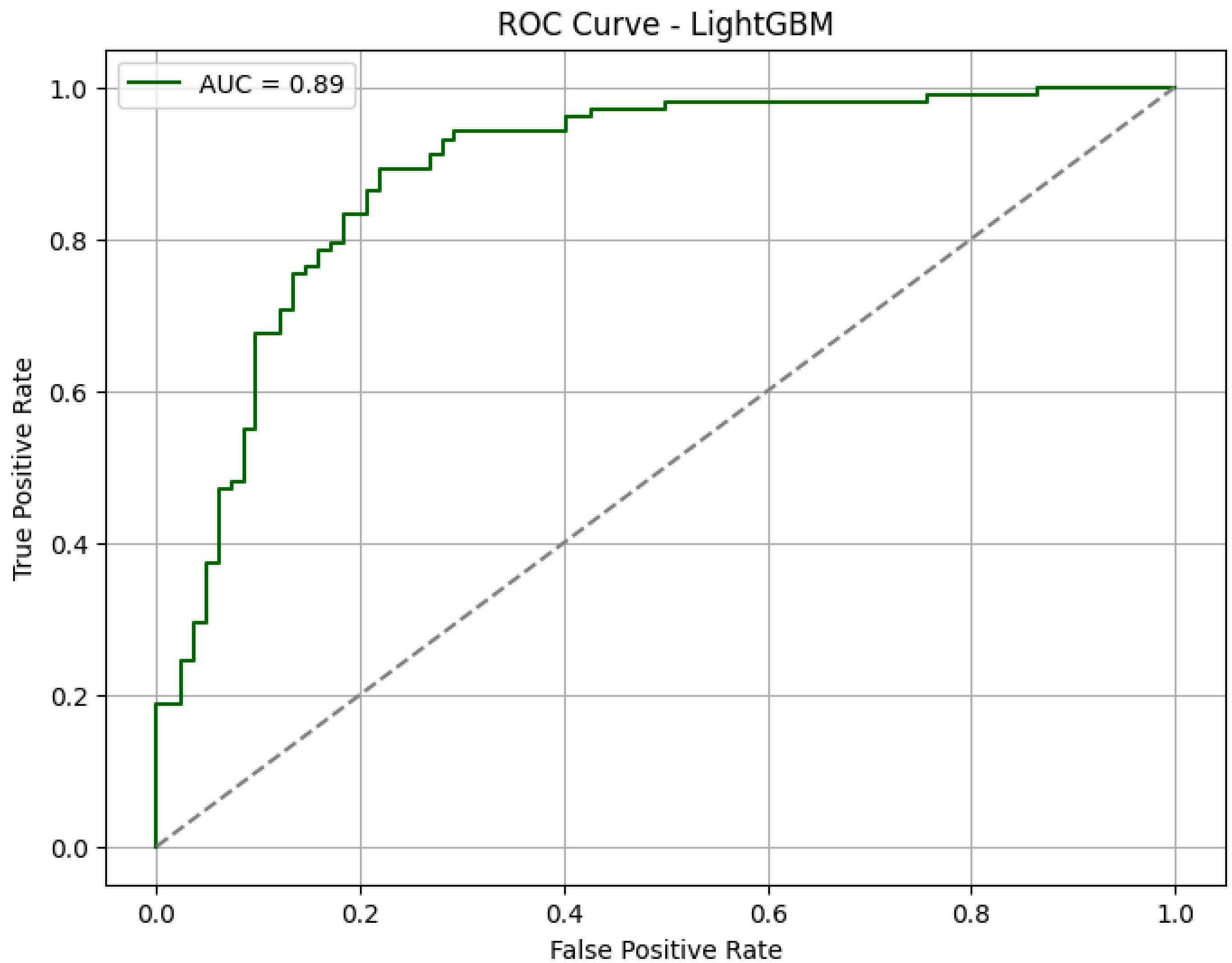
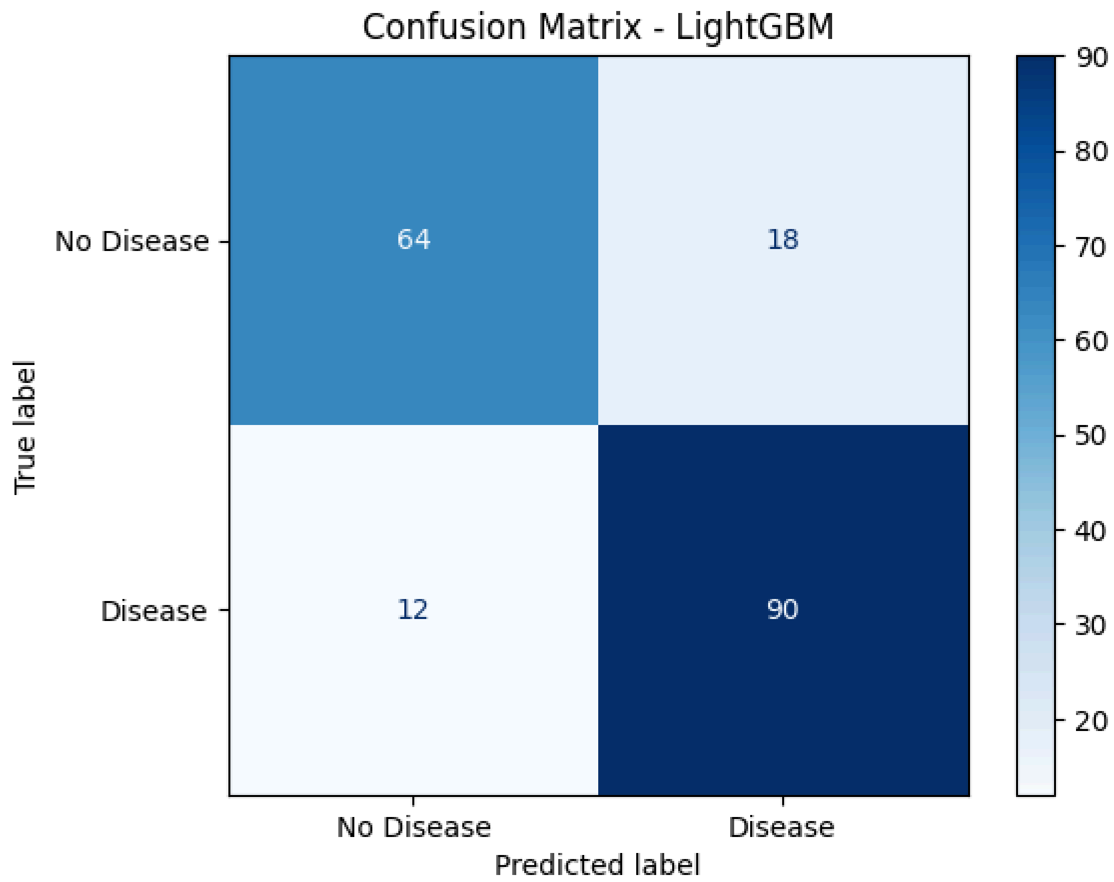



ROC Curve - LightGBM
AUC = 0.89
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



OVERFITTING ANALYSIS Categorical Embedding

In [14]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Load and clean dataset
df = pd.read_csv("heart_disease_uci.csv")
df.drop(columns=["id"], inplace=True)
df["target"] = df["num"].apply(lambda x: 1 if x > 0 else 0)
df.drop(columns=["num"], inplace=True)

# Handle missing values
for col in df.select_dtypes(include=["float64", "int64"]).columns:
    df[col].fillna(df[col].median(), inplace=True)

cat_cols = df.select_dtypes(include="object").columns
df[cat_cols] = df[cat_cols].astype(str).fillna("Unknown")

# Encode categorical to integer labels
encoders = {}
for col in cat_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    encoders[col] = le

# Split columns
X = df.drop("target", axis=1)
y = df["target"]

categorical_cols = cat_cols
numerical_cols = [col for col in X.columns if col not in categorical_cols]

# Normalize numeric data
scaler = StandardScaler()
X[numerical_cols] = scaler.fit_transform(X[numerical_cols])

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
```

In [15]:

```
import tensorflow as tf
from tensorflow.keras.layers import Input, Embedding, Dense, Concatenate, Flatten
from tensorflow.keras.models import Model

# Define embedding layers
inputs = []
embeddings = []

for col in categorical_cols:
    vocab_size = df[col].nunique()
    inp = Input(shape=(1,), name=col)
    emb = Embedding(input_dim=vocab_size + 1, output_dim=4, name=f"{col}_emb")(inp)
    inputs.append(inp)
    embeddings.append(Flatten()(emb))

# Numeric inputs
numeric_inp = Input(shape=(len(numerical_cols),), name="numeric")
inputs.append(numeric_inp)
x = Concatenate()(embeddings + [numeric_inp])

# Fully connected layers
x = Dense(64, activation="relu")(x)
x = Dense(32, activation="relu")(x)
output = Dense(1, activation="sigmoid")(x)

# Model
model_orig = Model(inputs=inputs, outputs=output)
model_orig.compile(optimizer="adam", loss="binary_crossentropy", metrics=["accuracy", tf.keras.metrics.AUC()])

# Prepare input dictionary
def prep_input(X):
    return {col: X[col].values for col in categorical_cols} | {"numeric": X[numerical_cols].values}

# Fit model
history_orig = model_orig.fit(
    prep_input(X_train), y_train,
    validation_data=(prep_input(X_test), y_test),
    epochs=30,
    batch_size=32,
    verbose=1
)
```

```
Epoch 1/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 6s 58ms/step - accuracy: 0.5751 - auc: 0.5750 - loss: 0.6893 - val_accuracy: 0.7663 - val_auc: 0.8394 - val_loss: 0.594
5
Epoch 2/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7432 - auc: 0.8273 - loss: 0.5757 - val_accuracy: 0.7772 - val_auc: 0.8430 - val_loss: 0.527
4
Epoch 3/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.7777 - auc: 0.8681 - loss: 0.4887 - val_accuracy: 0.7935 - val_auc: 0.8589 - val_loss: 0.478
9
Epoch 4/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.8264 - auc: 0.8884 - loss: 0.4277 - val_accuracy: 0.8261 - val_auc: 0.8767 - val_loss: 0.443
5
Epoch 5/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - accuracy: 0.7982 - auc: 0.8763 - loss: 0.4369 - val_accuracy: 0.8207 - val_auc: 0.8895 - val_loss: 0.420
2
Epoch 6/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - accuracy: 0.8495 - auc: 0.9069 - loss: 0.3930 - val_accuracy: 0.8152 - val_auc: 0.9035 - val_loss: 0.393
9
Epoch 7/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 0.8124 - auc: 0.8903 - loss: 0.4130 - val_accuracy: 0.8370 - val_auc: 0.9115 - val_loss: 0.376
6
Epoch 8/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.8505 - auc: 0.9110 - loss: 0.3725 - val_accuracy: 0.8315 - val_auc: 0.9164 - val_loss: 0.369
2
Epoch 9/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step - accuracy: 0.8439 - auc: 0.9258 - loss: 0.3445 - val_accuracy: 0.8424 - val_auc: 0.9188 - val_loss: 0.360
7
Epoch 10/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.8524 - auc: 0.9245 - loss: 0.3519 - val_accuracy: 0.8370 - val_auc: 0.9195 - val_loss: 0.360
2
Epoch 11/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - accuracy: 0.8853 - auc: 0.9308 - loss: 0.3322 - val_accuracy: 0.8370 - val_auc: 0.9191 - val_loss: 0.358
5
Epoch 12/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - accuracy: 0.8551 - auc: 0.9208 - loss: 0.3518 - val_accuracy: 0.8478 - val_auc: 0.9204 - val_loss: 0.357
5
Epoch 13/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - accuracy: 0.8543 - auc: 0.9159 - loss: 0.3650 - val_accuracy: 0.8478 - val_auc: 0.9186 - val_loss: 0.357
3
Epoch 14/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.8713 - auc: 0.9258 - loss: 0.3432 - val_accuracy: 0.8424 - val_auc: 0.9172 - val_loss: 0.361
9
Epoch 15/30
```

```
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - accuracy: 0.8779 - auc: 0.9359 - loss: 0.3224 - val_accuracy: 0.8424 - val_auc: 0.9177 - val_loss: 0.359
7
Epoch 16/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - accuracy: 0.8549 - auc: 0.9256 - loss: 0.3451 - val_accuracy: 0.8370 - val_auc: 0.9180 - val_loss: 0.356
6
Epoch 17/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - accuracy: 0.8811 - auc: 0.9305 - loss: 0.3297 - val_accuracy: 0.8370 - val_auc: 0.9184 - val_loss: 0.358
1
Epoch 18/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - accuracy: 0.8788 - auc: 0.9372 - loss: 0.3170 - val_accuracy: 0.8370 - val_auc: 0.9157 - val_loss: 0.369
0
Epoch 19/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - accuracy: 0.8777 - auc: 0.9378 - loss: 0.3144 - val_accuracy: 0.8261 - val_auc: 0.9176 - val_loss: 0.359
0
Epoch 20/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - accuracy: 0.8823 - auc: 0.9402 - loss: 0.3189 - val_accuracy: 0.8370 - val_auc: 0.9172 - val_loss: 0.364
4
Epoch 21/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8902 - auc: 0.9451 - loss: 0.2966 - val_accuracy: 0.8370 - val_auc: 0.9163 - val_loss: 0.370
0
Epoch 22/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.8938 - auc: 0.9553 - loss: 0.2764 - val_accuracy: 0.8315 - val_auc: 0.9157 - val_loss: 0.366
2
Epoch 23/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - accuracy: 0.8697 - auc: 0.9326 - loss: 0.3292 - val_accuracy: 0.8424 - val_auc: 0.9155 - val_loss: 0.369
5
Epoch 24/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - accuracy: 0.8910 - auc: 0.9539 - loss: 0.2803 - val_accuracy: 0.8370 - val_auc: 0.9146 - val_loss: 0.372
9
Epoch 25/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.8862 - auc: 0.9472 - loss: 0.2962 - val_accuracy: 0.8424 - val_auc: 0.9148 - val_loss: 0.372
4
Epoch 26/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 0.8996 - auc: 0.9588 - loss: 0.2666 - val_accuracy: 0.8370 - val_auc: 0.9142 - val_loss: 0.374
9
Epoch 27/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - accuracy: 0.9191 - auc: 0.9650 - loss: 0.2461 - val_accuracy: 0.8261 - val_auc: 0.9135 - val_loss: 0.381
4
Epoch 28/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 0.8896 - auc: 0.9542 - loss: 0.2715 - val_accuracy: 0.8424 - val_auc: 0.9123 - val_loss: 0.379
4
Epoch 29/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 35ms/step - accuracy: 0.8975 - auc: 0.9492 - loss: 0.2879 - val_accuracy: 0.8424 - val_auc: 0.9119 - val_loss: 0.381
```

```
6
Epoch 30/30
23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9004 - auc: 0.9553 - loss: 0.2761 - val_accuracy: 0.8315 - val_auc: 0.9122 - val_loss: 0.386
7
```

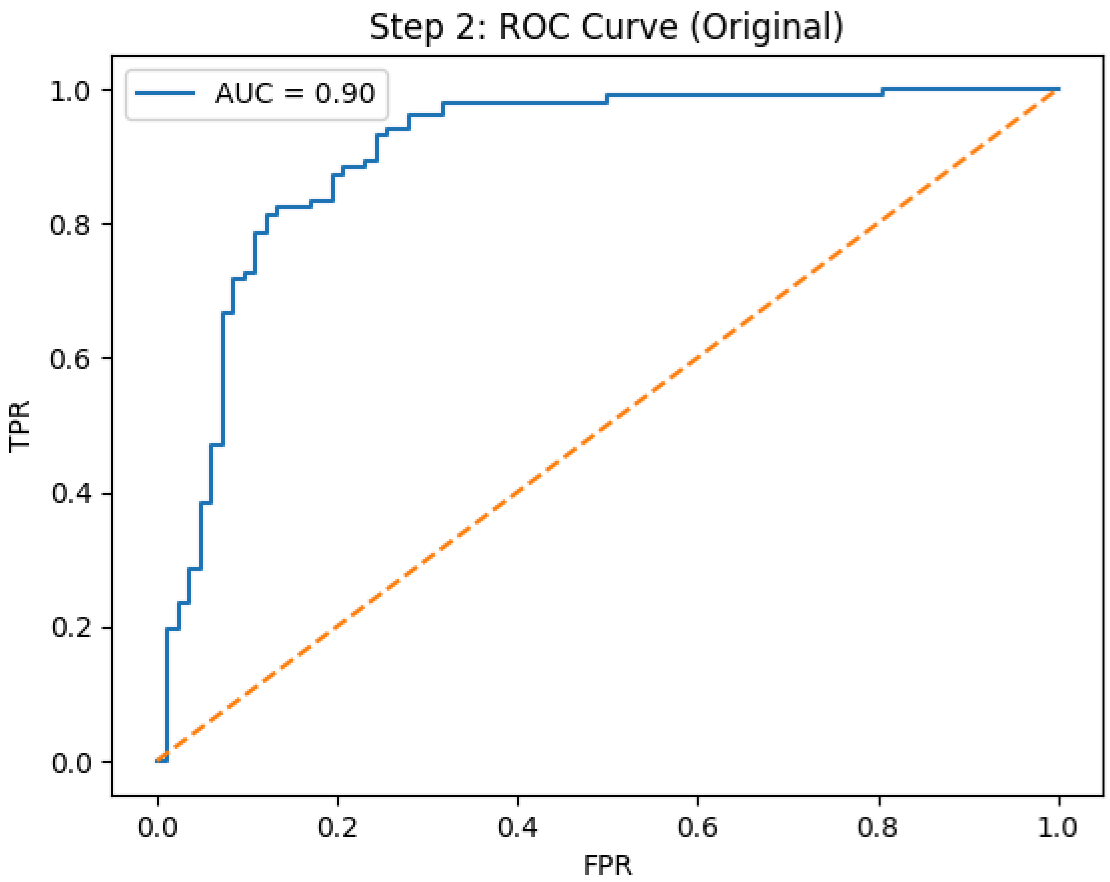
In [16]:

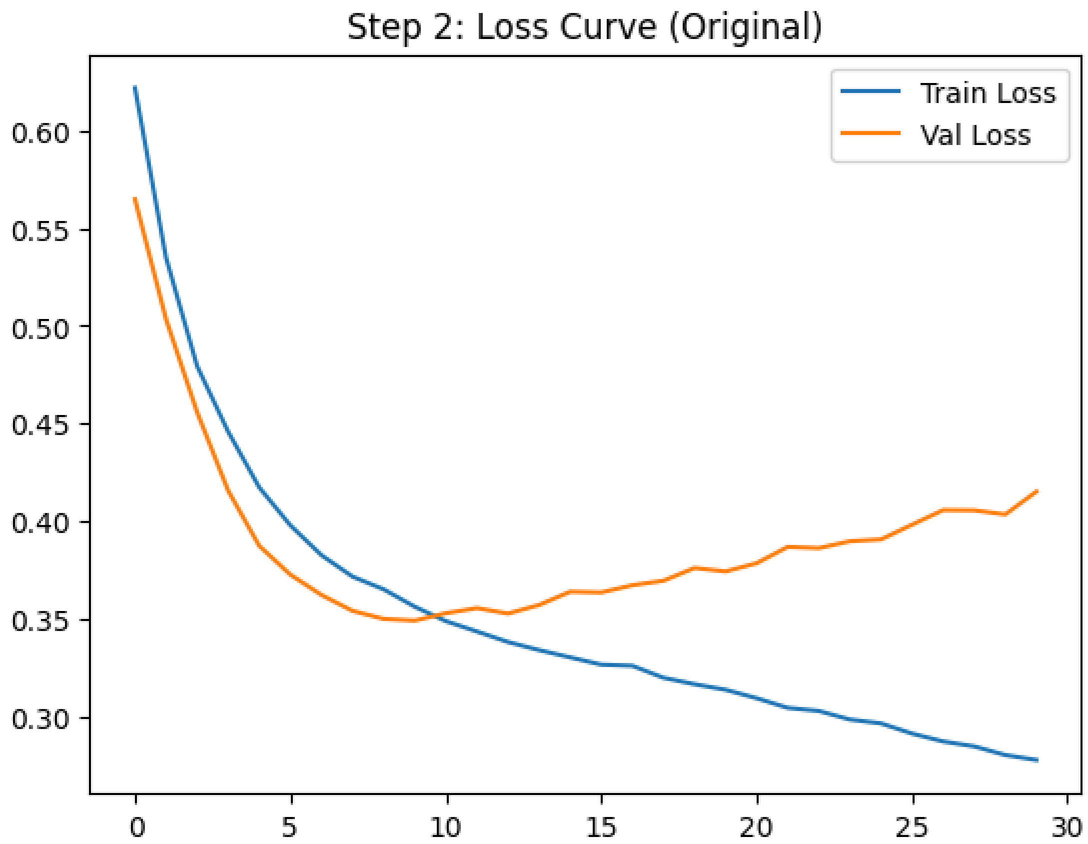
```python
import tensorflow as tf
from tensorflow.keras.layers import Input, Embedding, Dense, Concatenate, Flatten
from tensorflow.keras.models import Model
from sklearn.metrics import accuracy_score, roc_auc_score

# Build original model
inputs = []
embeddings = []

for col in categorical_cols:
    vocab_size = df[col].nunique()
    inp = Input(shape=(1,), name=col)
    emb = Embedding(input_dim=vocab_size + 1, output_dim=4)(inp)
    inputs.append(inp)
    embeddings.append(Flatten()(emb))

num_input = Input(shape=(len(numerical_cols),), name="numeric")
inputs.append(num_input)
x = Concatenate()(embeddings + [num_input])
x = Dense(64, activation="relu")(x)
x = Dense(32, activation="relu")(x)
output = Dense(1, activation="sigmoid")(x)

model_orig = Model(inputs=inputs, outputs=output)
model_orig.compile(optimizer="adam", loss="binary_crossentropy", metrics=["accuracy", tf.keras.metrics.AUC()])

# Train
history_orig = model_orig.fit(
    prep_input(X_train), y_train,
    validation_data=(prep_input(X_test), y_test),
    epochs=30,
    batch_size=32,
    verbose=0
)

# Predict & Evaluate
y_pred_prob_orig = model_orig.predict(prep_input(X_test)).ravel()
y_pred_class_orig = (y_pred_prob_orig > 0.5).astype(int)

# Accuracy and AUC outcomes
orig_acc = accuracy_score(y_test, y_pred_class_orig)
orig_auc = roc_auc_score(y_test, y_pred_prob_orig)
```

```python
print(f" Step 1: Original Model Accuracy = {orig_acc:.4f}")
print(f" Step 1: Original Model AUC = {orig_auc:.4f}")
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 67ms/step
 Step 1: Original Model Accuracy = 0.8370
 Step 1: Original Model AUC = 0.9036
```

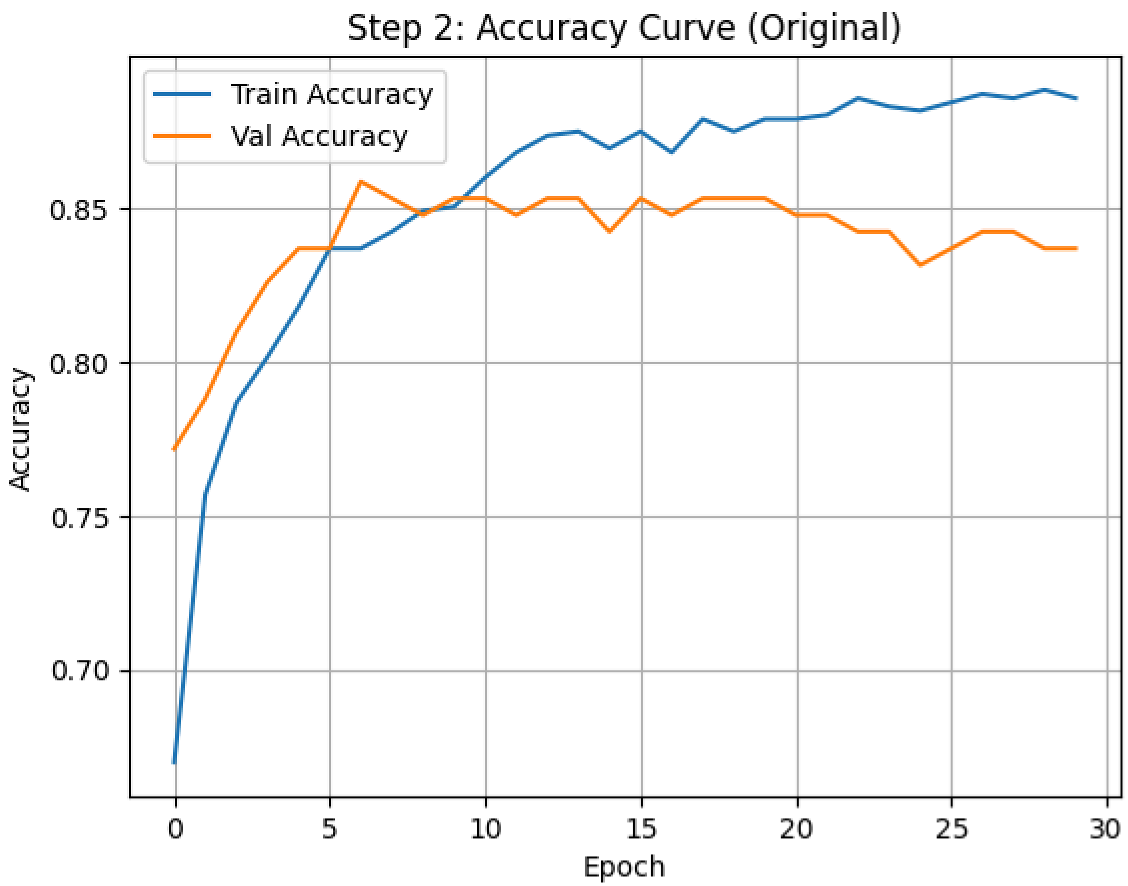
In [17]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_prob_orig)
plt.plot(fpr, tpr, label=f"AUC = {orig_auc:.2f}")
plt.plot([0, 1], [0, 1], linestyle="--")
plt.title("Step 2: ROC Curve (Original)")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.show()

# Loss & AUC curves
plt.plot(history_orig.history["loss"], label="Train Loss")
plt.plot(history_orig.history["val_loss"], label="Val Loss")
plt.title("Step 2: Loss Curve (Original)")
plt.legend()
plt.show()
```


Step 2: ROC Curve (Original)
AUC = 0.90
1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR


Step 2: Loss Curve (Original)
Train Loss
Val Loss
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0
5
10
15
20
25
30

In [18]:

```
# Step 2: Train vs Validation Accuracy (Original Model)
import matplotlib.pyplot as plt

plt.plot(history_orig.history["accuracy"], label="Train Accuracy")
plt.plot(history_orig.history["val_accuracy"], label="Val Accuracy")
plt.title("Step 2: Accuracy Curve (Original)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()
```



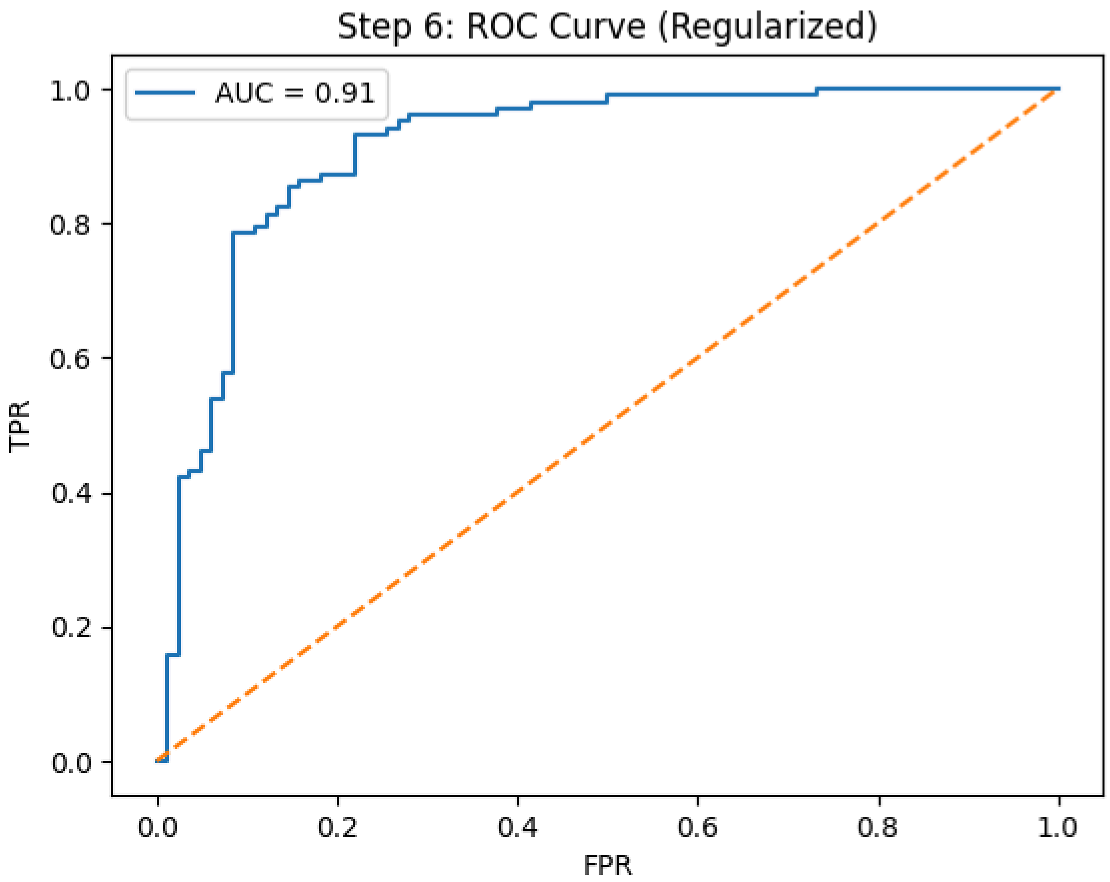
In [19]:
```
from tensorflow.keras.layers import Dropout, BatchNormalization

# Rebuild model with regularization
x = Concatenate()(embeddings + [num_input])
x = Dense(64, activation="relu")(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)
x = Dense(32, activation="relu")(x)
x = Dropout(0.3)(x)
output = Dense(1, activation="sigmoid")(x)

model_reg = Model(inputs=inputs, outputs=output)
model_reg.compile(optimizer="adam", loss="binary_crossentropy", metrics=["accuracy", tf.keras.metrics.AUC()])

# Train
history_reg = model_reg.fit(
    prep_input(X_train), y_train,
    validation_data=(prep_input(X_test), y_test),
    epochs=30,
    batch_size=32,
    verbose=0
)
```

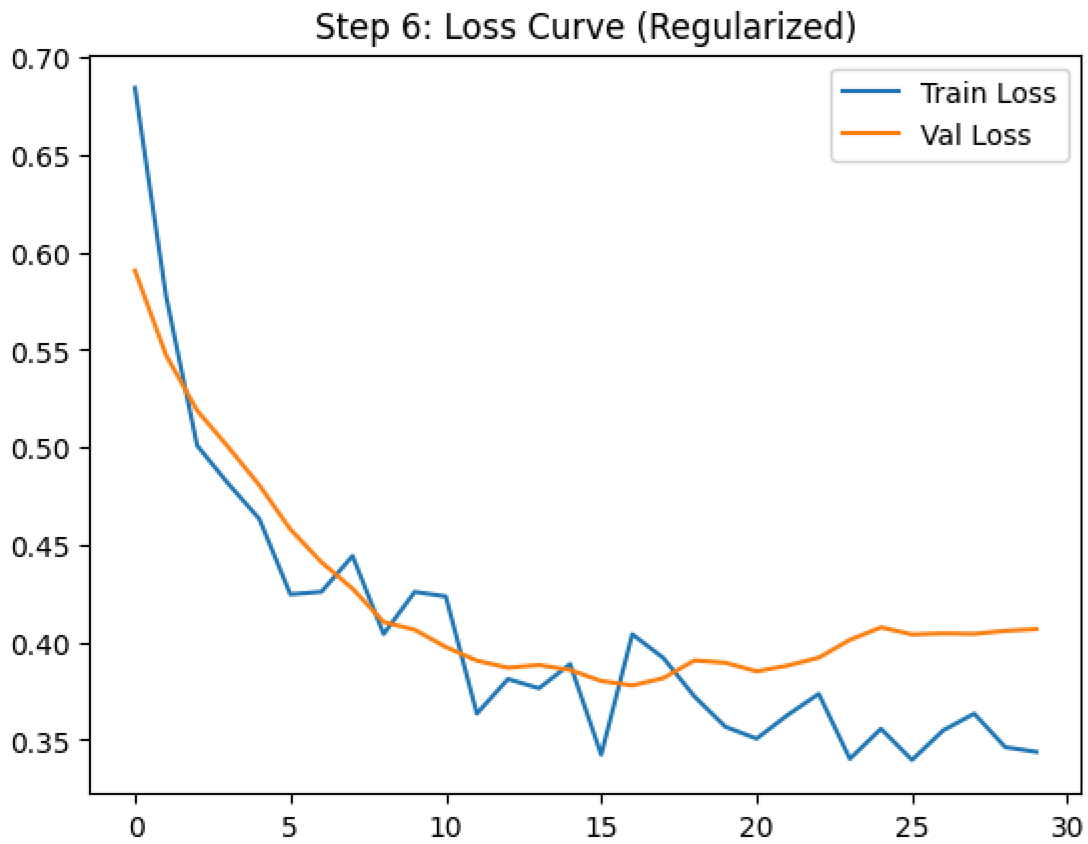
In [20]:

```
# Predict & Evaluate
y_pred_prob_reg = model_reg.predict(prep_input(X_test)).ravel()
y_pred_class_reg = (y_pred_prob_reg > 0.5).astype(int)

reg_acc = accuracy_score(y_test, y_pred_class_reg)
reg_auc = roc_auc_score(y_test, y_pred_prob_reg)

# Accuracy and AUC outcomes
print(f" Step 5: Regularized Model Accuracy = {reg_acc:.4f}")
print(f" Step 5: Regularized Model AUC = {reg_auc:.4f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_prob_reg)
plt.plot(fpr, tpr, label=f"AUC = {reg_auc:.2f}")
plt.plot([0, 1], [0, 1], linestyle="--")
plt.title("Step 6: ROC Curve (Regularized)")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.show()

# Loss & AUC curves
plt.plot(history_reg.history["loss"], label="Train Loss")
plt.plot(history_reg.history["val_loss"], label="Val Loss")
plt.title("Step 6: Loss Curve (Regularized)")
plt.legend()
plt.show()
```

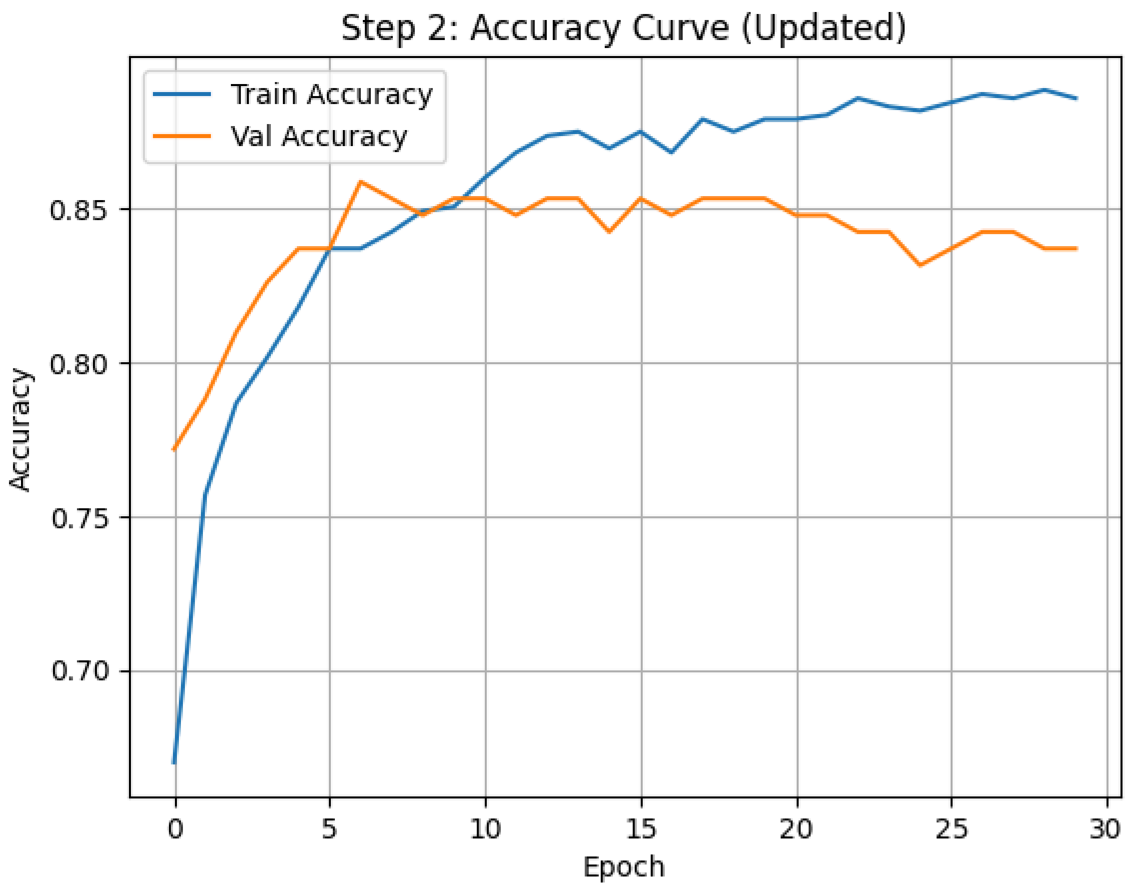
```
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x782d
b75d6c00> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function rep
eatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.funct
ion outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to htt
ps://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 50ms/step
 Step 5: Regularized Model Accuracy = 0.8478
 Step 5: Regularized Model AUC = 0.9115
```




Step 6: Loss Curve (Regularized)
Train Loss
Val Loss
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0
5
10
15
20
25
30

In [21]:
```
# Step 2: Train vs Validation Accuracy (Original Model)
import matplotlib.pyplot as plt

plt.plot(history_orig.history["accuracy"], label="Train Accuracy")
plt.plot(history_orig.history["val_accuracy"], label="Val Accuracy")
plt.title("Step 2: Accuracy Curve (Updated)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()
```



SHAP Lime

In [22]:
```
!pip install shap
```

```
Requirement already satisfied: shap in /usr/local/lib/python3.11/dist-packages (0.47.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from shap) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from shap) (1.15.3)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (from shap) (1.6.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from shap) (2.2.2)
Requirement already satisfied: tqdm>=4.27.0 in /usr/local/lib/python3.11/dist-packages (from shap) (4.67.1)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.11/dist-packages (from shap) (24.2)
Requirement already satisfied: slicer==0.0.8 in /usr/local/lib/python3.11/dist-packages (from shap) (0.0.8)
Requirement already satisfied: numba>=0.54 in /usr/local/lib/python3.11/dist-packages (from shap) (0.60.0)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.11/dist-packages (from shap) (3.1.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.11/dist-packages (from shap) (4.14.0)
Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in /usr/local/lib/python3.11/dist-packages (from numba>=0.54->shap) (0.43.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->shap) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->shap) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->shap) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas->shap) (1.17.0)
```

In [23]:
```
!pip install lime
```

```
Requirement already satisfied: lime in /usr/local/lib/python3.11/dist-packages (0.2.0.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from lime) (3.10.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from lime) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from lime) (1.15.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from lime) (4.67.1)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.11/dist-packages (from lime) (1.6.1)
Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/python3.11/dist-packages (from lime) (0.25.2)
Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (3.5)
Requirement already satisfied: pillow>=10.1 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (11.2.1)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (2.37.0)
Requirement already satisfied: tifffile>=2022.8.12 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (2025.6.1)
Requirement already satisfied: packaging>=21 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (24.2)
Requirement already satisfied: lazy-loader>=0.4 in /usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (0.4)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.18->lime) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.18->lime) (3.6.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (4.58.1)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (1.4.8)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib->lime) (1.17.0)
```

In [24]:
```
import shap
import numpy as np

# Flat input → model input dict
def model_predict_fn(X_flat):
    # Extract categorical and numeric split indices
    cat_len = len(categorical_cols)
    num_len = len(numerical_cols)

    # Split the flat array back into dict of model inputs
    input_dict = {}

    for i, col in enumerate(categorical_cols):
        input_dict[col] = X_flat[:, i].reshape(-1, 1).astype("int32")  # categorical: int32

    input_dict["numeric"] = X_flat[:, cat_len:].astype("float32")  # numeric: float32
    return model_reg.predict(input_dict).ravel()  # return flat output

# Flatten the categorical and numerical inputs into a single matrix
X_train_flat = np.hstack([
    X_train[categorical_cols].values,
    X_train[numerical_cols].values
])
X_test_flat = np.hstack([
    X_test[categorical_cols].values,
    X_test[numerical_cols].values
])

# Use only subset for speed
X_train_sample = X_train_flat[:100]
X_test_sample = X_test_flat[:50]

# SHAP feature names
feature_names = list(categorical_cols) + numerical_cols

# KernelExplainer setup
explainer = shap.KernelExplainer(model_predict_fn, X_train_sample)

# Compute SHAP values
shap_values = explainer.shap_values(X_test_sample, nsamples=100)
```

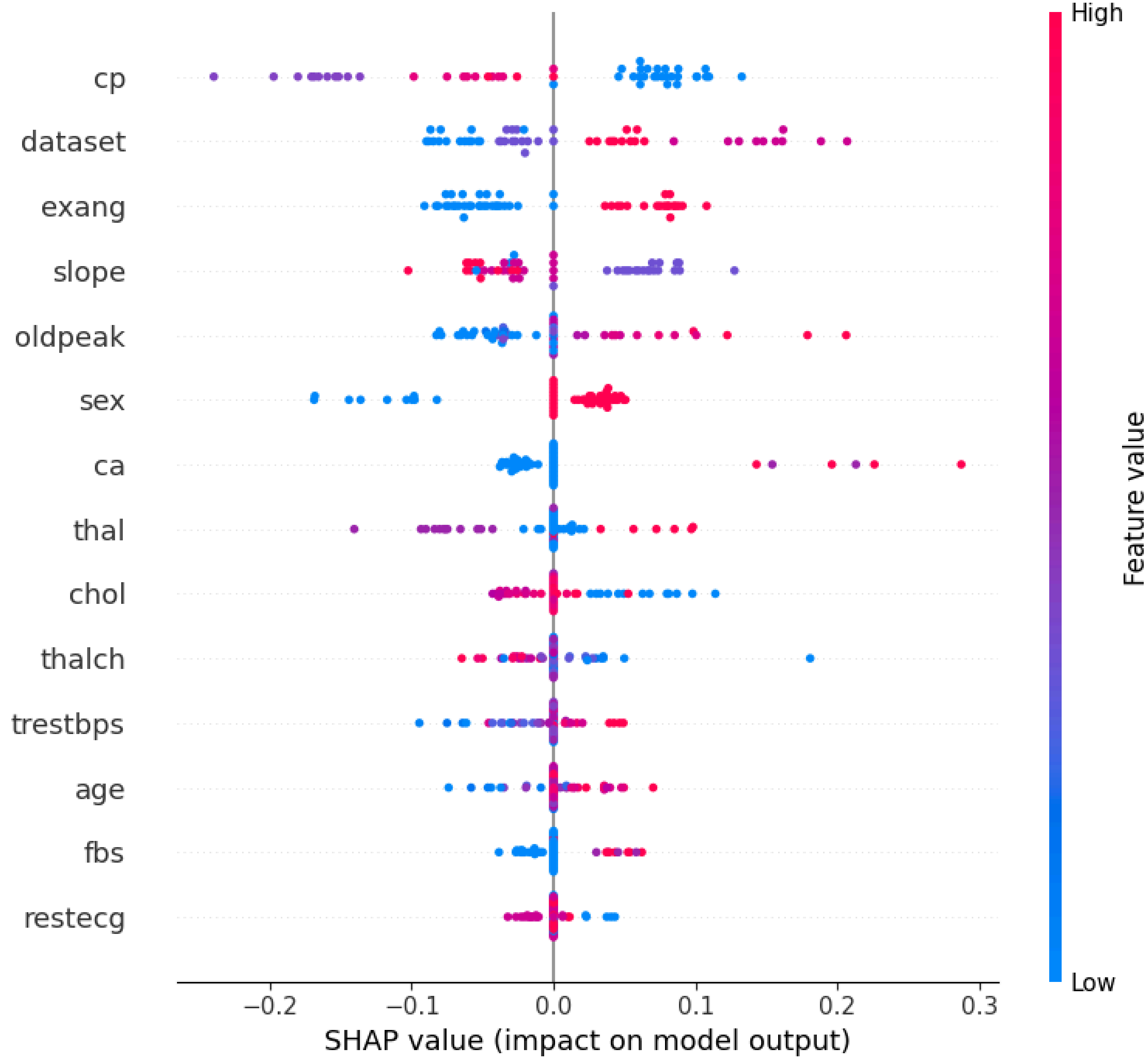
```python
# Summary Plot
shap.summary_plot(shap_values, X_test_sample, feature_names=feature_names)
```

```
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x782d
b75d6c00> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function rep
eatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.funct
ion outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to htt
ps://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.

4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 122ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 100ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 107ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 150ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 89ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 64ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 75ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 112ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 95ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 85ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 68ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 263ms/step
```

```
313/313 3s 8ms/step
1/1 0s 74ms/step
313/313 1s 3ms/step
1/1 0s 80ms/step
313/313 1s 3ms/step
1/1 0s 63ms/step
313/313 1s 2ms/step
1/1 0s 46ms/step
313/313 1s 2ms/step
1/1 0s 53ms/step
313/313 1s 2ms/step
1/1 0s 51ms/step
313/313 1s 2ms/step
1/1 0s 53ms/step
313/313 0s 1ms/step
1/1 0s 51ms/step
313/313 1s 2ms/step
1/1 0s 53ms/step
313/313 0s 1ms/step
1/1 0s 42ms/step
313/313 1s 2ms/step
1/1 0s 49ms/step
313/313 1s 2ms/step
1/1 0s 43ms/step
313/313 0s 1ms/step
1/1 0s 45ms/step
313/313 1s 2ms/step
1/1 0s 46ms/step
313/313 1s 2ms/step
1/1 0s 42ms/step
313/313 1s 2ms/step
1/1 0s 50ms/step
313/313 1s 2ms/step
1/1 0s 43ms/step
313/313 0s 1ms/step
1/1 0s 46ms/step
313/313 1s 2ms/step
1/1 0s 57ms/step
313/313 0s 2ms/step
1/1 0s 45ms/step
313/313 1s 2ms/step
1/1 0s 42ms/step
313/313 1s 2ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```

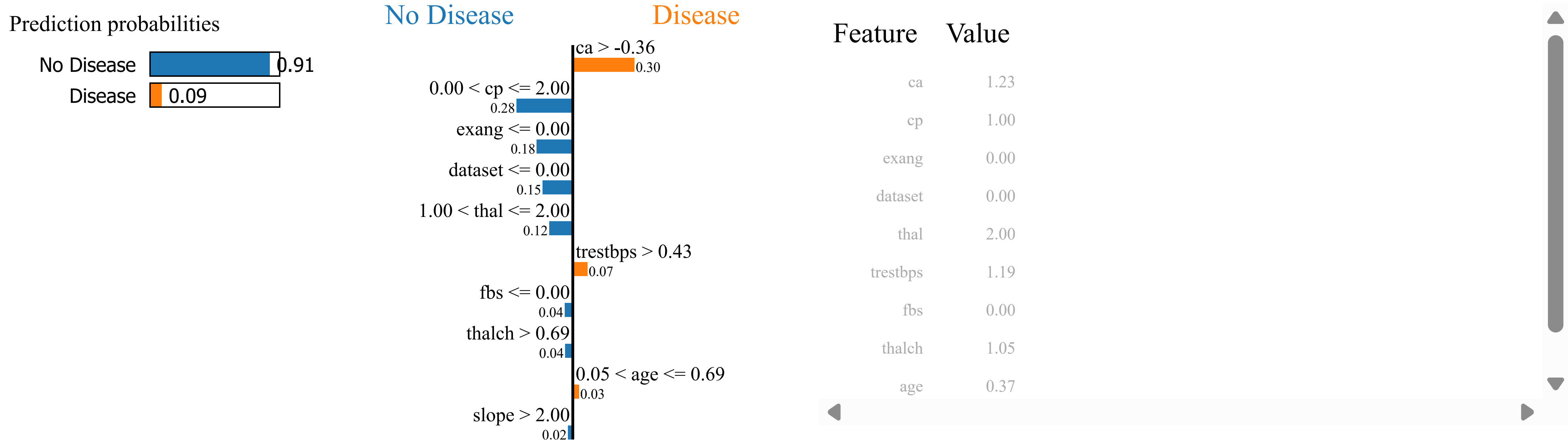


cp
dataset
exang
slope
oldpeak
sex
ca
thal
chol
thalch
trestbps
age
fbs
restecg
−0.2
−0.1
0.0
0.1
0.2
0.3
SHAP value (impact on model output)
High
Low
Feature value

In [26]:

```python
# LIME explainer setup
lime_explainer = lime.lime_tabular.LimeTabularExplainer(
    training_data=X_train.values,
    feature_names=X.columns.tolist(),
    class_names=["No Disease", "Disease"],
    mode="classification"
)

# Predict wrapper
def lime_predict_fn(data):
    input_dict = prep_input(pd.DataFrame(data, columns=X.columns))
    return np.concatenate(
        [1 - model_reg.predict(input_dict), model_reg.predict(input_dict)],
        axis=1
    )

# Explain one instance
idx = 10  # index from the sampled test set
lime_exp = lime_explainer.explain_instance(
    data_row=X_test.iloc[idx].values,
    predict_fn=lime_predict_fn,
    num_features=10
)

# Visualize explanation
lime_exp.show_in_notebook(show_table=True)
```

```
157/157 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step
157/157 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
```



OVERFITTING ANALYSIS LIGHT GBM

In [27]:

```python
# STEP 1: IMPORTS AND DATA PREP
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import lightgbm as lgb
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import shap

# Load data
df = pd.read_csv("heart_disease_uci.csv")
df.drop(columns=["id"], inplace=True)
df["target"] = df["num"].apply(lambda x: 1 if x > 0 else 0)
df.drop(columns=["num"], inplace=True)

# Fill missing values
for col in df.select_dtypes(include=["float64", "int64"]).columns:
    df[col].fillna(df[col].median(), inplace=True)

# Encode categorical columns
cat_cols = df.select_dtypes(include="object").columns
df[cat_cols] = df[cat_cols].astype(str)
cat_feature_indices = []

for i, col in enumerate(df.columns):
    if col in cat_cols:
        le = LabelEncoder()
        df[col] = le.fit_transform(df[col])
        cat_feature_indices.append(i)

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

X_train, X_test, y_train, y_test = train_test_split(
    X, y, stratify=y, test_size=0.2, random_state=42
)
```

In [28]:

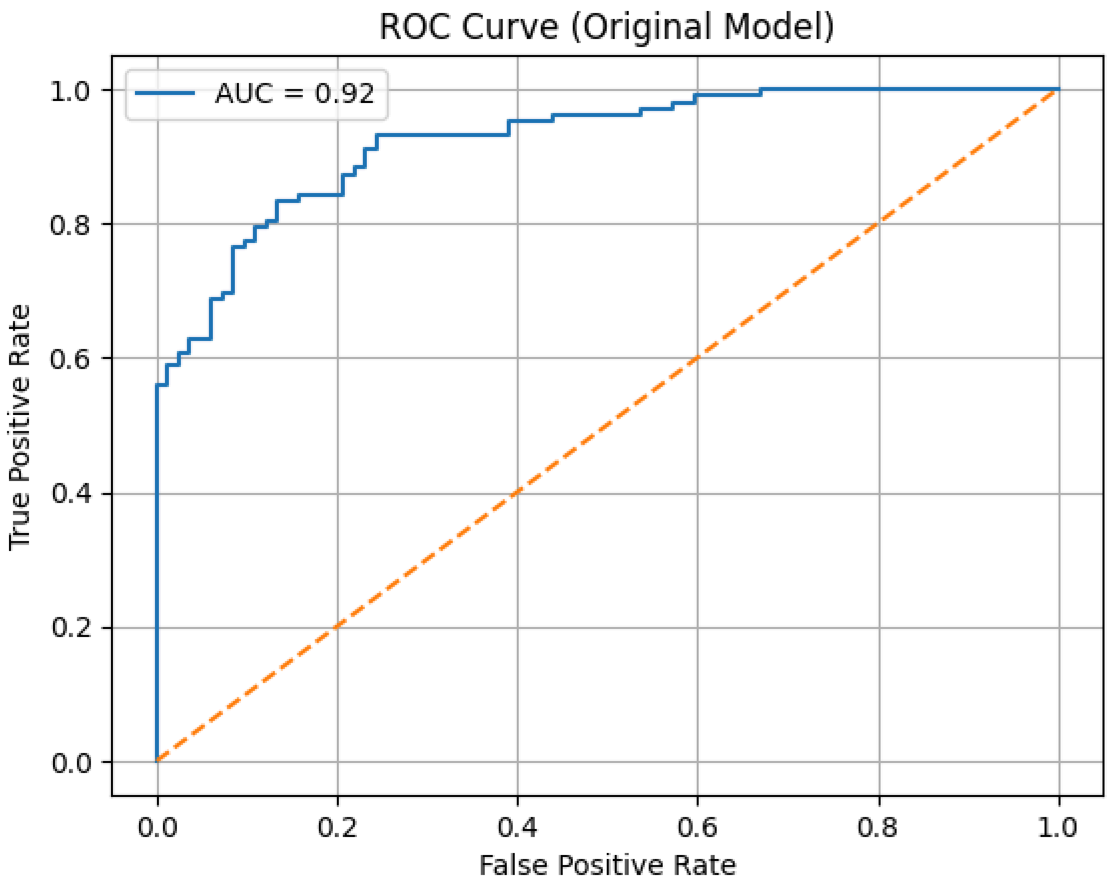
```
# STEP 1: IMPORTS AND DATA PREP
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import lightgbm as lgb
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
# import shap # Shap not used in this cell, can be commented out if not needed elsewhere for this model

# Load data
df = pd.read_csv("heart_disease_uci.csv")
df.drop(columns=["id"], inplace=True)
df["target"] = df["num"].apply(lambda x: 1 if x > 0 else 0)
df.drop(columns=["num"], inplace=True)

# Fill missing values
for col in df.select_dtypes(include=["float64", "int64"]).columns:
    df[col].fillna(df[col].median(), inplace=True)

# Encode categorical columns
cat_cols = df.select_dtypes(include="object").columns
df[cat_cols] = df[cat_cols].astype(str)
cat_feature_indices = []

for i, col in enumerate(df.columns):
    if col in cat_cols:
        le = LabelEncoder()
        df[col] = le.fit_transform(df[col])
        # Find the index of the column in the DataFrame *after* dropping 'id' and 'num'
        # This is more robust than using the loop index 'i' directly,
        # especially if columns were dropped or reordered.
        if col in X_train.columns: # Use X_train columns after split for indexing
            cat_feature_indices.append(X_train.columns.get_loc(col))


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

X_train, X_test, y_train, y_test = train_test_split(
    X, y, stratify=y, test_size=0.2, random_state=42
)
```

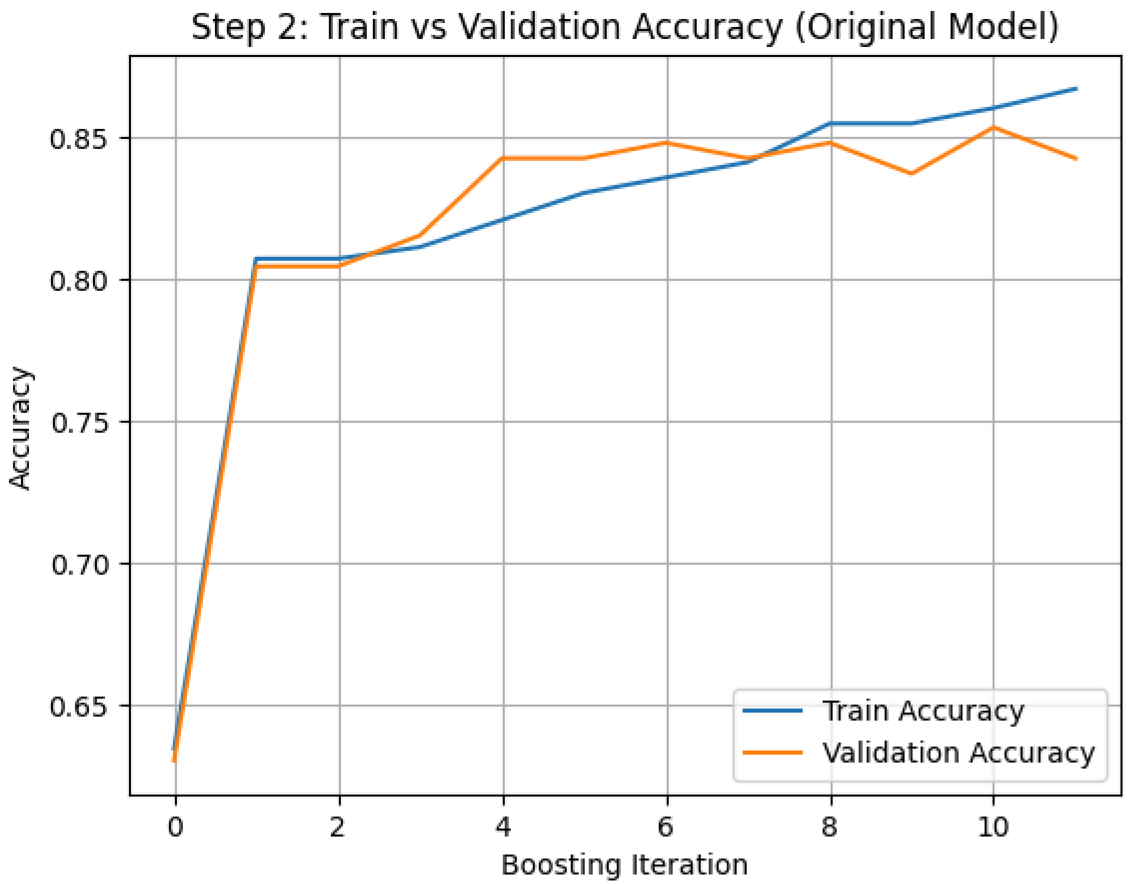
```python
# Re-calculate cat_feature_indices based on the columns in X_train
# This is safer as the original df had 'id' and 'num' before dropping.
cat_feature_indices = [X_train.columns.get_loc(col) for col in cat_cols if col in X_train.columns]

# STEP 2: TRAIN ORIGINAL MODEL (May Overfit)
train_set = lgb.Dataset(X_train, label=y_train, categorical_feature=cat_feature_indices)
test_set = lgb.Dataset(X_test, label=y_test, categorical_feature=cat_feature_indices, reference=train_set)

params_orig = {
    "objective": "binary",
    "metric": "auc",
    "boosting_type": "gbdt",
    "verbosity": -1,
}

evals_result_orig = {}

# Use lgb.early_stopping callback instead of early_stopping_rounds as a direct argument
# verbose=False is often preferred in notebooks to avoid epoch-by-epoch output
early_stopping_callback = lgb.early_stopping(stopping_rounds=10, verbose=False)

evals_result_orig = {}

model_orig = lgb.train(
    params_orig,
    train_set,
    valid_sets=[train_set, test_set],
    valid_names=["train", "valid"],
    num_boost_round=100,
    callbacks=[
        lgb.early_stopping(stopping_rounds=10),
        lgb.record_evaluation(evals_result_orig)
    ]
)

y_pred_orig = model_orig.predict(X_test)
y_pred_class_orig = (y_pred_orig > 0.5).astype(int)
orig_acc = accuracy_score(y_test, y_pred_class_orig)
orig_auc = roc_auc_score(y_test, y_pred_orig)

print(f"Original Model Accuracy: {orig_acc:.4f}")
print(f"Original Model AUC: {orig_auc:.4f}")
```

```
Training until validation scores don't improve for 10 rounds
Early stopping, best iteration is:
[12]	train's auc: 0.944721	valid's auc: 0.923362
Original Model Accuracy: 0.8424
Original Model AUC: 0.9234
```

In [29]:

```python
# STEP 3: AUC-ROC AND TRAIN/VALIDATION CURVES
fpr, tpr, _ = roc_curve(y_test, y_pred_orig)
plt.plot(fpr, tpr, label=f"AUC = {orig_auc:.2f}")
plt.plot([0, 1], [0, 1], linestyle="--")
plt.title("ROC Curve (Original Model)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid(True)
plt.show()

# Generate predictions per iteration for accuracy tracking
train_preds_orig = [model_orig.predict(X_train, num_iteration=i) for i in range(1, model_orig.best_iteration + 1)]
test_preds_orig = [model_orig.predict(X_test, num_iteration=i) for i in range(1, model_orig.best_iteration + 1)]

# Convert to binary predictions
train_acc_orig = [accuracy_score(y_train, (pred > 0.5).astype(int)) for pred in train_preds_orig]
test_acc_orig = [accuracy_score(y_test, (pred > 0.5).astype(int)) for pred in test_preds_orig]

# Plot
plt.plot(train_acc_orig, label="Train Accuracy")
plt.plot(test_acc_orig, label="Validation Accuracy")
plt.title("Step 2: Train vs Validation Accuracy (Original Model)")
plt.xlabel("Boosting Iteration")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.show()
```

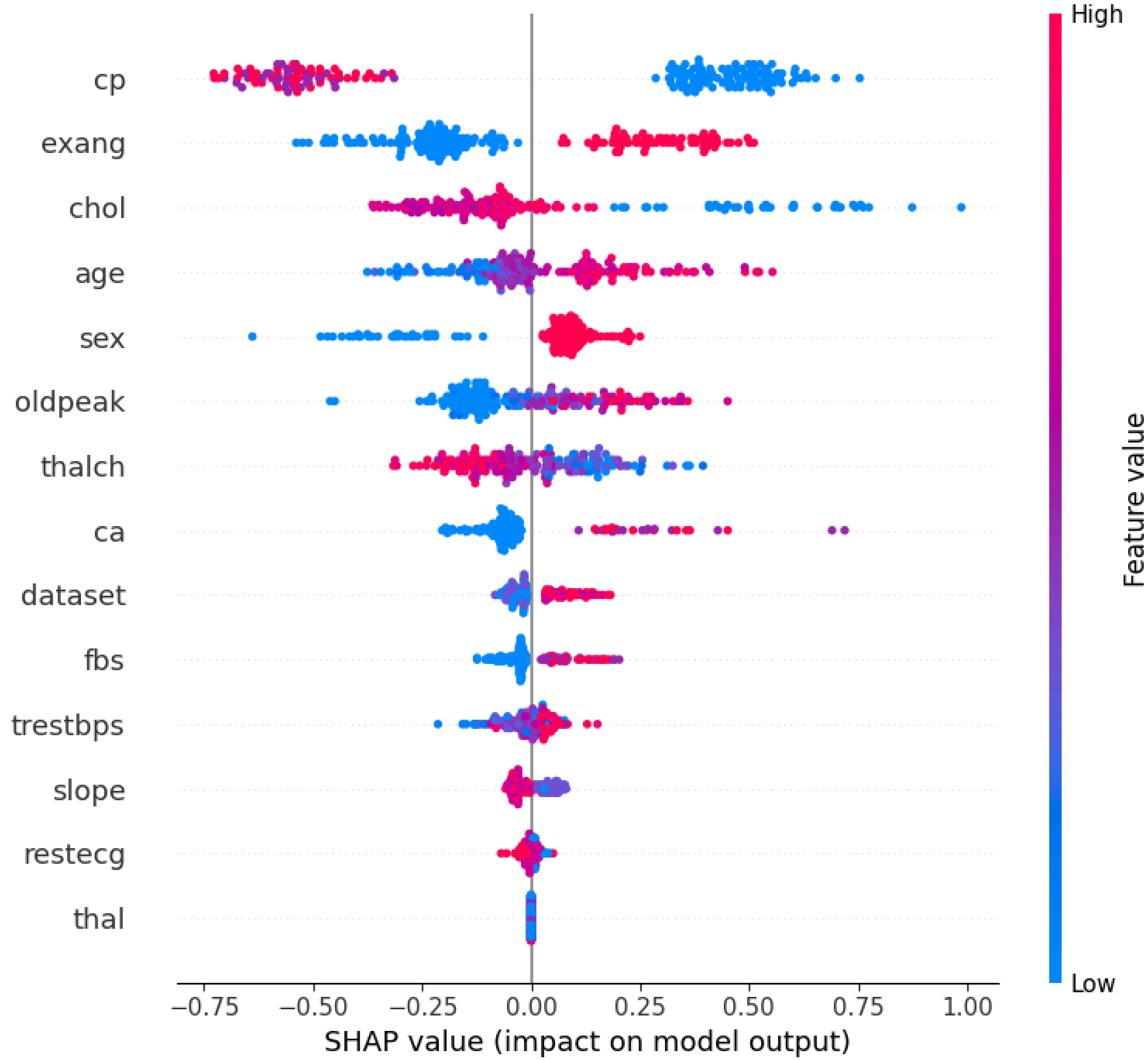

ROC Curve (Original Model)
AUC = 0.92
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Step 2: Train vs Validation Accuracy (Original Model)
Accuracy
0.85
0.80
0.75
0.70
0.65
0
2
4
6
8
10
Boosting Iteration
Train Accuracy
Validation Accuracy

SHAP and Lime

In [30]:
```
import shap

# TreeExplainer works with LightGBM
explainer = shap.TreeExplainer(model_orig)
shap_values = explainer.shap_values(X_test)

# Inspect what type of output we got
print("SHAP type:", type(shap_values))
if isinstance(shap_values, list):
    print("SHAP[0] shape:", np.array(shap_values[0]).shape)
else:
    print("SHAP shape:", np.array(shap_values).shape)

# Robust handling for binary classification (LightGBM)
if isinstance(shap_values, list) and len(shap_values) == 2:
    shap_to_plot = shap_values[1]  # class 1
else:
    shap_to_plot = shap_values  # fallback

# Summary plot
shap.summary_plot(shap_to_plot, X_test, feature_names=X_test.columns)
```

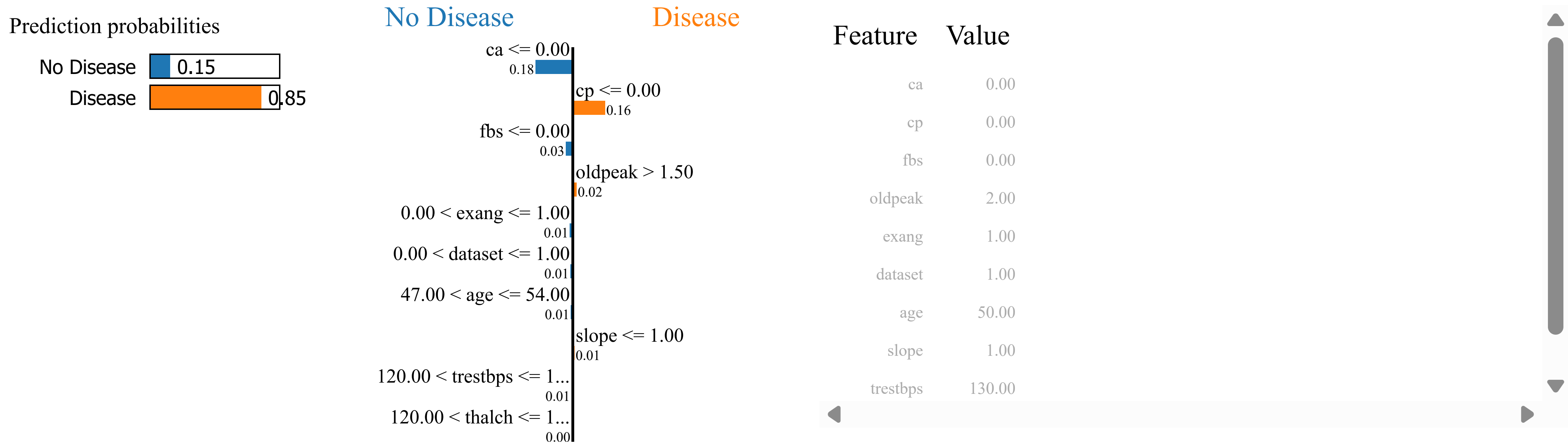
```
SHAP type: <class 'numpy.ndarray'>
SHAP shape: (184, 14)
```



cp
exang
chol
age
sex
oldpeak
thalch
ca
dataset
fbs
trestbps
slope
restecg
thal
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
SHAP value (impact on model output)
High
Low
Feature value

In [31]:

```python
import lime
import lime.lime_tabular
import numpy as np

# Setup LIME Explainer
lime_explainer = lime.lime_tabular.LimeTabularExplainer(
    training_data=X_train.values,
    feature_names=X_train.columns.tolist(),
    class_names=["No Disease", "Disease"],
    mode="classification"
)

# Define prediction function
def lime_predict_fn(data):
    return np.column_stack([
        1 - model_orig.predict(data),
        model_orig.predict(data)
    ])

# Explain a specific test sample
idx = 7  # change index to inspect different test cases
lime_exp = lime_explainer.explain_instance(
    data_row=X_test.iloc[idx].values,
    predict_fn=lime_predict_fn,
    num_features=10
)

# Show explanation
lime_exp.show_in_notebook(show_table=True)
```


Prediction probabilities
No Disease 0.15
Disease 0.85
No Disease
Disease
ca <= 0.00
0.18
cp <= 0.00
0.16
fbs <= 0.00
0.03
oldpeak > 1.50
0.02
0.00 < exang <= 1.00
0.01
0.00 < dataset <= 1.00
0.01
47.00 < age <= 54.00
0.01
slope <= 1.00
0.01
120.00 < trestbps <= 1...
0.01
120.00 < thalch <= 1...
0.00
Feature Value
ca 0.00
cp 0.00
fbs 0.00
oldpeak 2.00
exang 1.00
dataset 1.00
age 50.00
slope 1.00
trestbps 130.00