In [1]:

```
!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 (f
rom scikeras) (3.8.0)
Requirement already satisfied: scikit-learn>=1.4.2 in /usr/local/lib/python3.11/dist-pack
ages (from scikeras) (1.6.1)
Requirement already satisfied: absl-py in /usr/local/lib/python3.11/dist-packages (from k
eras>=3.2.0->scikeras) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from ker
as>=3.2.0->scikeras) (2.0.2)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from kera
s>=3.2.0->scikeras) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from ker
as>=3.2.0->scikeras) (0.1.0)
Requirement already satisfied: h5py in /usr/local/lib/python3.11/dist-packages (from kera
s>=3.2.0->scikeras) (3.13.0)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from ke
ras>=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 (f
rom 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-pac
kages (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-pa
ckages (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 (fro
m 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 [2]:

```
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 [3]:

```
df = pd.read_csv("cardio_disease.csv", delimiter=";")
```

Data Preprocessing

In [4]:

```
df.info()
df.describe()
df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70000 entries, 0 to 69999
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           70000 non-null  int64  
 1   age          70000 non-null  int64  
 2   gender       70000 non-null  int64  
 3   height       70000 non-null  int64  
 4   weight       70000 non-null  float64
 5   ap_hi        70000 non-null  int64  
 6   ap_lo        70000 non-null  int64  
 7   cholesterol  70000 non-null  int64  
 8   gluc         70000 non-null  int64  
 9   smoke        70000 non-null  int64  
 10  alco         70000 non-null  int64  
 11  active       70000 non-null  int64  
 12  cardio       70000 non-null  int64  
dtypes: float64(1), int64(12)
memory usage: 6.9 MB
```

Out[4]:

	0
id	0
age	0
gender	0
height	0
weight	0
ap_hi	0
ap_lo	0
cholesterol	0
gluc	0
smoke	0
alco	0
active	0
cardio	0

dtype: int64

In [5]:

```
# Convert age to years
df['age_years'] = (df['age'] / 365).astype(int)

# Create BMI
df['bmi'] = df['weight'] / (df['height'] / 100) ** 2

# Encode categorical values
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
df['smoke'] = df['smoke'].astype(bool)
```

```
df['alco'] = df['alco'].astype(bool)
df['active'] = df['active'].astype(bool)
df['cardio'] = df['cardio'].astype(bool)

# Drop unused columns
df.drop(columns=['id', 'age'], inplace=True)
```

In [6]:

```
numerical_features = ['age_years', 'height', 'weight', 'bmi', 'ap_hi', 'ap_lo']
categorical_features = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
```

In [7]:

```
df.head()
```

Out[7]:

	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio	age_years	bmi
0	male	168	62.0	110	80	normal	normal	False	False	True	False	50	21.967120
1	female	156	85.0	140	90	well above normal	normal	False	False	True	True	55	34.927679
2	female	165	64.0	130	70	well above normal	normal	False	False	False	True	51	23.507805
3	male	169	82.0	150	100	normal	normal	False	False	True	True	48	28.710479
4	female	156	56.0	100	60	normal	normal	False	False	False	False	47	23.011177

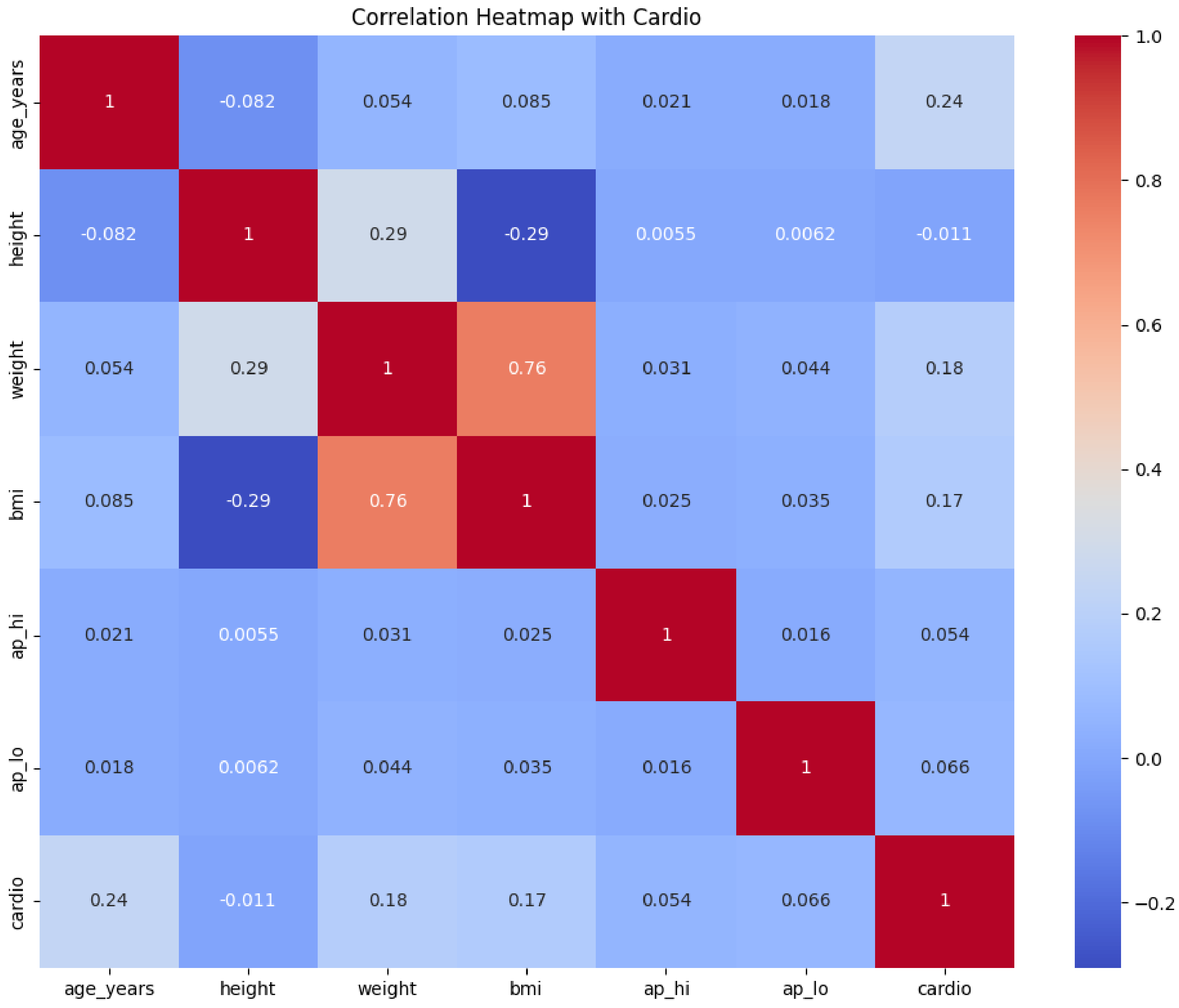
EDA

In [8]:

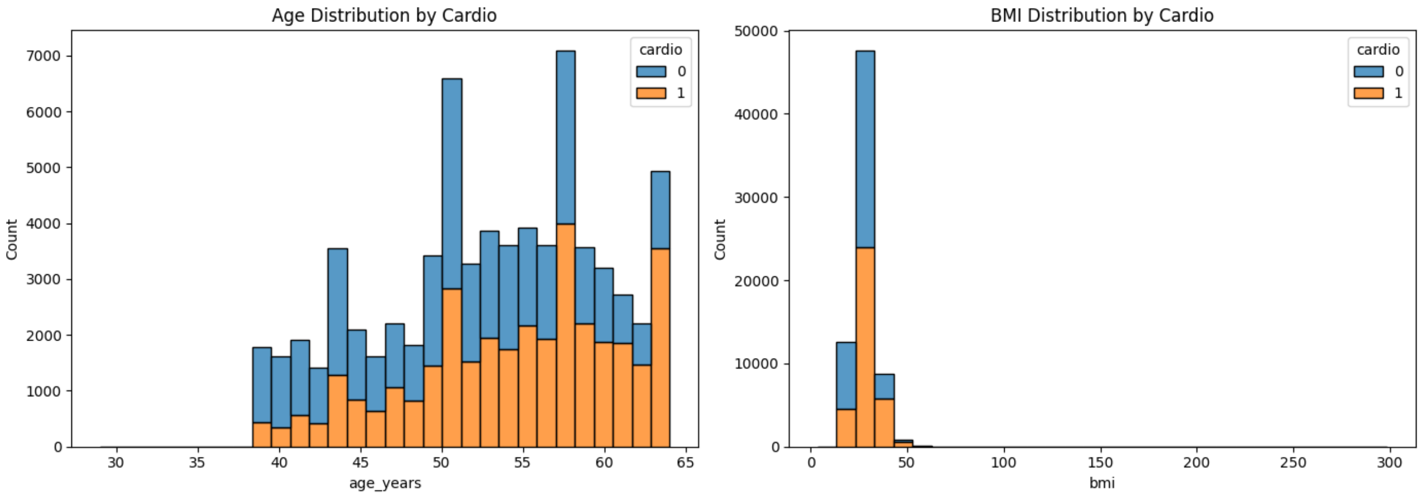
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

# Load the dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Preprocessing
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
df['smoke'] = df['smoke'].astype(bool)
df['alco'] = df['alco'].astype(bool)
df['active'] = df['active'].astype(bool)
df.drop(columns=['id', 'age'], inplace=True)

# Remove extreme blood pressure outliers
df_cleaned = df[(df['ap_hi'] > 80) & (df['ap_hi'] < 240) &
                (df['ap_lo'] > 40) & (df['ap_lo'] < 160)]
df_kde = df_cleaned[
    (df_cleaned['ap_hi'].between(df_cleaned['ap_hi'].quantile(0.01), df_cleaned['ap_hi']
.quantile(0.99))) &
    (df_cleaned['ap_lo'].between(df_cleaned['ap_lo'].quantile(0.01), df_cleaned['ap_lo']
.quantile(0.99)))
]

# 1. Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df[['age_years', 'height', 'weight', 'bmi', 'ap_hi', 'ap_lo', 'cardio']].cor
r(), annot=True, cmap='coolwarm')
```

```
plt.title("Correlation Heatmap with Cardio")
plt.tight_layout()
plt.show()
print("""
[1] Correlation Heatmap:
- 'age_years', 'ap_hi', and 'bmi' are positively correlated with 'cardio'.
- Indicates that older age, high systolic BP, and high BMI increase CVD risk.
- Height shows slight negative relation.
""")

# 2. Age and BMI Distributions
plt.figure(figsize=(14, 5))
plt.subplot(1, 2, 1)
sns.histplot(data=df, x='age_years', hue='cardio', bins=30, multiple='stack')
plt.title("Age Distribution by Cardio")

plt.subplot(1, 2, 2)
sns.histplot(data=df, x='bmi', hue='cardio', bins=30, multiple='stack')
plt.title("BMI Distribution by Cardio")
plt.tight_layout()
plt.show()
print("""
[2] Age & BMI Distributions:
- CVD cases (cardio=1) are more frequent after age 50.
- Higher BMI also correlates with increased CVD.
""")

# 3. Blood Pressure Distributions
plt.figure(figsize=(14, 5))
plt.subplot(1, 2, 1)
sns.histplot(data=df_kde, x='ap_hi', hue='cardio', kde=True, bins=40, element='step', st
at='density')
plt.title("Systolic BP by Cardio")

plt.subplot(1, 2, 2)
sns.histplot(data=df_kde, x='ap_lo', hue='cardio', kde=True, bins=40, element='step', st
at='density')
plt.title("Diastolic BP by Cardio")
plt.tight_layout()
plt.show()
print("""
[3] Blood Pressure:
- Systolic BP (ap_hi) is higher in CVD patients.
- Diastolic BP shows minor upward shift for CVD.
""")

# 4. Categorical Features
plt.figure(figsize=(16, 10))
cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
for i, col in enumerate(cat_cols):
    plt.subplot(2, 3, i+1)
    sns.countplot(data=df, x=col, hue='cardio')
    plt.title(f"{col.capitalize()} vs Cardio")
plt.tight_layout()
plt.show()
print("""
[4] Categorical Features:
- High cholesterol and glucose = higher CVD risk.
- Inactivity, alcohol use, and male gender slightly increase risk.
""")

# 5. Feature Interaction Plots
fig, axs = plt.subplots(2, 2, figsize=(14, 10))
sns.scatterplot(data=df_kde, x='age_years', y='ap_hi', hue='cardio', alpha=0.3, ax=axs[0
, 0])
axs[0, 0].set_title('Age vs Systolic BP by Cardio')

sns.scatterplot(data=df_kde, x='age_years', y='bmi', hue='cardio', alpha=0.3, ax=axs[0,
1])
axs[0, 1].set_title('Age vs BMI by Cardio')

sns.histplot(data=df_kde, x='bmi', hue='cardio', bins=30, kde=True, ax=axs[1, 0])
```

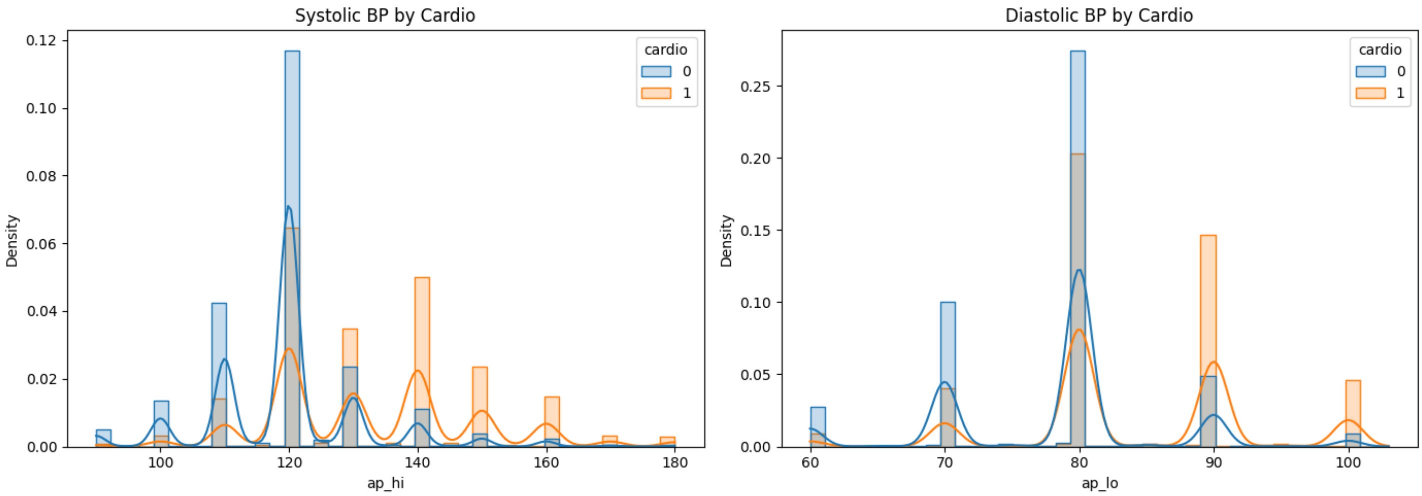
```
axs[1, 0].set_title('BMI Distribution by Cardio')

sns.histplot(data=df_kde, x='age_years', hue='cardio', bins=30, kde=True, ax=axs[1, 1])
axs[1, 1].set_title('Age Distribution by Cardio')
plt.tight_layout()
plt.show()
print("""
[5] Feature Interaction Insights:
- Older + hypertensive or high BMI = stronger CVD association.
- Clustering patterns are evident for CVD-positive patients.
""")

# 6. Target Class Distribution
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x='cardio')
plt.title("Target Variable Distribution (Cardio)")
plt.xlabel("Cardio (0 = No Disease, 1 = Disease)")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
print("""
[6] Target Variable Balance:
- Balanced dataset: ~50% have cardiovascular disease.
- Good for training classification models without imbalance correction.
""")
```



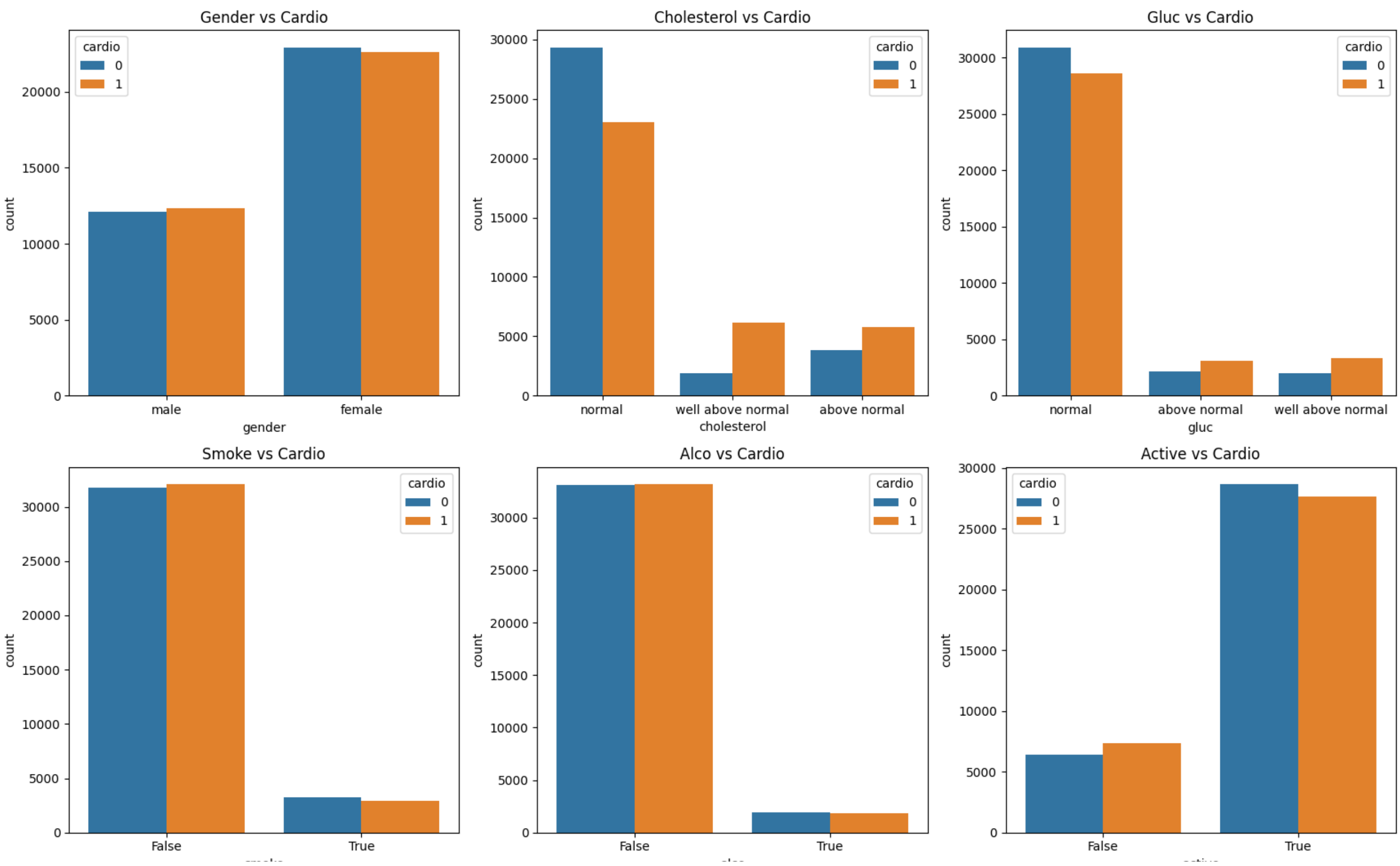

```
[1] Correlation Heatmap:
- 'age_years', 'ap_hi', and 'bmi' are positively correlated with 'cardio'.
- Indicates that older age, high systolic BP, and high BMI increase CVD risk.
- Height shows slight negative relation.
```



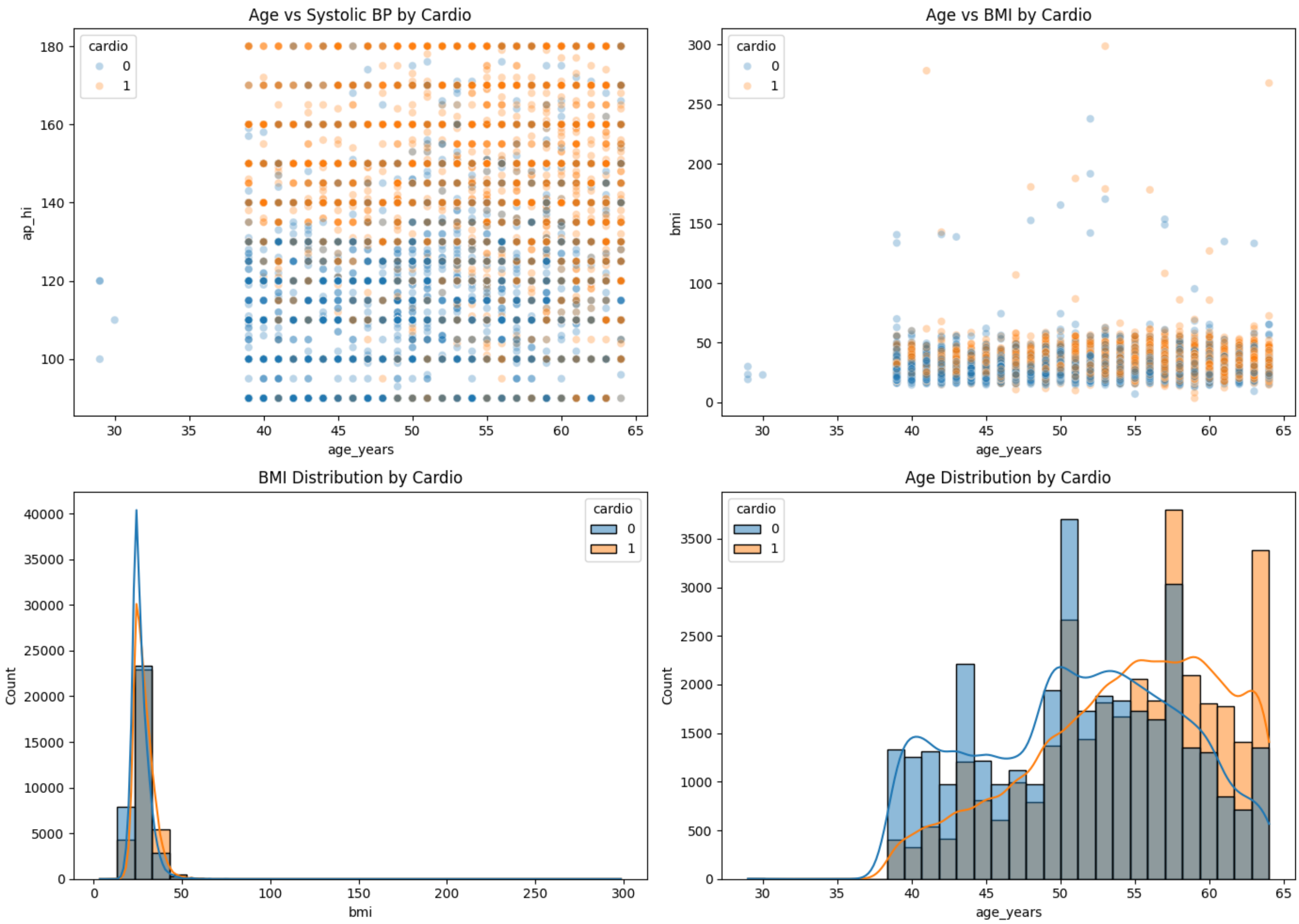

```
[2] Age & BMI Distributions:
- CVD cases (cardio=1) are more frequent after age 50.
- Higher BMI also correlates with increased CVD.
```



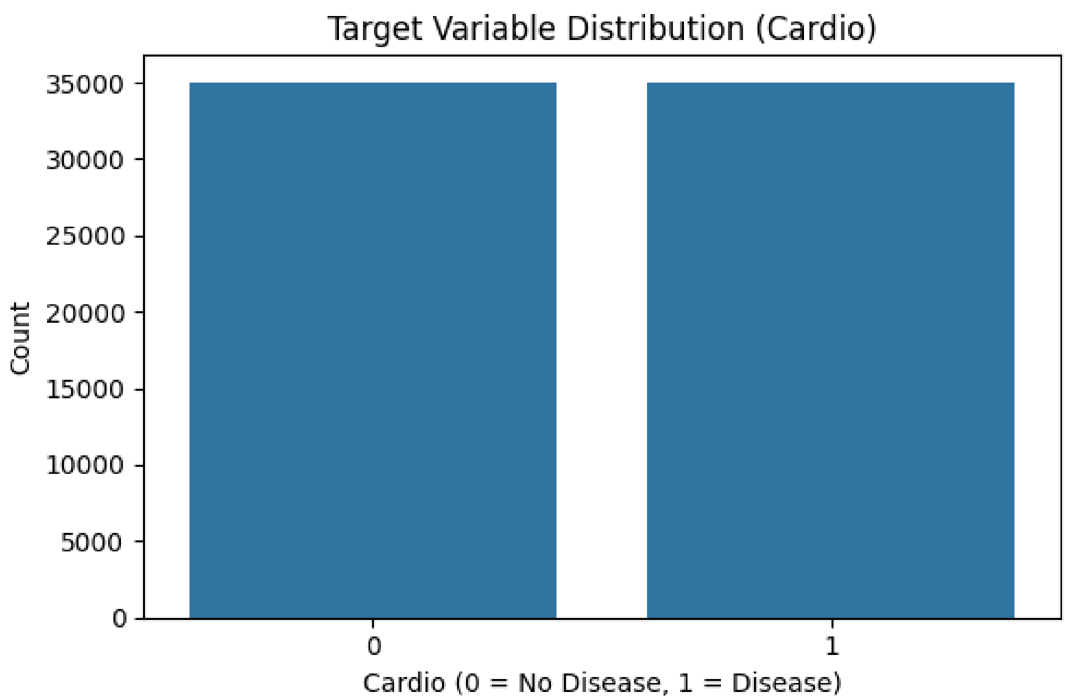

```
[3] Blood Pressure:
- Systolic BP (ap_hi) is higher in CVD patients.
- Diastolic BP shows minor upward shift for CVD.
```



```
[4] Categorical Features:
- High cholesterol and glucose = higher CVD risk.
- Inactivity, alcohol use, and male gender slightly increase risk.
```




```
[5] Feature Interaction Insights:
- Older + hypertensive or high BMI = stronger CVD association.
- Clustering patterns are evident for CVD-positive patients.
```




```
[6] Target Variable Balance:
- Balanced dataset: ~50% have cardiovascular disease.
- Good for training classification models without imbalance correction.
```

In [9]:

```
# !pip install pytorch-tabular scikit-learn matplotlib
```

In [10]:

```
# !pip install pytorch-tabular==0.8.0
```

In [11]:

```
# !pip install torch==2.6.0
```

In [12]:

```
# !pip install pytorch-tabular scikit-learn matplotlib pandas -q
# !pip install scikit-optimize
# !pip install omegaconf
# !pip install lightgbm scikit-learn matplotlib pandas -q
```

In [13]:

```
# # EDA + Embedding + Evaluation
# 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, classification_report, roc_auc_score,
#                              roc_curve, precision_recall_curve)

# from pytorch_tabular import TabularModel
# from pytorch_tabular.config import DataConfig, TrainerConfig, OptimizerConfig
# #from pytorch_tabular.models.category_embedding_model.config import CategoryEmbeddingMo
delConfig
# from pytorch_tabular.models import CategoryEmbeddingModelConfig

# # Load and preprocess
# df = pd.read_csv("cardio_disease.csv", delimiter=';')
# df['age_years'] = (df['age'] / 365).astype(int)
# df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
# df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
# df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abo
ve normal'})
# df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
# df['smoke'] = df['smoke'].astype(str)
# df['alco'] = df['alco'].astype(str)
# df['active'] = df['active'].astype(str)
# df.drop(columns=['id', 'age'], inplace=True)

# # Features
# target_col = "cardio"
# cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
# cont_cols = [col for col in df.columns if col not in cat_cols + [target_col]]

# train_df, test_df = train_test_split(df, test_size=0.2, random_state=42, stratify=df[ta
rget_col])

# # Configuration
# data_config = DataConfig(target=[target_col], continuous_cols=cont_cols, categorical_co
ls=cat_cols)
# model_config = CategoryEmbeddingModelConfig(
#     task="classification", layers="128-64", activation="ReLU",
#     learning_rate=1e-3, metrics=["accuracy", "roc_auc"]
# )
# trainer_config = TrainerConfig(auto_lr_find=True, batch_size=512, max_epochs=20, early_
stopping_patience=10)
# optimizer_config = OptimizerConfig()

# # Train Model
```

```
# tabular_model = TabularModel(
#     data_config=data_config, model_config=model_config,
#     optimizer_config=optimizer_config, trainer_config=trainer_config
# )
# tabular_model.fit(train=train_df, validation=test_df)

# # Evaluate
# pred_df = tabular_model.predict(test_df)
# y_true = test_df[target_col].values
# y_pred = (pred_df["prediction"].values > 0.5).astype(int)
# y_proba = pred_df["prediction"].values

# # Metrics
# print("Classification Report:\n", classification_report(y_true, y_pred))
# print(f"Accuracy: {accuracy_score(y_true, y_pred):.4f}")
# print(f"Precision: {precision_score(y_true, y_pred):.4f}")
# print(f"Recall: {recall_score(y_true, y_pred):.4f}")
# print(f"F1 Score: {f1_score(y_true, y_pred):.4f}")
# print(f"ROC AUC: {roc_auc_score(y_true, y_proba):.4f}")

# # ROC Curve
# fpr, tpr, _ = roc_curve(y_true, y_proba)
# plt.figure()
# plt.plot(fpr, tpr, label=f"ROC Curve (AUC = {roc_auc_score(y_true, y_proba):.2f})")
# plt.plot([0, 1], [0, 1], 'k--')
# plt.xlabel("False Positive Rate")
# plt.ylabel("True Positive Rate")
# plt.title("ROC Curve")
# plt.grid()
# plt.legend()
# plt.show()

# # PR Curve
# precision_vals, recall_vals, _ = precision_recall_curve(y_true, y_proba)
# plt.figure()
# plt.plot(recall_vals, precision_vals, label="Precision-Recall Curve")
# plt.xlabel("Recall")
# plt.ylabel("Precision")
# plt.title("Precision-Recall Curve")
# plt.grid()
# plt.legend()
# plt.show()
```

In [14]:

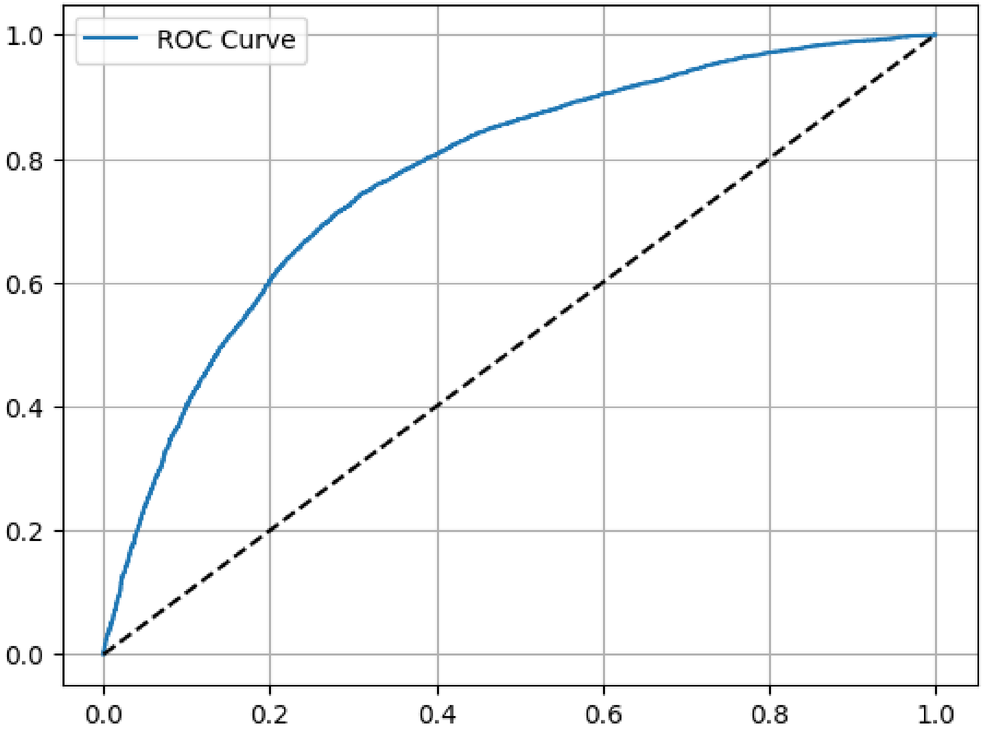
```
from fastai.tabular.all import *
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, classification_report, roc_auc_score,
                             roc_curve, precision_recall_curve)
import matplotlib.pyplot as plt

# Load and preprocess
df = pd.read_csv("cardio_disease.csv", delimiter=';')
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
df['smoke'] = df['smoke'].astype(str)
df['alco'] = df['alco'].astype(str)
df['active'] = df['active'].astype(str)
df.drop(columns=['id', 'age'], inplace=True)

# Split
train_df, test_df = train_test_split(df, test_size=0.2, random_state=42, stratify=df["ca
rdio"])

# Tabular model
```

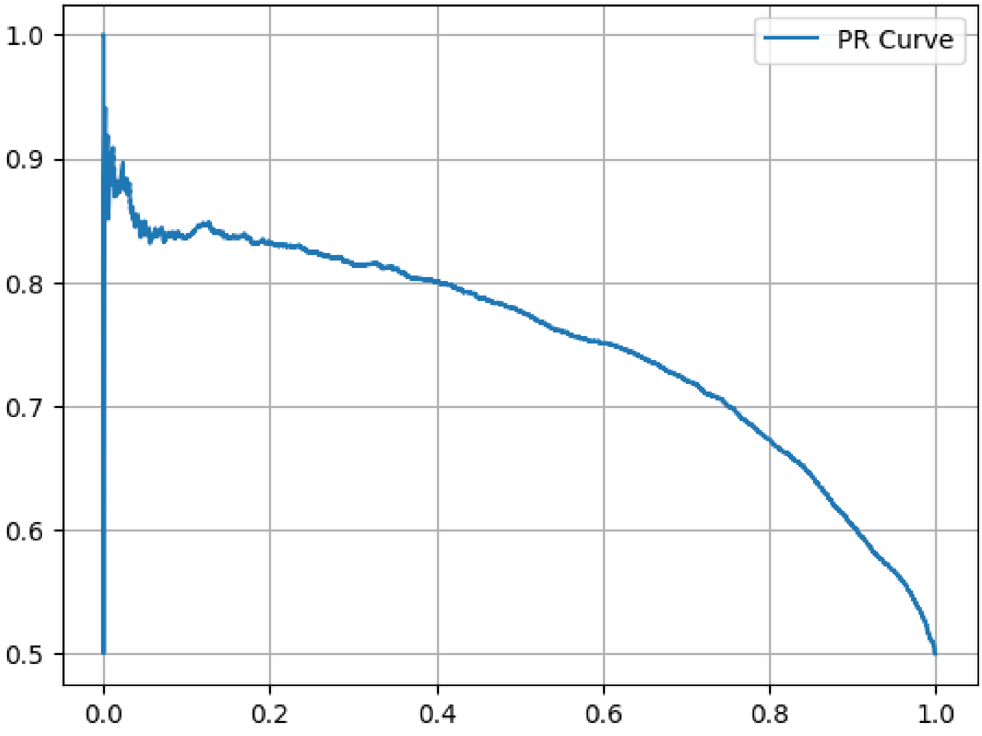
```
cat_names = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
cont_names = [col for col in df.columns if col not in cat_names + ['cardio']]
procs = [Categorify, FillMissing, Normalize]
dls = TabularDataLoaders.from_df(train_df, path='.', procs=procs, cat_names=cat_names,
                                  cont_names=cont_names, y_names='cardio', valid_idx=None
)

learn = tabular_learner(dls, metrics=[accuracy, RocAuc()])
learn.fit(10)

# Predict
test_dl = dls.test_dl(test_df)
preds, targs = learn.get_preds(dl=test_dl)
# Access the first column (index 0) for the predicted probabilities
pred_probs = preds[:, 0] # Use index 0 instead of 1
pred_labels = (pred_probs > 0.5).int()

# Evaluation
print("Classification Report:\n", classification_report(targs, pred_labels))
print(f"Accuracy: {accuracy_score(targs, pred_labels):.4f}")
print(f"Precision: {precision_score(targs, pred_labels):.4f}")
print(f"Recall: {recall_score(targs, pred_labels):.4f}")
print(f"F1 Score: {f1_score(targs, pred_labels):.4f}")
# Use the predicted probabilities for ROC AUC
print(f"ROC AUC: {roc_auc_score(targs, pred_probs):.4f}")

# ROC
fpr, tpr, _ = roc_curve(targs, pred_probs) # Use pred_probs
plt.figure()
plt.plot(fpr, tpr, label="ROC Curve")
plt.plot([0, 1], [0, 1], 'k--')
plt.grid()
plt.legend()
plt.show()

# PR Curve
precision_vals, recall_vals, _ = precision_recall_curve(targs, pred_probs) # Use pred_pr
obs
plt.figure()
plt.plot(recall_vals, precision_vals, label="PR Curve")
plt.grid()
plt.legend()
plt.show()
```

epoch	train_loss	valid_loss	accuracy	roc_auc_score	time
0	0.191778	0.376300	0.498839	0.500000	00:10
1	0.187951	0.213151	0.498839	0.500000	00:07
2	0.188584	0.416445	0.498839	0.500000	00:06
3	0.185223	0.190307	0.498839	0.500000	00:07
4	0.185504	0.217570	0.498839	0.500000	00:06
5	0.184526	0.203766	0.498839	0.500000	00:06
6	0.181332	0.548791	0.498839	0.500000	00:06
7	0.184406	0.202873	0.498839	0.500000	00:07
8	0.179879	0.219293	0.498839	0.500000	00:07
9	0.191189	0.206489	0.498839	0.500000	00:06

```
Classification Report:
               precision    recall  f1-score   support

           0       0.70      0.76      0.72      7004
           1       0.73      0.67      0.70      6996

    accuracy                           0.71     14000
   macro avg       0.71      0.71      0.71     14000
```

```
weighted avg       0.71      0.71      0.71     14000

Accuracy: 0.7123
Precision: 0.7322
Recall: 0.6688
F1 Score: 0.6991
ROC AUC: 0.7754
```





Trying Generalization

In [15]:

```
# Imports
from fastai.tabular.all import *
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, accuracy_score, precision_score, recal
l_score, f1_score, roc_auc_score, roc_curve, precision_recall_curve

# Load dataset
```

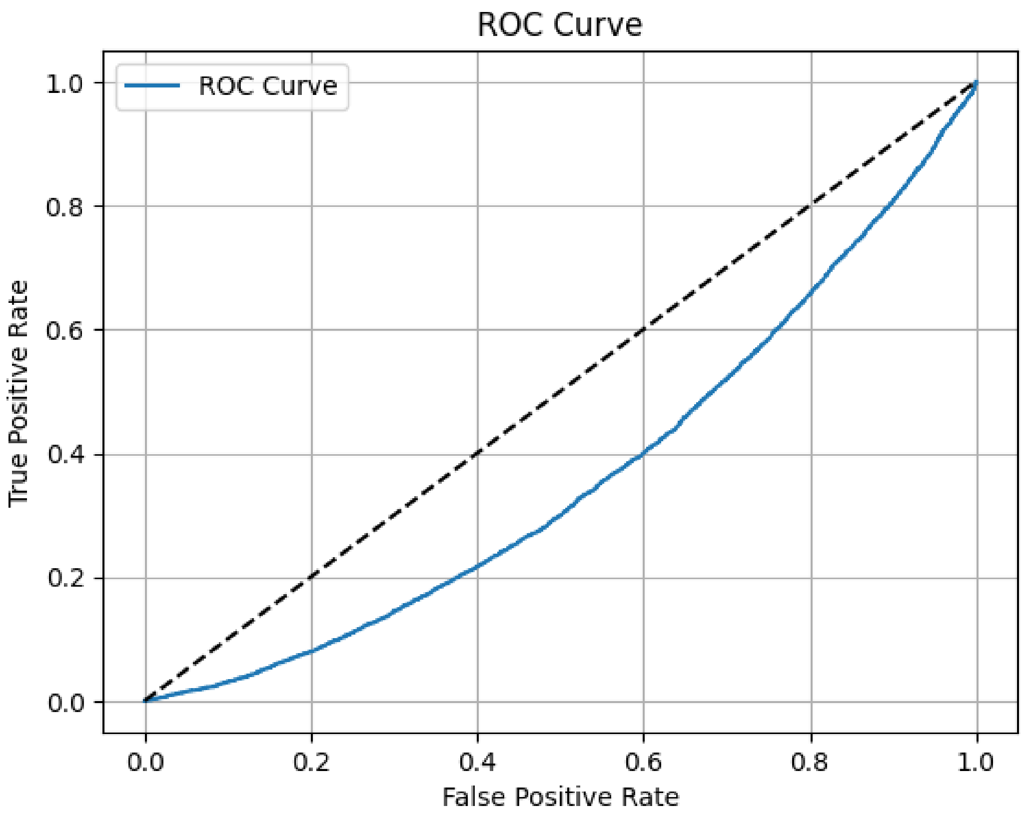
```
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
df['smoke'] = df['smoke'].astype(str)
df['alco'] = df['alco'].astype(str)
df['active'] = df['active'].astype(str)
df.drop(columns=['id', 'age'], inplace=True)

# Remove outliers
df = df[(df['bmi'] > 15) & (df['bmi'] < 45) & (df['ap_hi'] < 250)]

# Define categorical and continuous columns
cat_names = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
cont_names = [col for col in df.columns if col not in cat_names + ['cardio']]
procs = [Categorify, FillMissing, Normalize]

# Create DataLoaders
splits = RandomSplitter(seed=42)(range_of(df))
dls = TabularDataLoaders.from_df(df, path='.', procs=procs, cat_names=cat_names,
                                 cont_names=cont_names, y_names='cardio', splits=splits)

# Create model — DO NOT pass config or emb_drop directly
learn = tabular_learner(
    dls,
    layers=[300, 150, 75],  # Deep MLP
    metrics=[accuracy, RocAuc()]
)

# Train
learn.fit_one_cycle(30, lr_max=1e-2)

# Predict on validation set
test_df = dls.valid.items
test_dl = dls.test_dl(test_df)
preds, targs = learn.get_preds(dl=test_dl)

# Access the first column (index 0) for the predicted probabilities
# This column represents the probability of the positive class (cardio=1)
pred_probs = preds[:, 0]
pred_labels = (pred_probs > 0.5).int() # Use probabilities for thresholding

# Print metrics
print("Classification Report:\n", classification_report(targs, pred_labels))
print(f"Accuracy: {accuracy_score(targs, pred_labels):.4f}")
print(f"Precision: {precision_score(targs, pred_labels):.4f}")
print(f"Recall: {recall_score(targs, pred_labels):.4f}")
print(f"F1 Score: {f1_score(targs, pred_labels):.4f}")
# Use the probabilities for ROC AUC calculation
print(f"ROC AUC: {roc_auc_score(targs, pred_probs):.4f}")

# ROC Curve
# Use the probabilities for the ROC curve
fpr, tpr, _ = roc_curve(targs, pred_probs)
plt.figure()
plt.plot(fpr, tpr, label="ROC Curve")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()

# Precision-Recall Curve
# Use the probabilities for the PR curve
```

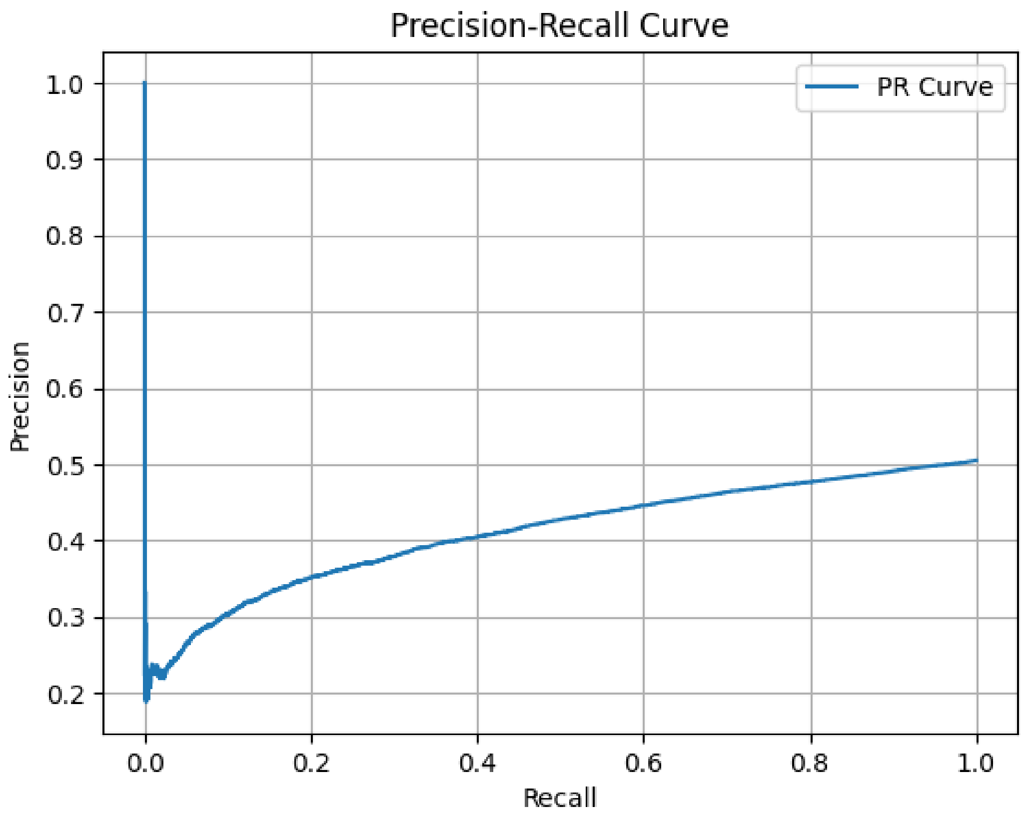
```
precision_vals, recall_vals, _ = precision_recall_curve(targs, pred_probs)
plt.figure()
plt.plot(recall_vals, precision_vals, label="PR Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.grid()
plt.show()
```

epoch	train_loss	valid_loss	accuracy	roc_auc_score	time
0	0.201516	0.197478	0.495204	0.500000	00:10
1	0.189139	0.187757	0.495204	0.500000	00:11
2	0.186769	0.185366	0.495204	0.500000	00:10
3	0.188496	0.183506	0.495204	0.500000	00:11
4	0.185505	0.182334	0.495204	0.500000	00:10
5	0.181116	0.181774	0.495204	0.500000	00:09
6	0.179416	0.182061	0.495204	0.500000	00:10
7	0.184826	0.181262	0.495204	0.500000	00:10
8	0.187631	0.183689	0.495204	0.500000	00:10
9	0.185630	0.185550	0.495204	0.500000	00:10
10	0.179606	0.183291	0.495204	0.500000	00:10
11	0.182223	0.182579	0.495204	0.500000	00:10
12	0.180662	0.183272	0.495204	0.500000	00:10
13	0.181876	0.183328	0.495204	0.500000	00:10
14	0.185026	0.211121	0.495204	0.500000	00:10
15	0.181082	0.181663	0.495204	0.500000	00:10
16	0.182921	0.181645	0.495204	0.500000	00:10
17	0.183468	0.181615	0.495204	0.500000	00:09
18	0.183088	0.180883	0.495204	0.500000	00:10
19	0.185615	0.181569	0.495204	0.500000	00:10
20	0.178112	0.181704	0.495204	0.500000	00:16
21	0.183961	0.182973	0.495204	0.500000	00:20
22	0.178090	0.186014	0.495204	0.500000	00:10
23	0.178698	0.181662	0.495204	0.500000	00:09
24	0.176137	0.180849	0.495204	0.500000	00:10
25	0.183606	0.181094	0.495204	0.500000	00:10
26	0.185565	0.180958	0.495204	0.500000	00:10
27	0.176852	0.183607	0.495204	0.500000	00:10
28	0.185330	0.182245	0.495204	0.500000	00:10
29	0.183166	0.181123	0.495204	0.500000	00:12

```
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      6866
           1       0.50      1.00      0.67      6999

    accuracy                           0.50     13865
   macro avg       0.25      0.50      0.34     13865
weighted avg       0.25      0.50      0.34     13865
```

```
Accuracy: 0.5048
Precision: 0.5048
Recall: 1.0000
F1 Score: 0.6709
ROC AUC: 0.3643
```





In [16]:

```
# TensorFlow categorical embedding model for classification
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report, roc_auc_score
```

```python
# Load data
df = pd.read_csv("cardio_disease.csv", delimiter=';')
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['age_chol'] = df['age_years'] * df['cholesterol']
df.drop(columns=['id', 'age'], inplace=True)

# Clean data
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 150)]
df = df[(df['bmi'] > 15) & (df['bmi'] < 45)]

# Encode categoricals
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Split
X = df.drop("cardio", axis=1)
y = df["cardio"]
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)

# Scale
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, activation='relu', input_shape=(X_train_scaled.shape[1],)
),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

# Compile
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', tf.kera
s.metrics.AUC(name='auc')])

# Train
history = model.fit(X_train_scaled, y_train, validation_split=0.2, epochs=30, batch_size
=64, verbose=1)

# Evaluate
y_pred_prob = model.predict(X_test_scaled).flatten()
y_pred = (y_pred_prob > 0.5).astype(int)
print("\n Classification Report:\n", classification_report(y_test, y_pred))
print(f"ROC AUC: {roc_auc_score(y_test, y_pred_prob):.4f}")
```

```
Epoch 1/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.7133 - auc: 0.7734 - loss: 0.5743
- val_accuracy: 0.7314 - val_auc: 0.8007 - val_loss: 0.5447
Epoch 2/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7281 - auc: 0.7919 - loss: 0.5538
- val_accuracy: 0.7314 - val_auc: 0.8027 - val_loss: 0.5430
Epoch 3/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7329 - auc: 0.7964 - loss: 0.5485
- val_accuracy: 0.7334 - val_auc: 0.8037 - val_loss: 0.5403
Epoch 4/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7279 - auc: 0.7961 - loss: 0.5485
- val_accuracy: 0.7353 - val_auc: 0.8042 - val_loss: 0.5388
Epoch 5/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7372 - auc: 0.8013 - loss: 0.5421
```

```
- val_accuracy: 0.7340 - val_auc: 0.8035 - val_loss: 0.5455
Epoch 6/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7341 - auc: 0.7991 - loss: 0.5441
- val_accuracy: 0.7369 - val_auc: 0.8054 - val_loss: 0.5378
Epoch 7/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7342 - auc: 0.7997 - loss: 0.5436
- val_accuracy: 0.7355 - val_auc: 0.8041 - val_loss: 0.5384
Epoch 8/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7359 - auc: 0.8026 - loss: 0.5403
- val_accuracy: 0.7367 - val_auc: 0.8036 - val_loss: 0.5394
Epoch 9/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7341 - auc: 0.8033 - loss: 0.5397
- val_accuracy: 0.7375 - val_auc: 0.8046 - val_loss: 0.5382
Epoch 10/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7364 - auc: 0.8020 - loss: 0.5409
- val_accuracy: 0.7360 - val_auc: 0.8048 - val_loss: 0.5374
Epoch 11/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7371 - auc: 0.8037 - loss: 0.5388
- val_accuracy: 0.7364 - val_auc: 0.8047 - val_loss: 0.5377
Epoch 12/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7398 - auc: 0.8042 - loss: 0.5377
- val_accuracy: 0.7355 - val_auc: 0.8046 - val_loss: 0.5375
Epoch 13/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7375 - auc: 0.8037 - loss: 0.5385
- val_accuracy: 0.7376 - val_auc: 0.8047 - val_loss: 0.5375
Epoch 14/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7320 - auc: 0.8005 - loss: 0.5417
- val_accuracy: 0.7350 - val_auc: 0.8050 - val_loss: 0.5375
Epoch 15/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7353 - auc: 0.8020 - loss: 0.5408
- val_accuracy: 0.7347 - val_auc: 0.8047 - val_loss: 0.5381
Epoch 16/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7332 - auc: 0.8021 - loss: 0.5407
- val_accuracy: 0.7352 - val_auc: 0.8050 - val_loss: 0.5371
Epoch 17/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7358 - auc: 0.8011 - loss: 0.5418
- val_accuracy: 0.7362 - val_auc: 0.8046 - val_loss: 0.5386
Epoch 18/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7339 - auc: 0.8007 - loss: 0.5415
- val_accuracy: 0.7342 - val_auc: 0.8045 - val_loss: 0.5392
Epoch 19/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7356 - auc: 0.8006 - loss: 0.5417
- val_accuracy: 0.7360 - val_auc: 0.8049 - val_loss: 0.5374
Epoch 20/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7350 - auc: 0.8021 - loss: 0.5408
- val_accuracy: 0.7354 - val_auc: 0.8046 - val_loss: 0.5378
Epoch 21/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7355 - auc: 0.8031 - loss: 0.5393
- val_accuracy: 0.7375 - val_auc: 0.8049 - val_loss: 0.5379
Epoch 22/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7358 - auc: 0.8023 - loss: 0.5405
- val_accuracy: 0.7370 - val_auc: 0.8033 - val_loss: 0.5387
Epoch 23/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 3ms/step - accuracy: 0.7390 - auc: 0.8076 - loss: 0.5340
- val_accuracy: 0.7337 - val_auc: 0.8046 - val_loss: 0.5397
Epoch 24/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7354 - auc: 0.8046 - loss: 0.5380
- val_accuracy: 0.7353 - val_auc: 0.8039 - val_loss: 0.5387
Epoch 25/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.7388 - auc: 0.8056 - loss: 0.5360
- val_accuracy: 0.7352 - val_auc: 0.8043 - val_loss: 0.5384
Epoch 26/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7364 - auc: 0.8012 - loss: 0.5416
- val_accuracy: 0.7351 - val_auc: 0.8038 - val_loss: 0.5402
Epoch 27/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7364 - auc: 0.8036 - loss: 0.5391
- val_accuracy: 0.7353 - val_auc: 0.8035 - val_loss: 0.5387
Epoch 28/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - accuracy: 0.7379 - auc: 0.8073 - loss: 0.5349
- val_accuracy: 0.7354 - val_auc: 0.8043 - val_loss: 0.5379
Epoch 29/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7350 - auc: 0.8013 - loss: 0.5417
```

```
- val_accuracy: 0.7347 - val_auc: 0.8039 - val_loss: 0.5386
Epoch 30/30
682/682 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7387 - auc: 0.8046 - loss: 0.5373
- val_accuracy: 0.7349 - val_auc: 0.8046 - val_loss: 0.5382
426/426 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step

 Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.81      0.75      6901
           1       0.77      0.66      0.71      6722

    accuracy                           0.73     13623
   macro avg       0.74      0.73      0.73     13623
weighted avg       0.74      0.73      0.73     13623

ROC AUC: 0.7971
```

In [17]:

```
# !pip install fastai --quiet
```

In [18]:

```
# !pip install -U fastai --quiet
```

In [19]:

```
# # Trying Generalization
# # Imports
# from fastai.tabular.all import *
# import pandas as pd
# import matplotlib.pyplot as plt
# from sklearn.metrics import classification_report, accuracy_score, precision_score, rec
all_score, f1_score, roc_auc_score, roc_curve, precision_recall_curve

# # Load dataset
# df = pd.read_csv("cardio_disease.csv", delimiter=';')

# # Feature engineering
# df['age_years'] = (df['age'] / 365).astype(int)
# df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
# df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
# df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
# df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abo
ve normal'})
# df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
# df['smoke'] = df['smoke'].astype(str)
# df['alco'] = df['alco'].astype(str)
# df['active'] = df['active'].astype(str)
# df.drop(columns=['id', 'age'], inplace=True)

# # Remove outliers
# df = df[(df['bmi'] > 15) & (df['bmi'] < 45) & (df['ap_hi'] < 250)]

# # Define categorical and continuous columns
# cat_names = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
# cont_names = [col for col in df.columns if col not in cat_names + ['cardio']]
# procs = [Categorify, FillMissing, Normalize]

# # Create DataLoaders
# splits = RandomSplitter(seed=42)(range_of(df))
# dls = TabularDataLoaders.from_df(df, path='.', procs=procs, cat_names=cat_names,
#                                  cont_names=cont_names, y_names='cardio', splits=split
s)

# # Create model — DO NOT pass config or emb_drop directly
# learn = tabular_learner(
#     dls,
#     layers=[300, 150, 75],  # Deep MLP
#     metrics=[accuracy, RocAuc()]
```

```
# )

# # Train
# learn.fit_one_cycle(30, lr_max=1e-2)

# # Predict on validation set
# test_df = dls.valid.items
# test_dl = dls.test_dl(test_df)
# preds, targs = learn.get_preds(dl=test_dl)

# # Access the first column (index 0) for the predicted probabilities
# # This column represents the probability of the positive class (cardio=1)
# pred_probs = preds[:, 0]
# pred_labels = (pred_probs > 0.5).int() # Use probabilities for thresholding

# # Print metrics
# print("Classification Report:\n", classification_report(targs, pred_labels))
# print(f"Accuracy: {accuracy_score(targs, pred_labels):.4f}")
# print(f"Precision: {precision_score(targs, pred_labels):.4f}")
# print(f"Recall: {recall_score(targs, pred_labels):.4f}")
# print(f"F1 Score: {f1_score(targs, pred_labels):.4f}")
# # Use the probabilities for ROC AUC calculation
# print(f"ROC AUC: {roc_auc_score(targs, pred_probs):.4f}")

# # ROC Curve
# # Use the probabilities for the ROC curve
# fpr, tpr, _ = roc_curve(targs, pred_probs)
# plt.figure()
# plt.plot(fpr, tpr, label="ROC Curve")
# plt.plot([0, 1], [0, 1], 'k--')
# plt.xlabel("False Positive Rate")
# plt.ylabel("True Positive Rate")
# plt.title("ROC Curve")
# plt.legend()
# plt.grid()
# plt.show()

# # Precision-Recall Curve
# # Use the probabilities for the PR curve
# precision_vals, recall_vals, _ = precision_recall_curve(targs, pred_probs)
# plt.figure()
# plt.plot(recall_vals, precision_vals, label="PR Curve")
# plt.xlabel("Recall")
# plt.ylabel("Precision")
# plt.title("Precision-Recall Curve")
# plt.legend()
# plt.grid()
# plt.show()
```

In [20]:

```
!pip install lightgbm --quiet
```

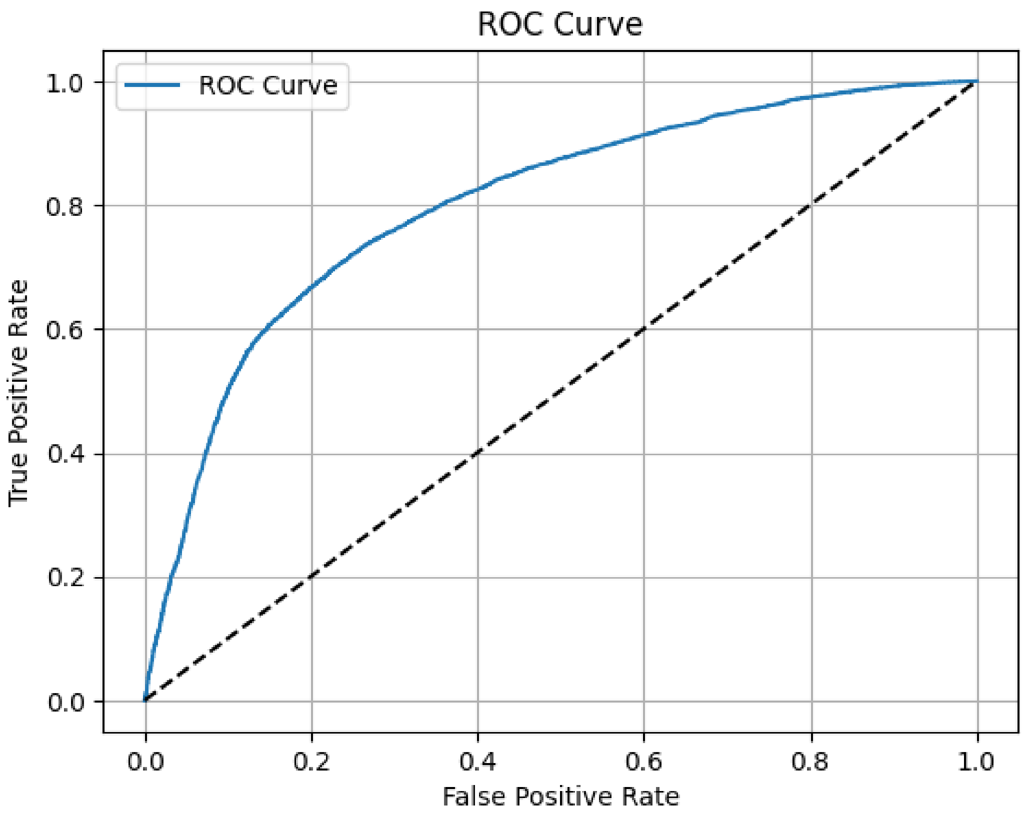
In [21]:

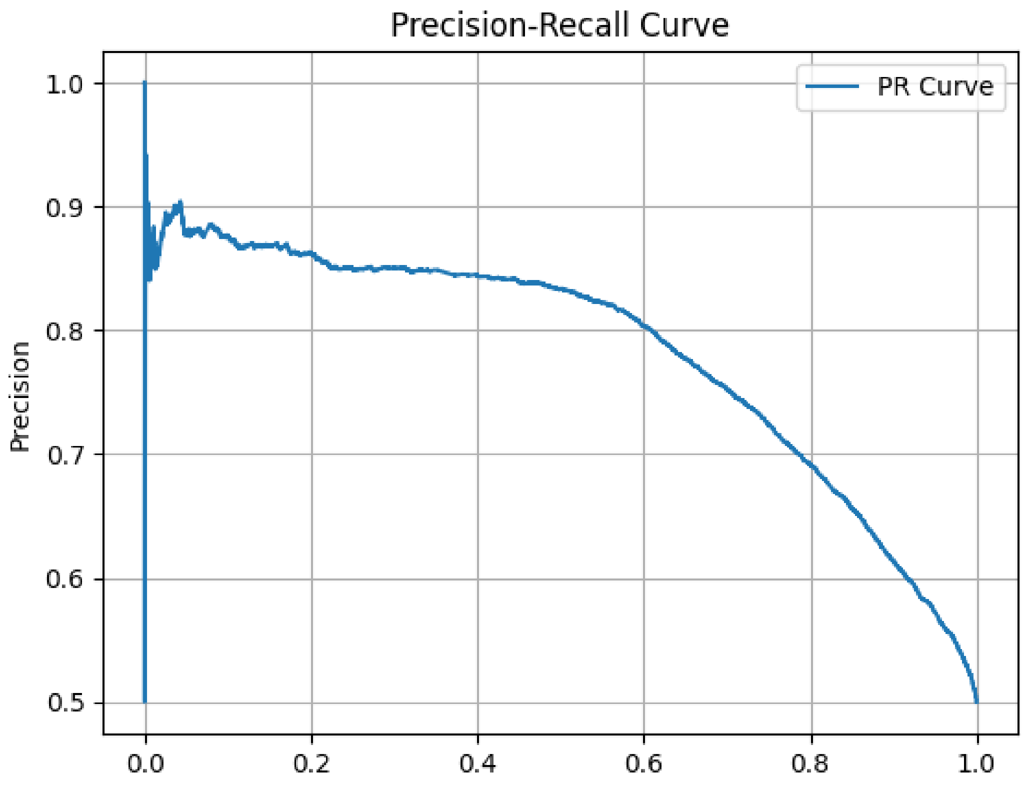
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, roc_auc_score, roc_curve,
                             precision_recall_curve, classification_report)
import lightgbm as lgb

# Load dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature Engineering
df['age_years'] = (df['age'] / 365).astype(int)
```

```
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df.drop(columns=['id', 'age'], inplace=True)

# Categorical encoding
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
df[cat_cols] = df[cat_cols].astype(str)

# Label encode for LightGBM
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Prepare data
X = df.drop('cardio', axis=1)
y = df['cardio']
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)

# Train LightGBM
train_data = lgb.Dataset(X_train, label=y_train)
valid_data = lgb.Dataset(X_test, label=y_test)

params = {
    'objective': 'binary',
    'metric': 'binary_logloss',
    'verbosity': -1,
    'random_state': 42
}

# Use lgb.early_stopping callback instead of early_stopping_rounds
callbacks = [lgb.early_stopping(10, verbose=False)] # 10 is the number of boosting rounds
without improvement

model = lgb.train(params, train_data, valid_sets=[valid_data], num_boost_round=100,
                  callbacks=callbacks) # Use the callbacks argument

# Predict
y_prob = model.predict(X_test)
y_pred = (y_prob > 0.5).astype(int)

# Metrics
print("Classification Report:\n", classification_report(y_test, y_pred))
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall: {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC: {roc_auc_score(y_test, y_prob):.4f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure()
plt.plot(fpr, tpr, label="ROC Curve")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()

# PR Curve
precision_vals, recall_vals, _ = precision_recall_curve(y_test, y_prob)
plt.figure()
plt.plot(recall_vals, precision_vals, label="PR Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
```

```
plt.grid()
plt.show()
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.77      0.74      7004
           1       0.75      0.70      0.73      6996

    accuracy                           0.74     14000
   macro avg       0.74      0.74      0.73     14000
weighted avg       0.74      0.74      0.73     14000

Accuracy: 0.7351
Precision: 0.7513
Recall: 0.7024
F1 Score: 0.7260
ROC AUC: 0.8004
```





Recall

Trying Generalization on LightGBM

In [22]:

```
!pip install lightgbm --quiet
```

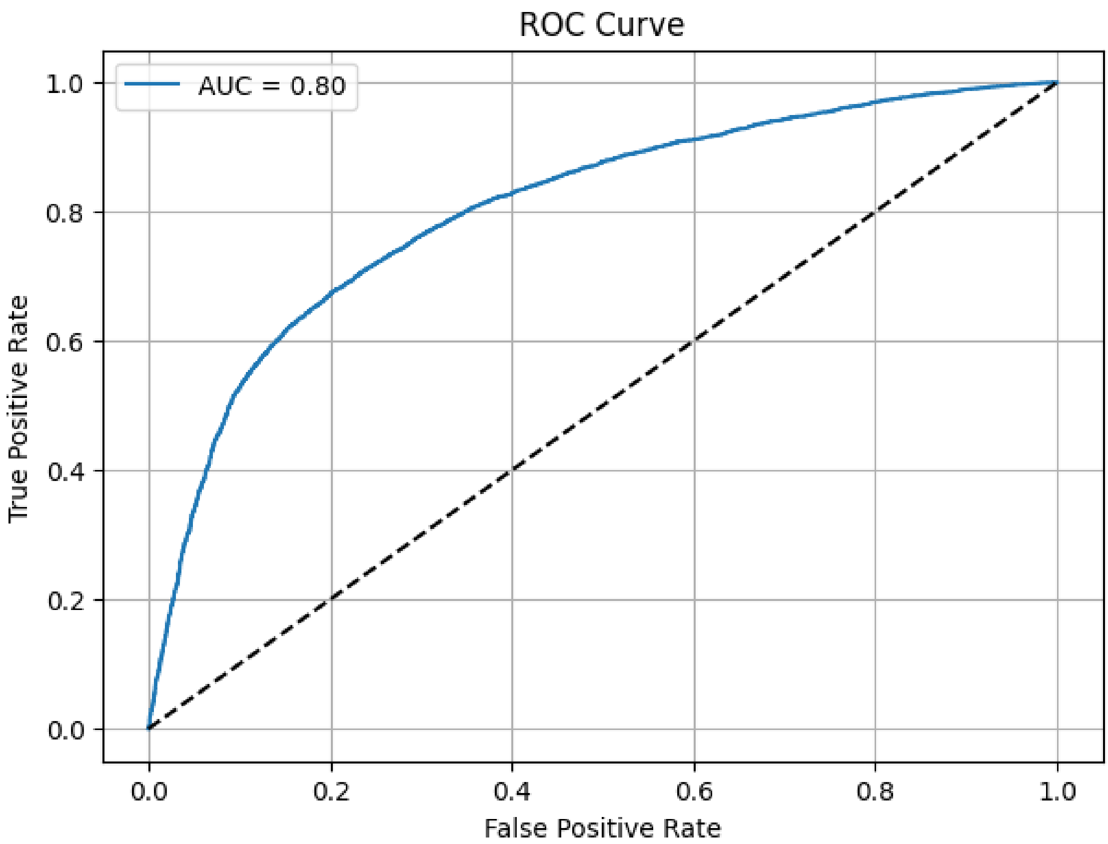
In [23]:

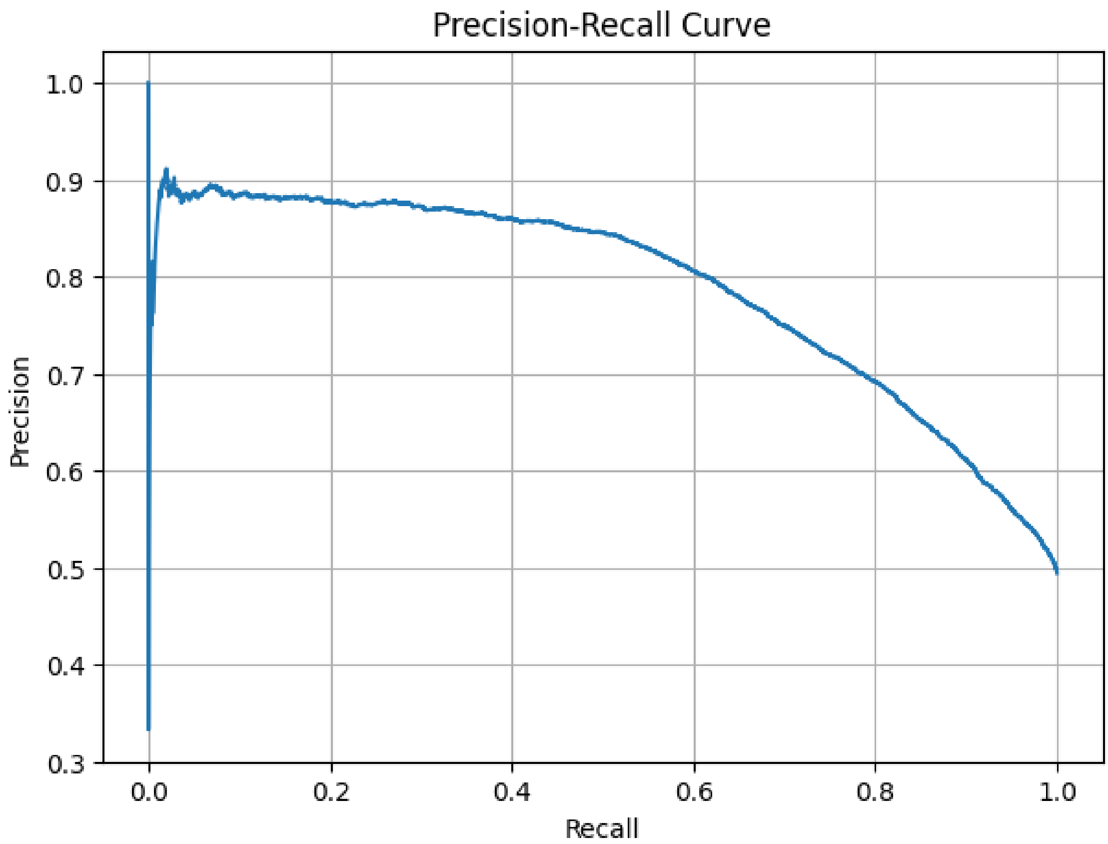
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import lightgbm as lgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    roc_auc_score, roc_curve, precision_recall_curve, classification_report
)

# Load dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['age_chol'] = df['age_years'] * df['cholesterol']
df.drop(columns=['id', 'age'], inplace=True)

# Outlier removal
df = df[(df['ap_hi'] > 80) & (df['ap_hi'] < 220)]
df = df[(df['ap_lo'] > 50) & (df['ap_lo'] < 150)]
df = df[(df['bmi'] > 15) & (df['bmi'] < 50)]

# Categorical cleanup + encoding
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})

cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
df[cat_cols] = df[cat_cols].astype(str)
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Features and target
X = df.drop('cardio', axis=1)
y = df['cardio']

# Stratified split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)

# Scale numeric features (optional but helps generalization)
scaler = StandardScaler()
X_train[X_train.columns] = scaler.fit_transform(X_train)
X_test[X_test.columns] = scaler.transform(X_test)

# Prepare LightGBM datasets
train_set = lgb.Dataset(X_train, label=y_train)
valid_set = lgb.Dataset(X_test, label=y_test)

# Strong LightGBM config for high accuracy
params = {
    'objective': 'binary',
    'metric': 'auc',
    'boosting_type': 'gbdt',
```

```
    'learning_rate': 0.005,
    'num_leaves': 64,
    'max_depth': 10,
    'min_child_samples': 80,
    'subsample': 0.9,
    'colsample_bytree': 0.9,
    'reg_alpha': 2,
    'reg_lambda': 2,
    'random_state': 42,
    'verbosity': -1
}

# Training with callback early stopping
model = lgb.train(
    params,
    train_set,
    num_boost_round=5000,
    valid_sets=[valid_set],
    callbacks=[lgb.early_stopping(stopping_rounds=100)]
)

# Prediction
y_prob = model.predict(X_test)
y_pred = (y_prob > 0.5).astype(int)

# Metrics
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall: {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC: {roc_auc_score(y_test, y_prob):.4f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label=f"AUC = {roc_auc_score(y_test, y_prob):.2f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.grid(True)
plt.legend()
plt.show()

# Precision-Recall Curve
precision, recall, _ = precision_recall_curve(y_test, y_prob)
plt.figure(figsize=(7, 5))
plt.plot(recall, precision)
plt.title("Precision-Recall Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.grid(True)
plt.show()
```

```
Training until validation scores don't improve for 100 rounds
Early stopping, best iteration is:
[999]	valid_0's auc: 0.804438

Classification Report:
               precision    recall  f1-score   support

           0       0.72      0.78      0.75      6901
           1       0.76      0.69      0.72      6755

    accuracy                           0.74     13656
   macro avg       0.74      0.74      0.74     13656
weighted avg       0.74      0.74      0.74     13656

Accuracy: 0.7360
Precision: 0.7552
Recall: 0.6900
```

```
F1 Score: 0.7211
ROC AUC: 0.8044
```





LightGBM and SHAP

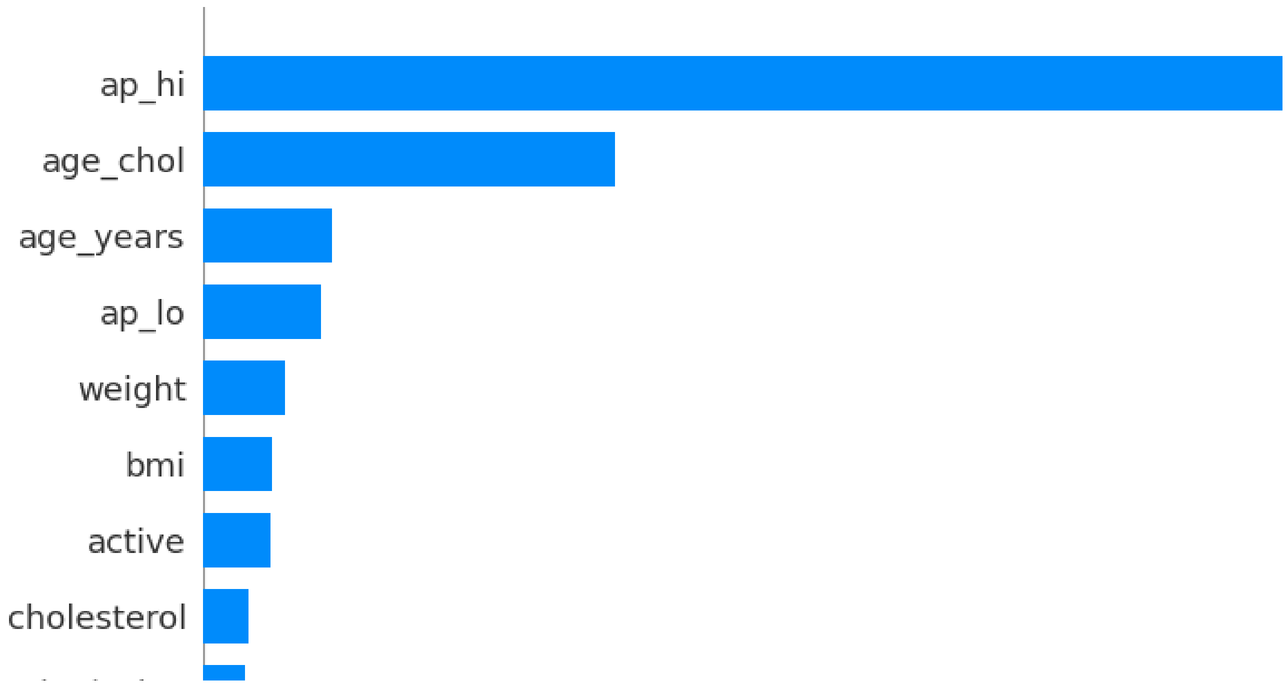
In [24]:

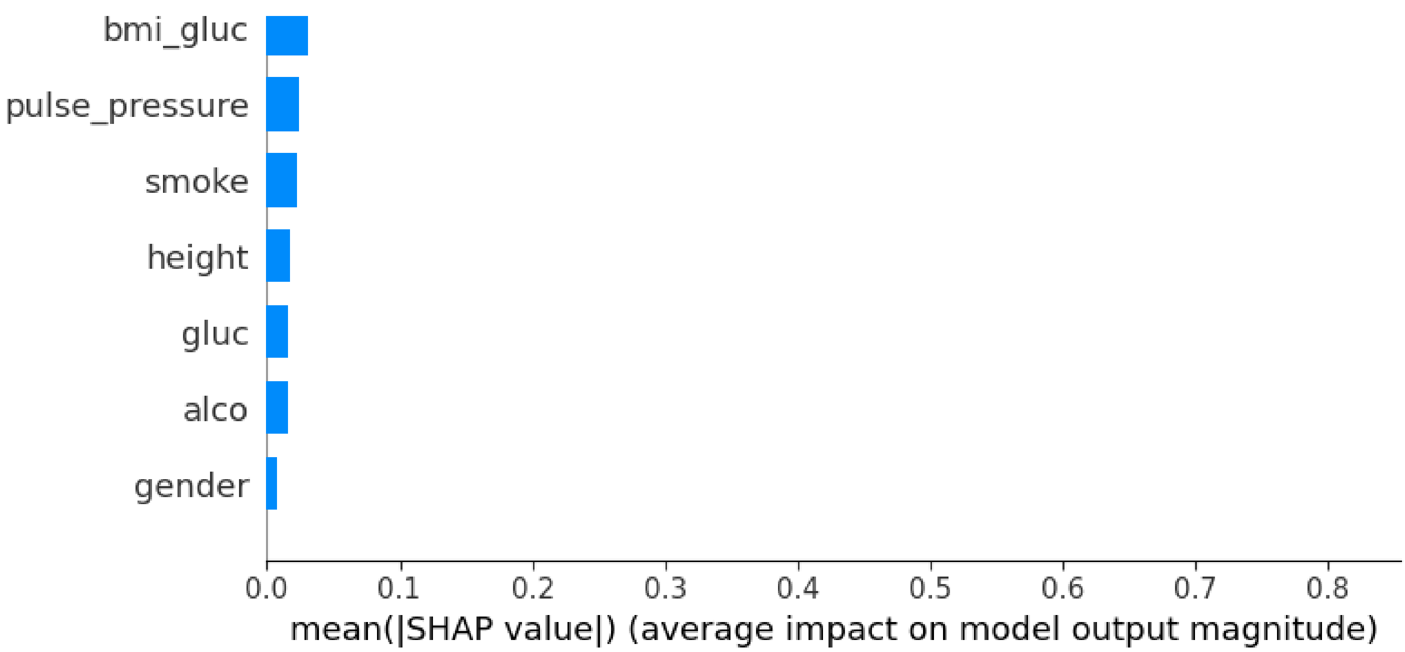
```
# Install packages (uncomment in Colab or local Jupyter)
# !pip install lightgbm shap scikit-learn matplotlib pandas --quiet

import pandas as pd
import numpy as np
import lightgbm as lgb
```

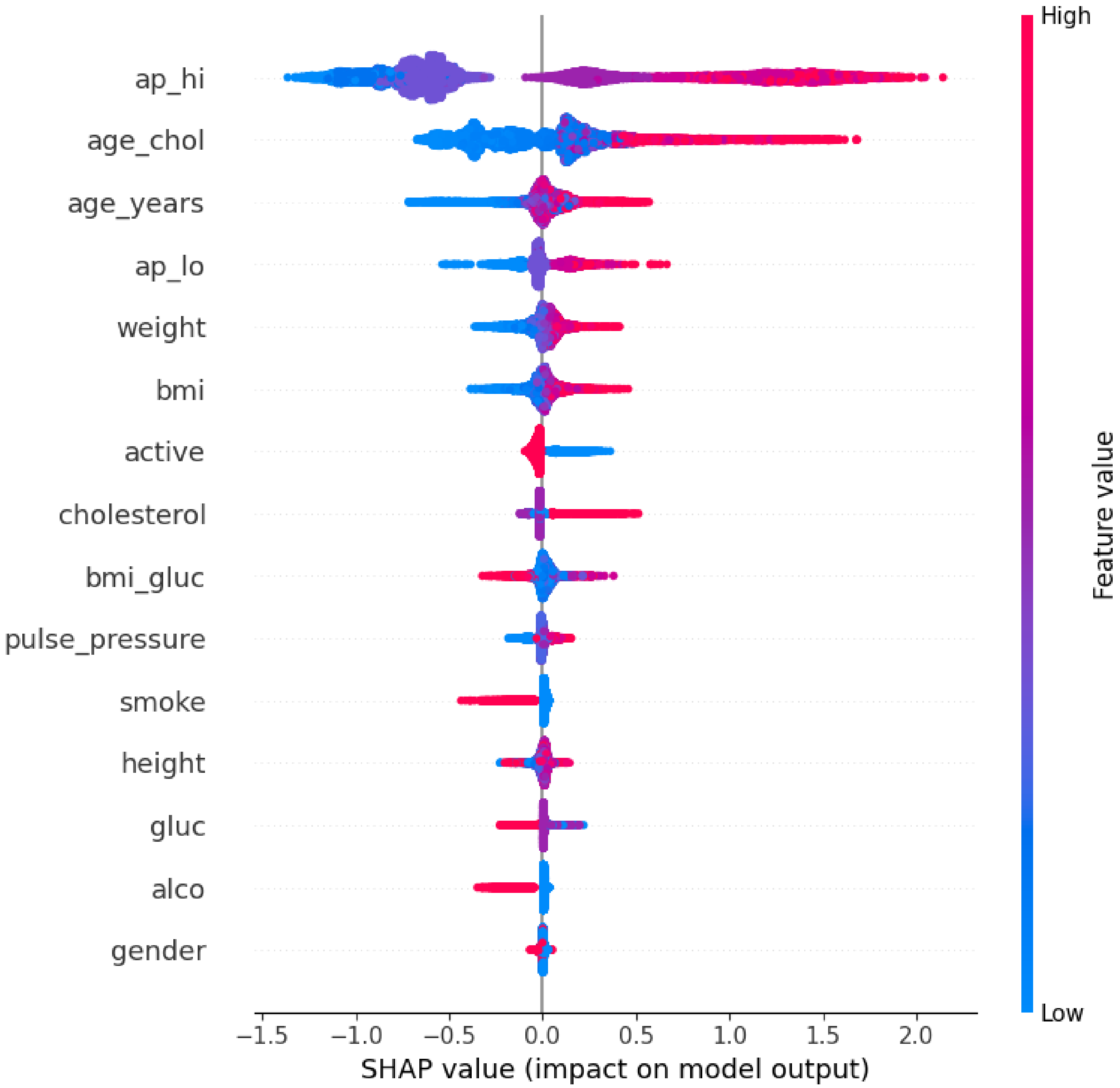
```
import shap
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score, classification_report

# Load dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['age_chol'] = df['age_years'] * df['cholesterol']
df.drop(columns=['id', 'age'], inplace=True)

# Remove outliers
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 150)]
df = df[(df['bmi'] > 15) & (df['bmi'] < 45)]

# Encode categoricals
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})

cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Split and scale
X = df.drop('cardio', axis=1)
y = df['cardio']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Prepare LightGBM datasets
train_set = lgb.Dataset(X_train_scaled, label=y_train)
valid_set = lgb.Dataset(X_test_scaled, label=y_test)

# LightGBM parameters
params = {
    'objective': 'binary',
    'metric': 'auc',
    'boosting_type': 'gbdt',
    'learning_rate': 0.01,
    'num_leaves': 64,
    'max_depth': 10,
    'min_child_samples': 80,
    'subsample': 0.9,
    'colsample_bytree': 0.9,
    'reg_alpha': 2,
    'reg_lambda': 2,
    'random_state': 42,
    'verbosity': -1
}

# Train model
model = lgb.train(
    params,
    train_set,
    num_boost_round=3000,
    valid_sets=[valid_set],
    callbacks=[lgb.early_stopping(stopping_rounds=100)]
)
```

```
# Save & Load Model
model.save_model("lightgbm_cvd_model.txt")
model = lgb.Booster(model_file="lightgbm_cvd_model.txt")

# Predict
y_prob = model.predict(X_test_scaled)
y_pred = (y_prob > 0.5).astype(int)

# Metrics
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print(f"Accuracy:  {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall:    {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score:  {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC:   {roc_auc_score(y_test, y_prob):.4f}")

# SHAP Interpretability
explainer = shap.Explainer(model)
shap_values = explainer(X_test_scaled)

# Global importance
shap.summary_plot(shap_values, X_test, plot_type="bar")

# Full SHAP summary
shap.summary_plot(shap_values, X_test)

# Explain a single prediction
shap.plots.waterfall(shap_values[0])
```

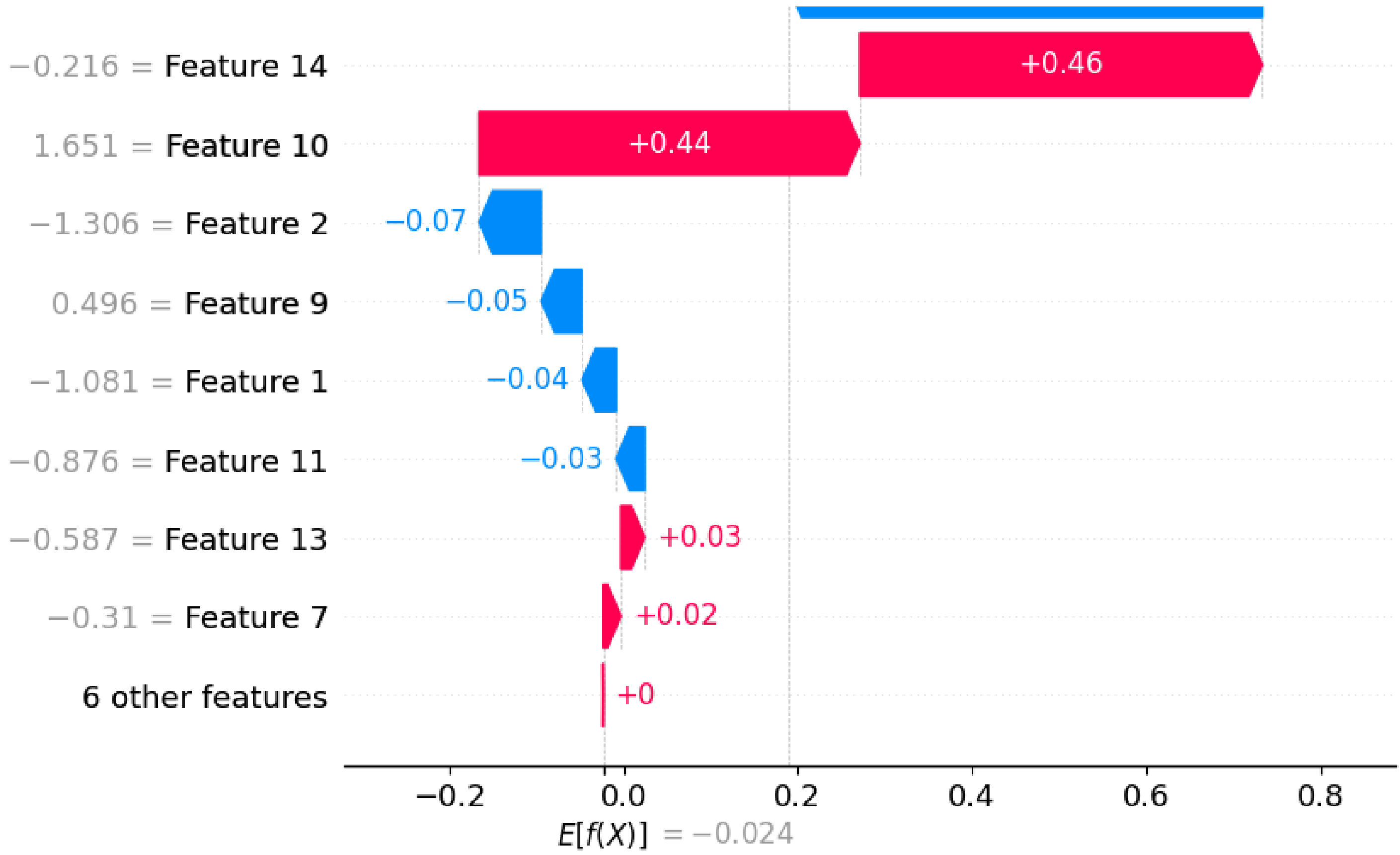
```
Training until validation scores don't improve for 100 rounds
Early stopping, best iteration is:
[399] valid_0's auc: 0.798061

Classification Report:
               precision    recall  f1-score   support

           0       0.72      0.78      0.75      6901
           1       0.75      0.69      0.72      6722

    accuracy                           0.74     13623
   macro avg       0.74      0.74      0.74     13623
weighted avg       0.74      0.74      0.74     13623

Accuracy:  0.7362
Precision: 0.7545
Recall:    0.6898
F1 Score:  0.7207
ROC AUC:   0.7981
```




bmi_gluc
pulse_pressure
smoke
height
gluc
alco
gender
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8
mean(|SHAP value|) (average impact on model output magnitude)


ap_hi
age_chol
age_years
ap_lo
weight
bmi
active
cholesterol
bmi_gluc
pulse_pressure
smoke
height
gluc
alco
gender
−1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0
SHAP value (impact on model output)
High
Low
Feature value


f(x) = 0.189
−0.392 = Feature 3
−0.54



LSTM

In [25]:

```
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report, roc_auc_score

# Load and preprocess dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['age_chol'] = df['age_years'] * df['cholesterol']
df.drop(columns=['id', 'age'], inplace=True)

# Remove outliers
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 150)]
df = df[(df['bmi'] > 15) & (df['bmi'] < 45)]

# Encode categoricals
df['gender'] = df['gender'].map({1: 'female', 2: 'male'})
df['cholesterol'] = df['cholesterol'].map({1: 'normal', 2: 'above normal', 3: 'well abov
e normal'})
df['gluc'] = df['gluc'].map({1: 'normal', 2: 'above normal', 3: 'well above normal'})
cat_cols = ['gender', 'cholesterol', 'gluc', 'smoke', 'alco', 'active']
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Prepare data
X = df.drop("cardio", axis=1)
y = df["cardio"]

# Standardize
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```python
# Treat features as sequence → reshape: [samples, time_steps, features=1]
X_seq = X_scaled.reshape((X_scaled.shape[0], X_scaled.shape[1], 1))

# Split
X_train, X_test, y_train, y_test = train_test_split(X_seq, y, stratify=y, test_size=0.2,
random_state=42)

# Build LSTM model
model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(X_train.shape[1], 1)),
    tf.keras.layers.LSTM(64, return_sequences=False),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', tf.kera
s.metrics.AUC()])

# Train
model.fit(X_train, y_train, validation_split=0.2, epochs=20, batch_size=64, verbose=1)

# Evaluate
y_prob = model.predict(X_test).flatten()
y_pred = (y_prob > 0.5).astype(int)

print("\nClassification Report:\n", classification_report(y_test, y_pred))
print(f"ROC AUC: {roc_auc_score(y_test, y_prob):.4f}")
```

```
Epoch 1/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 14s 14ms/step - accuracy: 0.6763 - auc: 0.7272 - loss: 0.614
0 - val_accuracy: 0.7119 - val_auc: 0.7741 - val_loss: 0.5716
Epoch 2/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 9s 13ms/step - accuracy: 0.7141 - auc: 0.7732 - loss: 0.5704
- val_accuracy: 0.7214 - val_auc: 0.7872 - val_loss: 0.5582
Epoch 3/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 12s 16ms/step - accuracy: 0.7180 - auc: 0.7805 - loss: 0.563
0 - val_accuracy: 0.7219 - val_auc: 0.7875 - val_loss: 0.5566
Epoch 4/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 22s 18ms/step - accuracy: 0.7224 - auc: 0.7840 - loss: 0.559
1 - val_accuracy: 0.7278 - val_auc: 0.7961 - val_loss: 0.5479
Epoch 5/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 18s 14ms/step - accuracy: 0.7300 - auc: 0.7944 - loss: 0.549
0 - val_accuracy: 0.7299 - val_auc: 0.7991 - val_loss: 0.5446
Epoch 6/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 8s 12ms/step - accuracy: 0.7258 - auc: 0.7938 - loss: 0.5497
- val_accuracy: 0.7280 - val_auc: 0.7997 - val_loss: 0.5449
Epoch 7/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 8s 12ms/step - accuracy: 0.7348 - auc: 0.7992 - loss: 0.5440
- val_accuracy: 0.7330 - val_auc: 0.8002 - val_loss: 0.5434
Epoch 8/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 11s 13ms/step - accuracy: 0.7317 - auc: 0.7972 - loss: 0.546
5 - val_accuracy: 0.7326 - val_auc: 0.8015 - val_loss: 0.5414
Epoch 9/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 9s 13ms/step - accuracy: 0.7332 - auc: 0.7992 - loss: 0.5438
- val_accuracy: 0.7319 - val_auc: 0.8011 - val_loss: 0.5420
Epoch 10/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 8s 12ms/step - accuracy: 0.7340 - auc: 0.8000 - loss: 0.5423
- val_accuracy: 0.7308 - val_auc: 0.8006 - val_loss: 0.5421
Epoch 11/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 9s 13ms/step - accuracy: 0.7348 - auc: 0.7985 - loss: 0.5445
- val_accuracy: 0.7305 - val_auc: 0.8020 - val_loss: 0.5407
Epoch 12/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 10s 13ms/step - accuracy: 0.7336 - auc: 0.8005 - loss: 0.542
5 - val_accuracy: 0.7345 - val_auc: 0.8024 - val_loss: 0.5411
Epoch 13/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 10s 13ms/step - accuracy: 0.7353 - auc: 0.8037 - loss: 0.539
2 - val_accuracy: 0.7276 - val_auc: 0.8020 - val_loss: 0.5437
Epoch 14/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 8s 11ms/step - accuracy: 0.7338 - auc: 0.8010 - loss: 0.5417
- val_accuracy: 0.7325 - val_auc: 0.8026 - val_loss: 0.5402
Epoch 15/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 11s 12ms/step - accuracy: 0.7344 - auc: 0.8021 - loss: 0.540
```

```
0 - val_accuracy: 0.7315 - val_auc: 0.8036 - val_loss: 0.5414
Epoch 16/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 11s 14ms/step - accuracy: 0.7335 - auc: 0.8010 - loss: 0.541
8 - val_accuracy: 0.7318 - val_auc: 0.8030 - val_loss: 0.5415
Epoch 17/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 9s 13ms/step - accuracy: 0.7352 - auc: 0.8015 - loss: 0.5412
- val_accuracy: 0.7336 - val_auc: 0.8025 - val_loss: 0.5410
Epoch 18/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 8s 12ms/step - accuracy: 0.7355 - auc: 0.8019 - loss: 0.5403
- val_accuracy: 0.7347 - val_auc: 0.8039 - val_loss: 0.5390
Epoch 19/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 11s 12ms/step - accuracy: 0.7353 - auc: 0.8010 - loss: 0.541
5 - val_accuracy: 0.7318 - val_auc: 0.8029 - val_loss: 0.5404
Epoch 20/20
682/682 ━━━━━━━━━━━━━━━━━━━━ 9s 11ms/step - accuracy: 0.7334 - auc: 0.7993 - loss: 0.5429
- val_accuracy: 0.7313 - val_auc: 0.8004 - val_loss: 0.5427
426/426 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step

Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.76      0.74      6901
           1       0.74      0.70      0.72      6722

    accuracy                           0.73     13623
   macro avg       0.73      0.73      0.73     13623
weighted avg       0.73      0.73      0.73     13623

ROC AUC: 0.7948
```

In [26]:

```
# Install required libraries
# !pip install pandas numpy scikit-learn tensorflow matplotlib --quiet

import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score, precision_score, recal
l_score, f1_score, roc_auc_score
import matplotlib.pyplot as plt

# Load the dataset (use local path if downloaded from Kaggle)
df = pd.read_csv("cardio_disease.csv", delimiter=';')  # Assuming dataset is renamed and
uploaded

# Data preprocessing as per paper

# Convert age from days to years
df['age'] = (df['age'] / 365).astype(int)

# Add BMI (weight in kg / height in meters squared)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)

# Remove outliers (based on medical ranges)
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 180)]
df = df[(df['bmi'] > 10) & (df['bmi'] < 50)]
df = df[(df['height'] > 100) & (df['height'] < 220)]
df = df[(df['weight'] > 30) & (df['weight'] < 200)]

# Drop ID column if present
df.drop(columns=['id'], inplace=True)

# Define features and target
X = df.drop(columns=['cardio'])  # Features
y = df['cardio']                 # Target

# Standard scaling
scaler = StandardScaler()
```

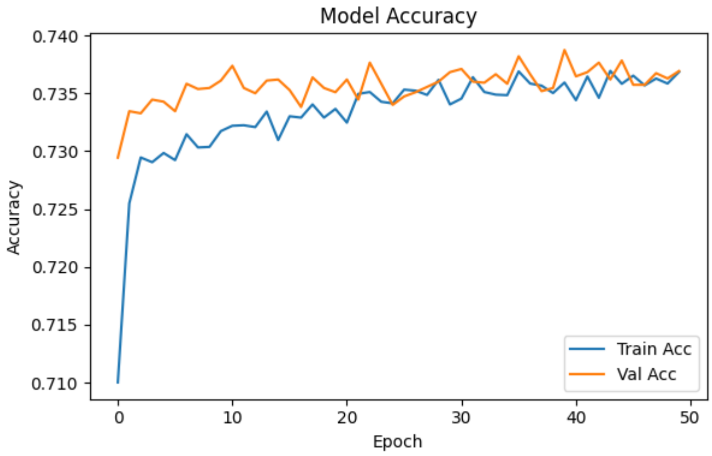
```python
X_scaled = scaler.fit_transform(X)

# Train-test split (80-20)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, stratify
=y, random_state=42)

# Build DNN model (based on paper)
model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

# Compile
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy', tf.keras.metrics.AUC(name='auc')]
)

# Train
history = model.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=50,
    batch_size=128,
    verbose=1
)

# Predict and Evaluate
y_prob = model.predict(X_test).flatten()
y_pred = (y_prob > 0.5).astype(int)

# Print metrics
print("\n Classification Report:\n", classification_report(y_test, y_pred))
print(f"Accuracy:  {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall:    {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score:  {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC:   {roc_auc_score(y_test, y_prob):.4f}")

# Plot training performance
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

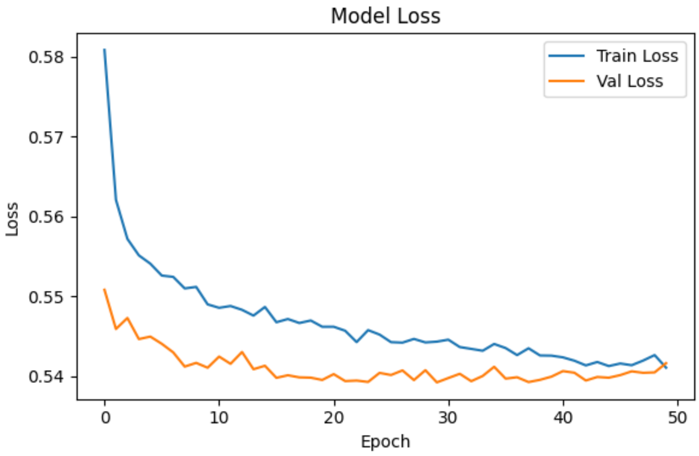
```
Epoch 1/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.6909 - auc: 0.7476 - loss: 0.6006
- val_accuracy: 0.7294 - val_auc: 0.7977 - val_loss: 0.5508
Epoch 2/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7243 - auc: 0.7855 - loss: 0.5657
- val_accuracy: 0.7335 - val_auc: 0.7997 - val_loss: 0.5459
```

```
Epoch 3/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7289 - auc: 0.7902 - loss: 0.5578
- val_accuracy: 0.7333 - val_auc: 0.7997 - val_loss: 0.5473
Epoch 4/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7319 - auc: 0.7937 - loss: 0.5532
- val_accuracy: 0.7345 - val_auc: 0.8005 - val_loss: 0.5446
Epoch 5/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7262 - auc: 0.7888 - loss: 0.5576
- val_accuracy: 0.7343 - val_auc: 0.8003 - val_loss: 0.5449
Epoch 6/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7285 - auc: 0.7928 - loss: 0.5535
- val_accuracy: 0.7335 - val_auc: 0.8009 - val_loss: 0.5440
Epoch 7/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7299 - auc: 0.7942 - loss: 0.5515
- val_accuracy: 0.7358 - val_auc: 0.8006 - val_loss: 0.5429
Epoch 8/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.7281 - auc: 0.7933 - loss: 0.5518
- val_accuracy: 0.7354 - val_auc: 0.8013 - val_loss: 0.5412
Epoch 9/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7305 - auc: 0.7954 - loss: 0.5500
- val_accuracy: 0.7355 - val_auc: 0.8013 - val_loss: 0.5416
Epoch 10/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7292 - auc: 0.7949 - loss: 0.5505
- val_accuracy: 0.7361 - val_auc: 0.8012 - val_loss: 0.5410
Epoch 11/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7290 - auc: 0.7932 - loss: 0.5513
- val_accuracy: 0.7374 - val_auc: 0.8012 - val_loss: 0.5424
Epoch 12/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7316 - auc: 0.7957 - loss: 0.5481
- val_accuracy: 0.7355 - val_auc: 0.8017 - val_loss: 0.5415
Epoch 13/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7307 - auc: 0.7974 - loss: 0.5468
- val_accuracy: 0.7350 - val_auc: 0.8017 - val_loss: 0.5430
Epoch 14/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.7346 - auc: 0.7967 - loss: 0.5471
- val_accuracy: 0.7361 - val_auc: 0.8011 - val_loss: 0.5408
Epoch 15/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7307 - auc: 0.7942 - loss: 0.5502
- val_accuracy: 0.7362 - val_auc: 0.8015 - val_loss: 0.5413
Epoch 16/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7313 - auc: 0.7963 - loss: 0.5480
- val_accuracy: 0.7353 - val_auc: 0.8017 - val_loss: 0.5398
Epoch 17/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7301 - auc: 0.7908 - loss: 0.5536
- val_accuracy: 0.7338 - val_auc: 0.8013 - val_loss: 0.5401
Epoch 18/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7350 - auc: 0.7993 - loss: 0.5444
- val_accuracy: 0.7364 - val_auc: 0.8018 - val_loss: 0.5398
Epoch 19/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7313 - auc: 0.7952 - loss: 0.5489
- val_accuracy: 0.7355 - val_auc: 0.8014 - val_loss: 0.5398
Epoch 20/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.7321 - auc: 0.7969 - loss: 0.5472
- val_accuracy: 0.7351 - val_auc: 0.8019 - val_loss: 0.5395
Epoch 21/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7302 - auc: 0.7975 - loss: 0.5458
- val_accuracy: 0.7362 - val_auc: 0.8018 - val_loss: 0.5402
Epoch 22/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7347 - auc: 0.7977 - loss: 0.5456
- val_accuracy: 0.7345 - val_auc: 0.8013 - val_loss: 0.5394
Epoch 23/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7359 - auc: 0.8012 - loss: 0.5415
- val_accuracy: 0.7377 - val_auc: 0.8018 - val_loss: 0.5394
Epoch 24/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7318 - auc: 0.7955 - loss: 0.5480
- val_accuracy: 0.7358 - val_auc: 0.8014 - val_loss: 0.5392
Epoch 25/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7361 - auc: 0.7988 - loss: 0.5451
- val_accuracy: 0.7340 - val_auc: 0.8013 - val_loss: 0.5404
Epoch 26/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7348 - auc: 0.7997 - loss: 0.5428
- val_accuracy: 0.7347 - val_auc: 0.8013 - val_loss: 0.5401
```

```
Epoch 27/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.7348 - auc: 0.7986 - loss: 0.5452
- val_accuracy: 0.7351 - val_auc: 0.8011 - val_loss: 0.5407
Epoch 28/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.7352 - auc: 0.7985 - loss: 0.5449
- val_accuracy: 0.7356 - val_auc: 0.8018 - val_loss: 0.5395
Epoch 29/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7334 - auc: 0.7962 - loss: 0.5476
- val_accuracy: 0.7360 - val_auc: 0.8012 - val_loss: 0.5407
Epoch 30/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7343 - auc: 0.7992 - loss: 0.5438
- val_accuracy: 0.7368 - val_auc: 0.8014 - val_loss: 0.5392
Epoch 31/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7337 - auc: 0.7998 - loss: 0.5431
- val_accuracy: 0.7371 - val_auc: 0.8014 - val_loss: 0.5397
Epoch 32/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7377 - auc: 0.8002 - loss: 0.5439
- val_accuracy: 0.7360 - val_auc: 0.8011 - val_loss: 0.5403
Epoch 33/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.7339 - auc: 0.7986 - loss: 0.5439
- val_accuracy: 0.7359 - val_auc: 0.8018 - val_loss: 0.5393
Epoch 34/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7391 - auc: 0.8026 - loss: 0.5397
- val_accuracy: 0.7367 - val_auc: 0.8012 - val_loss: 0.5400
Epoch 35/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7389 - auc: 0.8014 - loss: 0.5415
- val_accuracy: 0.7358 - val_auc: 0.8009 - val_loss: 0.5411
Epoch 36/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7393 - auc: 0.8015 - loss: 0.5413
- val_accuracy: 0.7382 - val_auc: 0.8010 - val_loss: 0.5397
Epoch 37/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7330 - auc: 0.7985 - loss: 0.5443
- val_accuracy: 0.7367 - val_auc: 0.8012 - val_loss: 0.5398
Epoch 38/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.7351 - auc: 0.7978 - loss: 0.5454
- val_accuracy: 0.7352 - val_auc: 0.8011 - val_loss: 0.5392
Epoch 39/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7357 - auc: 0.8021 - loss: 0.5400
- val_accuracy: 0.7355 - val_auc: 0.8008 - val_loss: 0.5395
Epoch 40/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7341 - auc: 0.8002 - loss: 0.5434
- val_accuracy: 0.7388 - val_auc: 0.8010 - val_loss: 0.5399
Epoch 41/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7357 - auc: 0.8020 - loss: 0.5410
- val_accuracy: 0.7365 - val_auc: 0.8011 - val_loss: 0.5406
Epoch 42/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7383 - auc: 0.8036 - loss: 0.5389
- val_accuracy: 0.7368 - val_auc: 0.8014 - val_loss: 0.5404
Epoch 43/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7324 - auc: 0.7990 - loss: 0.5433
- val_accuracy: 0.7377 - val_auc: 0.8014 - val_loss: 0.5394
Epoch 44/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 4s 7ms/step - accuracy: 0.7380 - auc: 0.8051 - loss: 0.5371
- val_accuracy: 0.7362 - val_auc: 0.8006 - val_loss: 0.5399
Epoch 45/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.7362 - auc: 0.7992 - loss: 0.5439
- val_accuracy: 0.7378 - val_auc: 0.8008 - val_loss: 0.5398
Epoch 46/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7370 - auc: 0.8020 - loss: 0.5406
- val_accuracy: 0.7357 - val_auc: 0.8009 - val_loss: 0.5401
Epoch 47/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7366 - auc: 0.8041 - loss: 0.5394
- val_accuracy: 0.7357 - val_auc: 0.8009 - val_loss: 0.5406
Epoch 48/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7383 - auc: 0.8031 - loss: 0.5400
- val_accuracy: 0.7367 - val_auc: 0.8009 - val_loss: 0.5404
Epoch 49/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.7366 - auc: 0.8016 - loss: 0.5414
- val_accuracy: 0.7363 - val_auc: 0.8007 - val_loss: 0.5404
Epoch 50/50
343/343 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7382 - auc: 0.8031 - loss: 0.5395
- val_accuracy: 0.7369 - val_auc: 0.8007 - val_loss: 0.5416
```

```
429/429 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step

 Classification Report:
               precision    recall  f1-score   support

           0       0.71      0.80      0.75      6926
           1       0.77      0.66      0.71      6773

    accuracy                           0.74     13699
   macro avg       0.74      0.73      0.73     13699
weighted avg       0.74      0.74      0.73     13699

Accuracy:  0.7352
Precision: 0.7683
Recall:    0.6650
F1 Score:  0.7129
ROC AUC:   0.8019
```





In [27]:

```python
# Install LightGBM (only if you're using Google Colab)
# !pip install lightgbm --quiet

# Imports
import pandas as pd
import numpy as np
import lightgbm as lgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler, KBinsDiscretizer
from sklearn.feature_selection import SelectKBest, mutual_info_classif
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score
from lightgbm import early_stopping, log_evaluation

# Load Dataset
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature Engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['age_cholesterol'] = df['age_years'] * df['cholesterol']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['bp_product'] = df['ap_hi'] * df['ap_lo']
df.drop(columns=['id', 'age'], inplace=True)

# Outlier Removal
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 180)]
df = df[(df['bmi'] > 10) & (df['bmi'] < 50)]

# Define Features and Target
X = df.drop(columns=['cardio'])
y = df['cardio']

# Binning for non-linearity
```

```python
bin_cols = ['age_years', 'bmi', 'pulse_pressure']
binner = KBinsDiscretizer(n_bins=5, encode='ordinal', strategy='quantile')
X[bin_cols] = binner.fit_transform(X[bin_cols])

# Robust Scaling
scaler = RobustScaler()
X_scaled = scaler.fit_transform(X)

# Feature Selection
selector = SelectKBest(score_func=mutual_info_classif, k='all')
X_selected = selector.fit_transform(X_scaled, y)

# Train/Test Split
X_train, X_test, y_train, y_test = train_test_split(
    X_selected, y, test_size=0.2, stratify=y, random_state=42)

# Class Weight Calculation
scale_pos_weight = np.round(y_train.value_counts()[0] / y_train.value_counts()[1], 2)

# LightGBM Model
model = lgb.LGBMClassifier(
    boosting_type='gbdt',
    objective='binary',
    n_estimators=1000,
    learning_rate=0.03,
    max_depth=12,
    num_leaves=60,
    min_child_samples=50,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.2,
    reg_lambda=0.4,
    scale_pos_weight=scale_pos_weight,
    random_state=42
)

# Train with Early Stopping
model.fit(
    X_train, y_train,
    eval_set=[(X_test, y_test)],
    eval_metric='auc',
    callbacks=[early_stopping(stopping_rounds=50), log_evaluation(0)]
)

# Predict & Evaluate
y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print("\n Model Evaluation Metrics")
print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall    : {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC   : {roc_auc_score(y_test, y_prob):.4f}")
```

```
Training until validation scores don't improve for 50 rounds
Early stopping, best iteration is:
[134] valid_0's auc: 0.80426 valid_0's binary_logloss: 0.537959

 Model Evaluation Metrics
Accuracy : 0.7404
Precision: 0.7606
Recall    : 0.6931
F1 Score : 0.7253
ROC AUC   : 0.8043
```

In [28]:

```python
# Install (for Google Colab only)
# !pip install xgboost pandas scikit-learn numpy

import pandas as pd
```

```python
import numpy as np
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler, KBinsDiscretizer, FunctionTransformer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score

# Load data
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature Engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['age_cholesterol'] = df['age_years'] * df['cholesterol']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['bp_product'] = df['ap_hi'] * df['ap_lo']
df.drop(columns=['id', 'age'], inplace=True)

# Remove outliers
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 180)]
df = df[(df['bmi'] > 10) & (df['bmi'] < 50)]

# Define features and target
X = df.drop(columns=['cardio'])
y = df['cardio']

# Transform pipeline
bin_cols = ['age_years', 'bmi', 'pulse_pressure']
log_cols = ['ap_hi', 'ap_lo', 'bp_product', 'bmi']
remaining_cols = list(set(X.columns) - set(bin_cols) - set(log_cols))

preprocessor = ColumnTransformer(transformers=[
    ('bin', KBinsDiscretizer(n_bins=5, encode='ordinal', strategy='quantile'), bin_cols)
,
    ('log', FunctionTransformer(np.log1p, validate=False), log_cols),
    ('scale', RobustScaler(), remaining_cols)
])

X_transformed = preprocessor.fit_transform(X)

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

# DMatrix conversion
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)

# Class weight balancing
scale_pos_weight = y_train.value_counts()[0] / y_train.value_counts()[1]

# XGBoost parameters
params = {
    'objective': 'binary:logistic',
    'eval_metric': 'auc',
    'learning_rate': 0.02,
    'max_depth': 8,
    'subsample': 0.85,
    'colsample_bytree': 0.85,
    'reg_alpha': 0.1,
    'reg_lambda': 0.1,
    'scale_pos_weight': scale_pos_weight,
    'seed': 42
}

# Train the model with early stopping
evals = [(dtrain, 'train'), (dtest, 'eval')]
bst = xgb.train(params, dtrain, num_boost_round=1000,
```

```
                evals=evals, early_stopping_rounds=50, verbose_eval=False)

# Predictions
y_prob = bst.predict(dtest)
y_pred = (y_prob > 0.5).astype(int)

# Evaluation
print("Model Evaluation Metrics")
print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall   : {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC  : {roc_auc_score(y_test, y_prob):.4f}")
```

```
Model Evaluation Metrics
Accuracy : 0.7391
Precision: 0.7592
Recall   : 0.6918
F1 Score : 0.7239
ROC AUC  : 0.8034
```

In [29]:

```
# Run this first if you're using Google Colab:
!pip install xgboost lightgbm scikit-learn pandas numpy

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler, KBinsDiscretizer, FunctionTransformer
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score
import xgboost as xgb
import lightgbm as lgb

# Load data
df = pd.read_csv("cardio_disease.csv", delimiter=';')

# Feature engineering
df['age_years'] = (df['age'] / 365).astype(int)
df['bmi'] = df['weight'] / ((df['height'] / 100) ** 2)
df['pulse_pressure'] = df['ap_hi'] - df['ap_lo']
df['age_cholesterol'] = df['age_years'] * df['cholesterol']
df['bmi_gluc'] = df['bmi'] * df['gluc']
df['bp_product'] = df['ap_hi'] * df['ap_lo']
df.drop(columns=['id', 'age'], inplace=True)

# Outlier removal
df = df[(df['ap_hi'] > 70) & (df['ap_hi'] < 250)]
df = df[(df['ap_lo'] > 40) & (df['ap_lo'] < 180)]
df = df[(df['bmi'] > 10) & (df['bmi'] < 50)]

# Define features and target
X = df.drop(columns=['cardio'])
y = df['cardio']

# Preprocessing pipeline
bin_cols = ['age_years', 'bmi', 'pulse_pressure']
log_cols = ['ap_hi', 'ap_lo', 'bp_product', 'bmi']
remaining_cols = list(set(X.columns) - set(bin_cols) - set(log_cols))

preprocessor = ColumnTransformer(transformers=[
    ('bin', KBinsDiscretizer(n_bins=5, encode='ordinal', strategy='quantile'), bin_cols)
,
    ('log', FunctionTransformer(np.log1p, validate=False), log_cols),
    ('scale', RobustScaler(), remaining_cols)
])

X_processed = preprocessor.fit_transform(X)
```

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

# Handle class imbalance
scale_pos_weight = y_train.value_counts()[0] / y_train.value_counts()[1]

# Base models
rf_model = RandomForestClassifier(n_estimators=300, max_depth=12, random_state=42)
xgb_model = xgb.XGBClassifier(n_estimators=800, learning_rate=0.03, max_depth=7,
                              subsample=0.8, colsample_bytree=0.8,
                              scale_pos_weight=scale_pos_weight,
                              use_label_encoder=False, eval_metric='logloss', random_sta
te=42)
lgb_model = lgb.LGBMClassifier(n_estimators=800, learning_rate=0.03, max_depth=7,
                               subsample=0.8, colsample_bytree=0.8,
                               scale_pos_weight=scale_pos_weight,
                               random_state=42)

# Ensemble via soft voting
ensemble = VotingClassifier(estimators=[
    ('rf', rf_model),
    ('xgb', xgb_model),
    ('lgb', lgb_model)
], voting='soft')

# Train ensemble
ensemble.fit(X_train, y_train)

# Predict
y_pred = ensemble.predict(X_test)
y_prob = ensemble.predict_proba(X_test)[:, 1]

# Evaluation
print("Ensemble Evaluation Metrics")
print(f"Accuracy : {accuracy_score(y_test, y_pred):.4f}")
print(f"Precision: {precision_score(y_test, y_pred):.4f}")
print(f"Recall   : {recall_score(y_test, y_pred):.4f}")
print(f"F1 Score : {f1_score(y_test, y_pred):.4f}")
print(f"ROC AUC  : {roc_auc_score(y_test, y_prob):.4f}")
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: lightgbm in /usr/local/lib/python3.11/dist-packages (4.5.0
)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1
.6.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-package
s (from xgboost) (2.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgb
oost) (1.15.3)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (
from scikit-learn) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-pac
kages (from scikit-learn) (3.6.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-p
ackages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (f
rom pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages
(from pandas) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from
python-dateutil>=2.8.2->pandas) (1.17.0)
Ensemble Evaluation Metrics
Accuracy : 0.7396
Precision: 0.7583
Recall   : 0.6950
F1 Score : 0.7253
ROC AUC  : 0.8030
```

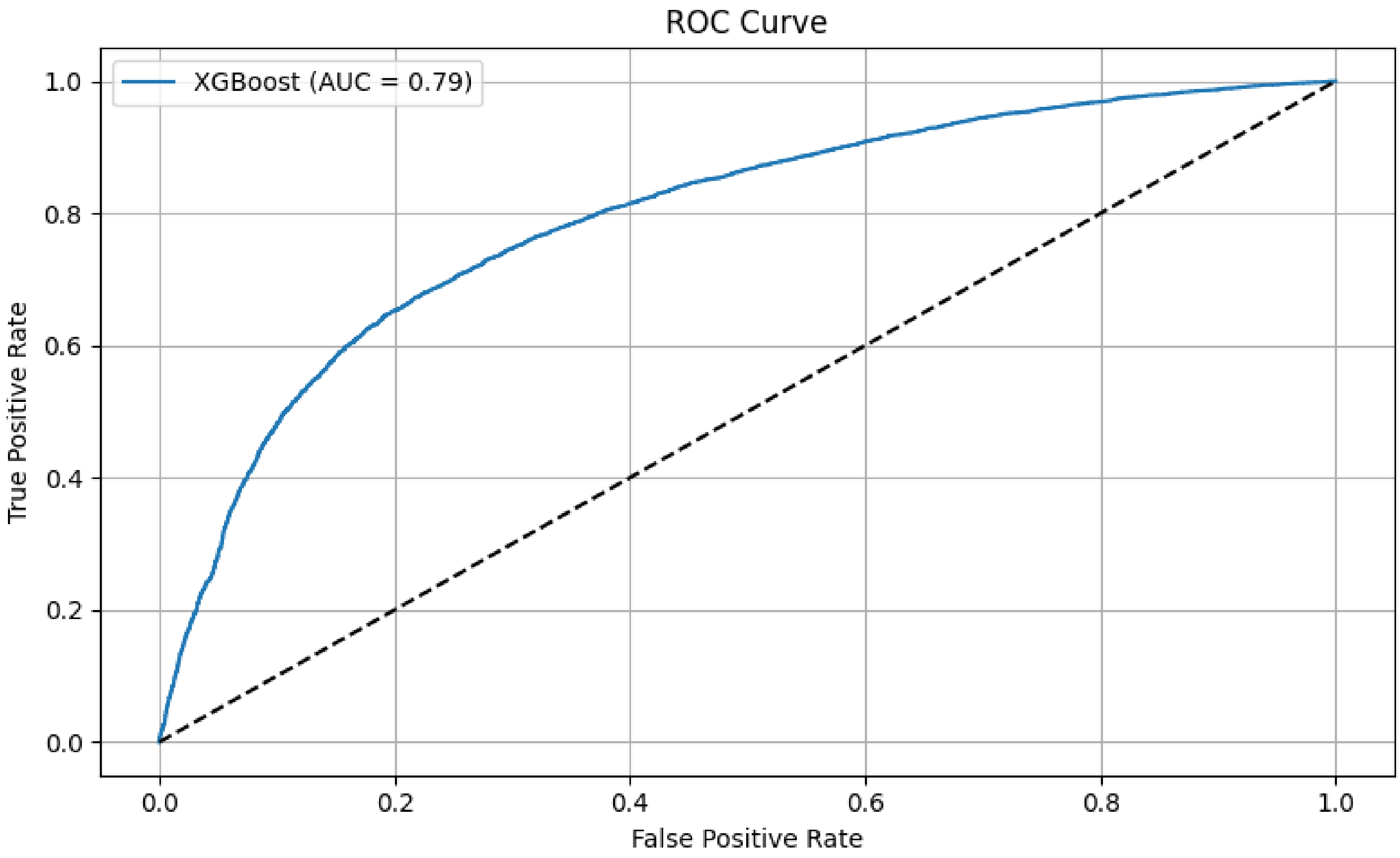
ML Models

In [30]:

```
# Imports
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score, roc_curve
from xgboost import XGBClassifier
import matplotlib.pyplot as plt

# Load and Clean Data
df = pd.read_csv("cardio_disease.csv", delimiter=";")
df = df.drop(columns=["id"])
df = df.dropna()

# Fix Age (from days to years)
df["age"] = df["age"] // 365

# Remove blood pressure outliers
df = df[(df["ap_hi"] >= 80) & (df["ap_hi"] <= 200)]
df = df[(df["ap_lo"] >= 50) & (df["ap_lo"] <= 130)]

# Features and Target
X = df.drop("cardio", axis=1)
y = df["cardio"]

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

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train XGBoost Classifier (tuned)
xgb = XGBClassifier(
    use_label_encoder=False,
    eval_metric='logloss',
    max_depth=6,
    learning_rate=0.1,
    n_estimators=300,
    subsample=0.8,
    colsample_bytree=0.8,
    scale_pos_weight=1.2,
    random_state=42
)

xgb.fit(X_train_scaled, y_train)

# Predictions
y_pred = xgb.predict(X_test_scaled)
y_prob = xgb.predict_proba(X_test_scaled)[:, 1]

# Evaluation
print("\n XGBoost Performance")
print("Accuracy :", round(accuracy_score(y_test, y_pred), 4))
print("Precision:", round(precision_score(y_test, y_pred), 4))
print("Recall   :", round(recall_score(y_test, y_pred), 4))
print("F1 Score :", round(f1_score(y_test, y_pred), 4))
print("ROC AUC  :", round(roc_auc_score(y_test, y_prob), 4))

# Plot ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 5))
plt.plot(fpr, tpr, label=f"XGBoost (AUC = {roc_auc_score(y_test, y_prob):.2f})")
plt.plot([0, 1], [0, 1], 'k--')
```

```
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
 XGBoost Performance
Accuracy : 0.7252
Precision: 0.7239
Recall   : 0.7182
F1 Score : 0.721
ROC AUC  : 0.7928
```



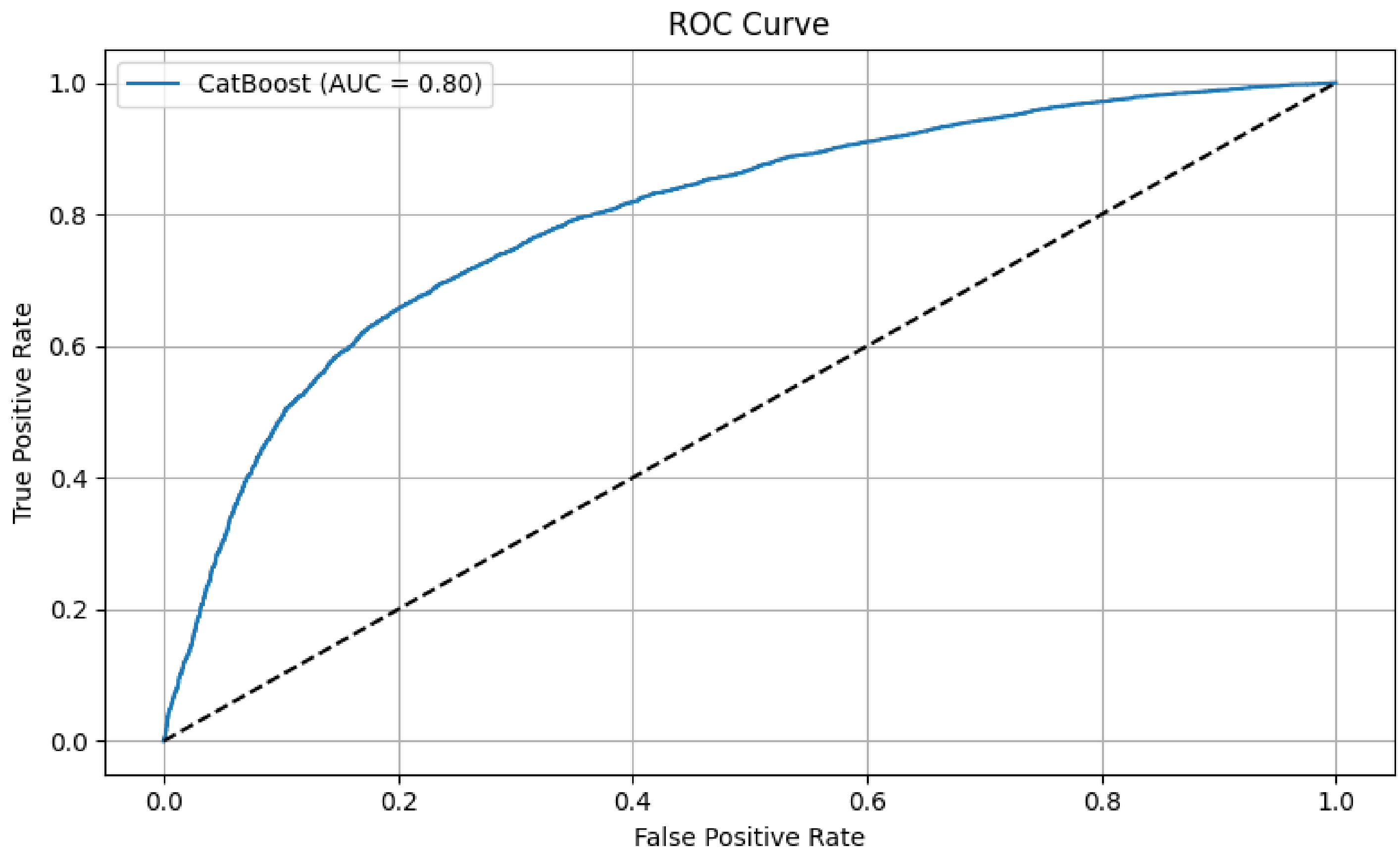
In [31]:

```
# Install if needed
!pip install catboost

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score, roc_curve
from sklearn.preprocessing import StandardScaler
from catboost import CatBoostClassifier, Pool
import matplotlib.pyplot as plt

# Load & clean data
df = pd.read_csv("cardio_disease.csv", delimiter=";")
df = df.drop(columns=["id"])
df = df.dropna()
df["age"] = df["age"] // 365
df = df[(df["ap_hi"] >= 80) & (df["ap_hi"] <= 200)]
df = df[(df["ap_lo"] >= 50) & (df["ap_lo"] <= 130)]

# Features & target
X = df.drop("cardio", axis=1)
y = df["cardio"]

# Train-test split
```

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

# CatBoost Pool (no scaling needed!)
train_pool = Pool(X_train, y_train)
test_pool = Pool(X_test, y_test)

# CatBoost Classifier
catboost_model = CatBoostClassifier(
    iterations=500,
    learning_rate=0.1,
    depth=6,
    loss_function='Logloss',
    eval_metric='AUC',
    verbose=100,
    random_seed=42
)

catboost_model.fit(train_pool, eval_set=test_pool, verbose=0)

# Predict
y_pred = catboost_model.predict(X_test)
y_prob = catboost_model.predict_proba(X_test)[:, 1]

# Evaluation
print("\n CatBoost Performance")
print("Accuracy :", round(accuracy_score(y_test, y_pred), 4))
print("Precision:", round(precision_score(y_test, y_pred), 4))
print("Recall   :", round(recall_score(y_test, y_pred), 4))
print("F1 Score :", round(f1_score(y_test, y_pred), 4))
print("ROC AUC  :", round(roc_auc_score(y_test, y_prob), 4))

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 5))
plt.plot(fpr, tpr, label=f"CatBoost (AUC = {roc_auc_score(y_test, y_prob):.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Collecting catboost
  Downloading catboost-1.2.8-cp311-cp311-manylinux2014_x86_64.whl.metadata (1.2 kB)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (from
catboost) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (fro
m catboost) (3.10.0)
Requirement already satisfied: numpy<3.0,>=1.16.0 in /usr/local/lib/python3.11/dist-packa
ges (from catboost) (2.0.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.11/dist-packages (f
rom catboost) (2.2.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from cat
boost) (1.15.3)
Requirement already satisfied: plotly in /usr/local/lib/python3.11/dist-packages (from ca
tboost) (5.24.1)
Requirement already satisfied: six in /usr/local/lib/python3.11/dist-packages (from catbo
ost) (1.17.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-p
ackages (from pandas>=0.24->catboost) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (f
rom pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages
(from pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-package
s (from matplotlib->catboost) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (f
rom matplotlib->catboost) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packag
```

```
es (from matplotlib->catboost) (4.58.1)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packag
es (from matplotlib->catboost) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages
(from matplotlib->catboost) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from
matplotlib->catboost) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-package
s (from matplotlib->catboost) (3.2.3)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.11/dist-packages
(from plotly->catboost) (9.1.2)
Downloading catboost-1.2.8-cp311-cp311-manylinux2014_x86_64.whl (99.2 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 99.2/99.2 MB 6.9 MB/s eta 0:00:00
Installing collected packages: catboost
Successfully installed catboost-1.2.8

 CatBoost Performance
Accuracy : 0.7283
Precision: 0.7483
Recall   : 0.6788
F1 Score : 0.7119
ROC AUC  : 0.7957
```



In [32]:

```python
# Required Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import StackingClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
import warnings
warnings.filterwarnings("ignore")

# Load Dataset
df = pd.read_csv("cardio_disease.csv", delimiter=";").drop(columns=["id"]).dropna()
df["age"] = df["age"] // 365
```

```python
# Feature Engineering
df["bmi"] = df["weight"] / (df["height"] / 100)**2
df["pulse_pressure"] = df["ap_hi"] - df["ap_lo"]
df = df[(df["ap_hi"] >= 80) & (df["ap_hi"] <= 200)]
df = df[(df["ap_lo"] >= 50) & (df["ap_lo"] <= 130)]

# X, y
X = df.drop("cardio", axis=1)
y = df["cardio"]

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)

# Scale Numerical
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Define Base Models
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
cat = CatBoostClassifier(verbose=0, random_state=42)
lr = LogisticRegression(max_iter=1000)

# Stacked Ensemble
ensemble = StackingClassifier(
    estimators=[('xgb', xgb), ('cat', cat)],
    final_estimator=lr,
    passthrough=True,
    cv=5
)

# Train
ensemble.fit(X_train_scaled, y_train)

# Predict
y_pred = ensemble.predict(X_test_scaled)
y_prob = ensemble.predict_proba(X_test_scaled)[:, 1]

# Evaluate
print("\n Stacked Ensemble (XGB + CatBoost + LR)")
print("Accuracy :", round(accuracy_score(y_test, y_pred), 4))
print("Precision:", round(precision_score(y_test, y_pred), 4))
print("Recall    :", round(recall_score(y_test, y_pred), 4))
print("F1 Score :", round(f1_score(y_test, y_pred), 4))
print("ROC AUC   :", round(roc_auc_score(y_test, y_prob), 4))
```

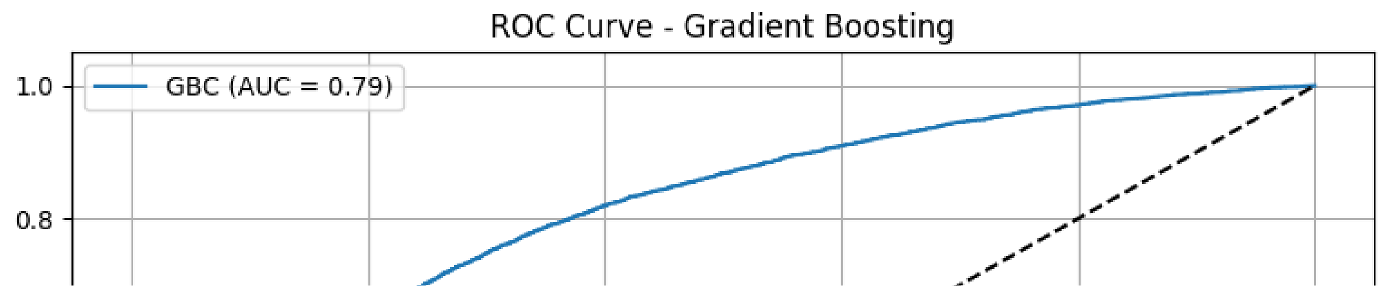
```
 Stacked Ensemble (XGB + CatBoost + LR)
Accuracy : 0.7278
Precision: 0.7467
Recall    : 0.6802
F1 Score : 0.7119
ROC AUC   : 0.7947
```

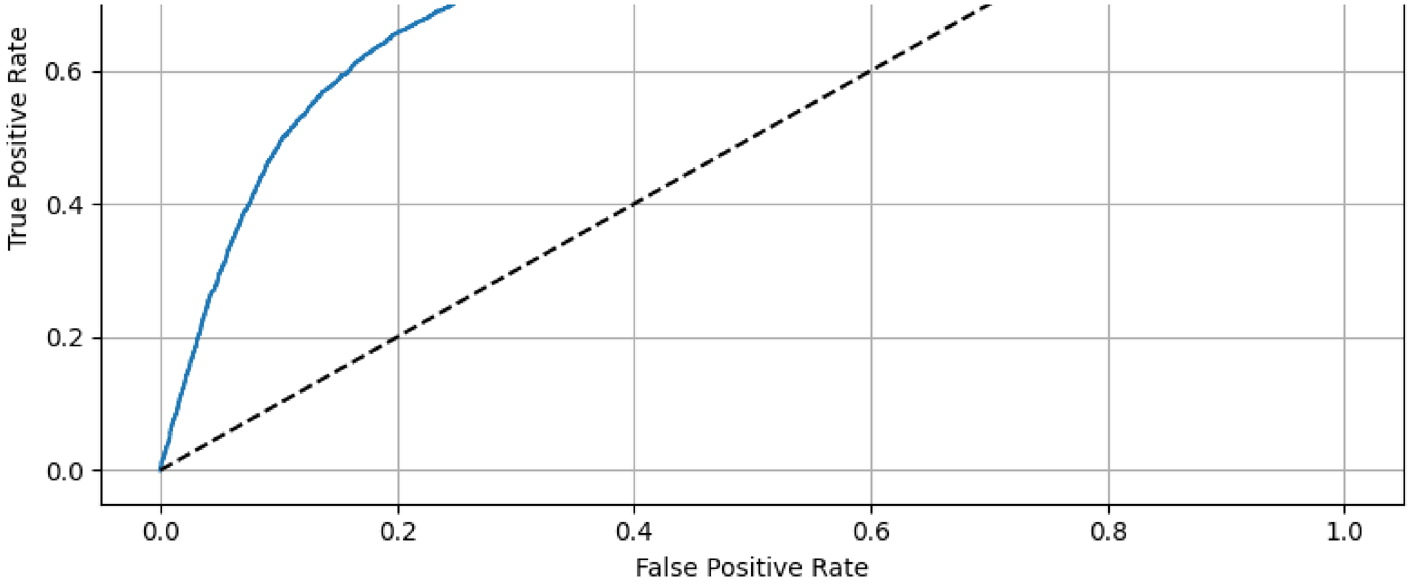
In [33]:

```python
# Imports
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_
auc_score, roc_curve
import matplotlib.pyplot as plt

# Load & Clean
df = pd.read_csv("cardio_disease.csv", delimiter=";")
df = df.drop(columns=["id"]).dropna()
df["age"] = df["age"] // 365
df = df[(df["ap_hi"] >= 80) & (df["ap_hi"] <= 200)]
```

```
df = df[(df["ap_lo"] >= 50) & (df["ap_lo"] <= 130)]

# Feature Engineering
df["bmi"] = df["weight"] / (df["height"] / 100) ** 2
df["pulse_pressure"] = df["ap_hi"] - df["ap_lo"]

# X and y
X = df.drop("cardio", axis=1)
y = df["cardio"]

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, ran
dom_state=42)

# Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Gradient Boosting Classifier
gbc = GradientBoostingClassifier(
    n_estimators=300,
    learning_rate=0.05,
    max_depth=5,
    subsample=0.8,
    random_state=42
)

# Fit
gbc.fit(X_train_scaled, y_train)

# Predict
y_pred = gbc.predict(X_test_scaled)
y_prob = gbc.predict_proba(X_test_scaled)[:, 1]

# Evaluate
print("\n Gradient Boosting Classifier Performance")
print("Accuracy :", round(accuracy_score(y_test, y_pred), 4))
print("Precision:", round(precision_score(y_test, y_pred), 4))
print("Recall   :", round(recall_score(y_test, y_pred), 4))
print("F1 Score :", round(f1_score(y_test, y_pred), 4))
print("ROC AUC  :", round(roc_auc_score(y_test, y_prob), 4))

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 5))
plt.plot(fpr, tpr, label=f"GBC (AUC = {roc_auc_score(y_test, y_prob):.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - Gradient Boosting")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
 Gradient Boosting Classifier Performance
Accuracy : 0.7275
Precision: 0.7475
Recall   : 0.6778
F1 Score : 0.711
ROC AUC  : 0.7943
```





True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate