```
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

df=pd.read_csv("cardio_train.csv")
df1=pd.read_csv("cardio_train.csv", delimiter=';')
df1

          id    age  gender  height  weight  ap_hi  ap_lo  cholesterol
gluc  \
0          0  18393       2     168    62.0    110     80            1
1
1          1  20228       1     156    85.0    140     90            3
1
2          2  18857       1     165    64.0    130     70            3
1
3          3  17623       2     169    82.0    150    100            1
1
4          4  17474       1     156    56.0    100     60            1
1
...      ...    ...     ...     ...     ...    ...    ...          ...
...
69995  99993  19240       2     168    76.0    120     80            1
1
69996  99995  22601       1     158   126.0    140     90            2
2
69997  99996  19066       2     183   105.0    180     90            3
1
69998  99998  22431       1     163    72.0    135     80            1
2
69999  99999  20540       1     170    72.0    120     80            2
1

       smoke  alco  active  cardio
0          0     0       1       0
1          0     0       1       1
2          0     0       0       1
3          0     0       1       1
4          0     0       0       0
...      ...   ...     ...     ...
69995      1     0       1       0
69996      0     0       1       1
69997      0     1       0       1
69998      0     0       0       1
69999      0     0       1       0

[70000 rows x 13 columns]
```

Perform data pre-processing operations.

```
print(df1.columns)
```

```
Index(['id', 'age', 'gender', 'height', 'weight', 'ap_hi', 'ap_lo',
       'cholesterol', 'gluc', 'smoke', 'alco', 'active', 'cardio'],
      dtype='object')
```

```
from sklearn.preprocessing import StandardScaler

# Step 1: Convert 'age' from days to years
df1['age'] = (df1['age'] / 365).astype(int)

# Step 2: Check for missing values
missing_values = df1.isnull().sum()

# Step 3: Remove duplicate rows
df1.drop_duplicates(inplace=True)

# Step 4: Scale numerical features
scaler = StandardScaler()
# Define column names (not DataFrame slices)
numerical_cols = ['age', 'height', 'weight', 'ap_hi', 'ap_lo']
df1[numerical_cols] = scaler.fit_transform(df1[numerical_cols])

# Check results
df1.info(), missing_values
df1
```

```
<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  float64
 2   gender       70000 non-null  int64  
 3   height       70000 non-null  float64
 4   weight       70000 non-null  float64
 5   ap_hi        70000 non-null  float64
 6   ap_lo        70000 non-null  float64
 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(5), int64(8)
memory usage: 6.9 MB
```

```
          id       age  gender    height    weight     ap_hi     ap_lo  \
0          0 -0.419800       2  0.443452 -0.847873 -0.122182 -0.088238

1          1  0.319110       1 -1.018168  0.749831  0.072610 -0.035180

2          2 -0.272018       1  0.078047 -0.708942  0.007679 -0.141297

3          3 -0.715364       2  0.565254  0.541435  0.137541  0.017879

4          4 -0.863146       1 -1.018168 -1.264666 -0.187113 -0.194356

...      ...       ...     ...       ...       ...       ...       ...

69995  99993 -0.124236       2  0.443452  0.124642 -0.057251 -0.088238

69996  99995  1.205802       1 -0.774565  3.597913  0.072610 -0.035180

69997  99996 -0.124236       2  2.270477  2.139139  0.332333 -0.035180

69998  99998  1.205802       1 -0.165556 -0.153219  0.040145 -0.088238

69999  99999  0.466892       1  0.687055 -0.153219 -0.057251 -0.088238


       cholesterol  gluc  smoke  alco  active  cardio
0                1     1      0     0       1       0
1                3     1      0     0       1       1
2                3     1      0     0       0       1
3                1     1      0     0       1       1
4                1     1      0     0       0       0
...            ...   ...    ...   ...     ...     ...
69995            1     1      1     0       1       0
69996            2     2      0     0       1       1
69997            3     1      0     1       0       1
69998            1     2      0     0       0       1
69999            2     1      0     0       1       0

[70000 rows x 13 columns]
```

As a part of data analysis and visualizations draw all the possible plots to provide essential informations and to derive some meaningful insights.

```
# Step 2: Remove duplicates
df1.drop_duplicates(inplace=True)

# Step 3: Basic summary statistics
summary_stats = df1.describe()

# Step 4: Plotting
plt.figure(figsize=(18, 24))

# 1. Age distribution
plt.subplot(3, 2, 1)
sns.histplot(df1['age'], bins=30, kde=True, color='skyblue')
plt.title('Age Distribution')

# 2. Gender distribution
plt.subplot(3, 2, 2)
sns.countplot(x='gender', data=df1, palette='Set2')
plt.title('Gender Distribution')

# 3. Target distribution (Cardiovascular Disease presence)
plt.subplot(3, 2, 3)
sns.countplot(x='cardio', data=df1, palette='Set1')
plt.title('Cardiovascular Disease (Target) Distribution')

# 4. Smoking vs Cardiovascular Disease
plt.subplot(3, 2, 4)
sns.countplot(x='smoke', hue='cardio', data=df1, palette='Set3')
plt.title('Smoking vs Cardiovascular Disease')

# 5. Alcohol intake vs Cardiovascular Disease
plt.subplot(3, 2, 5)
sns.countplot(x='alco', hue='cardio', data=df1, palette='Set2')
plt.title('Alcohol Intake vs Cardiovascular Disease')

# 6. Physical activity vs Cardiovascular Disease
plt.subplot(3, 2, 6)
sns.countplot(x='active', hue='cardio', data=df1, palette='Set1')
plt.title('Physical Activity vs Cardiovascular Disease')

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

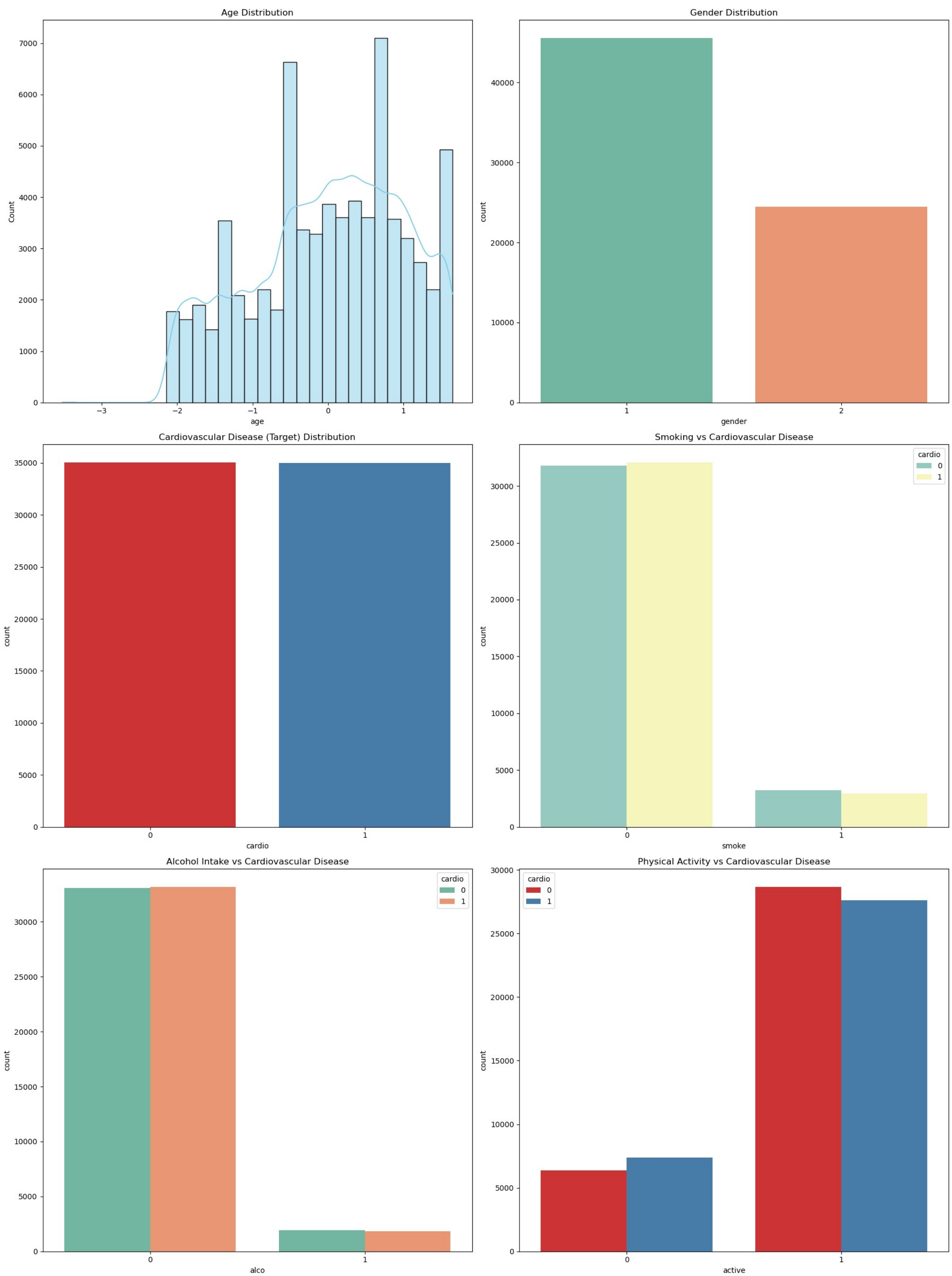
```
C:\Users\user\AppData\Local\Temp\ipykernel_19824\856624396.py:17:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='gender', data=df1, palette='Set2')
C:\Users\user\AppData\Local\Temp\ipykernel_19824\856624396.py:22:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='cardio', data=df1, palette='Set1')
```


Age Distribution
Count
age
−3
−2
−1
0
1
Gender Distribution
count
gender
Cardiovascular Disease (Target) Distribution
count
cardio
Smoking vs Cardiovascular Disease
count
smoke
cardio
Alcohol Intake vs Cardiovascular Disease
count
alco
cardio
Physical Activity vs Cardiovascular Disease
count
active
cardio

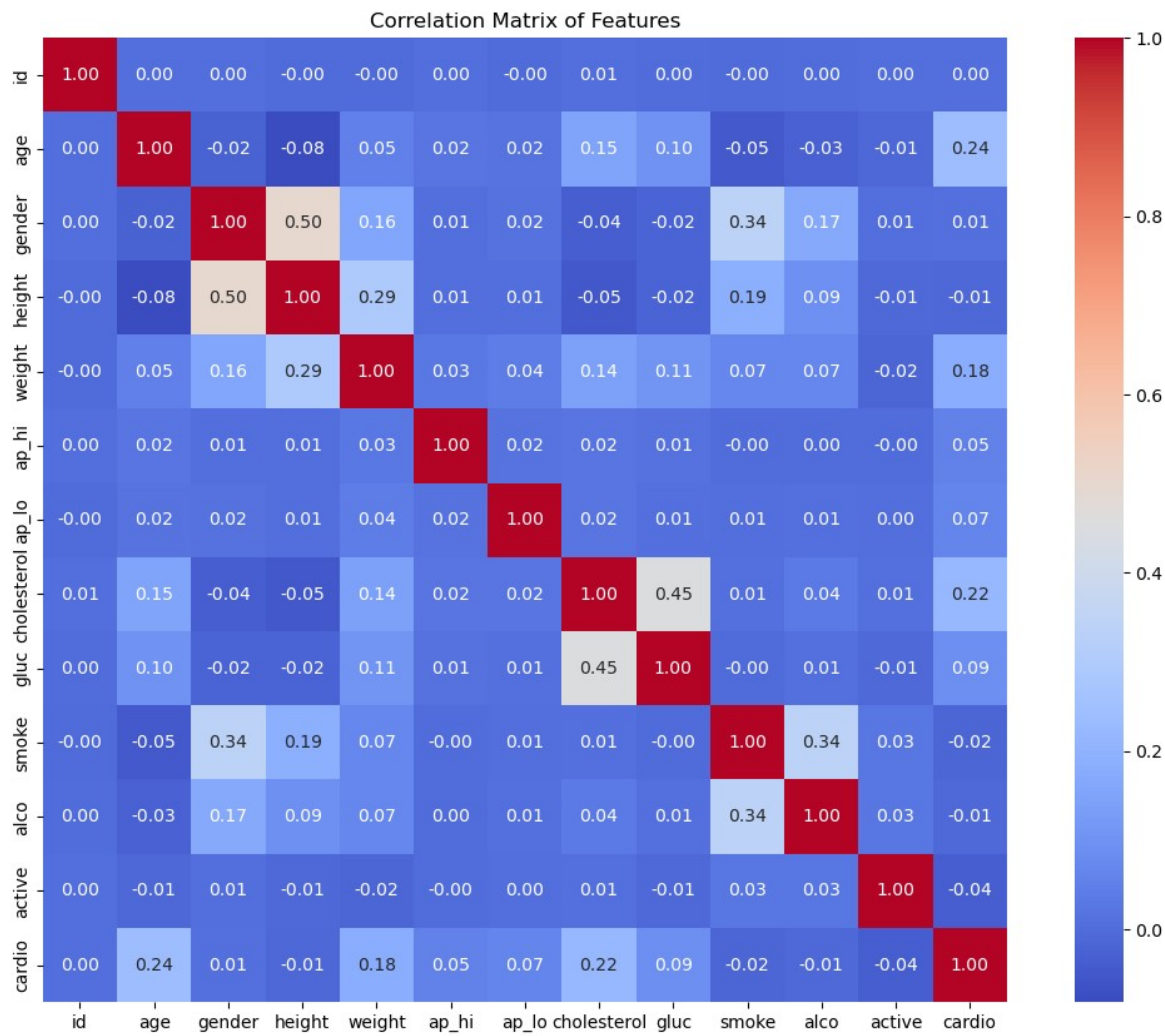
Show your correlation matrix of features according to the datasets.

```
# Compute correlation matrix
correlation_matrix = df1.corr()

# Set the plot size
plt.figure(figsize=(14, 10))

# Create a heatmap
sns.heatmap(correlation_matrix, annot=True, fmt=".2f",
cmap="coolwarm", square=True)

# Title
plt.title("Correlation Matrix of Features")
plt.show()
```



Find out accuracy levels of various machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Trees (DT) ,Logistic Regression (LR) and Random Forest (RF).

```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import StandardScaler
```

```python
# ML Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier

# Features and target
X = df1.drop(columns='cardio')
y = df1['cardio']

# Split data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}

for name, model in models.items():
    try:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

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

    except Exception as e:
        print(f"\n{name} failed with error: {e}")
```

```
Logistic Regression
Accuracy  : 0.7145
Precision : 0.7320
Recall    : 0.6762
F1 Score  : 0.7030

Decision Tree
Accuracy  : 0.6345
Precision : 0.6334
Recall    : 0.6377
F1 Score  : 0.6355

Random Forest
Accuracy  : 0.7197
Precision : 0.7286
Recall    : 0.6998
F1 Score  : 0.7139

KNN
Accuracy  : 0.6275
Precision : 0.6317
Recall    : 0.6105
F1 Score  : 0.6209

SVM
Accuracy  : 0.7253
Precision : 0.7397
Recall    : 0.6947
F1 Score  : 0.7165
```

```
from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score

# 4. Initialize the best-performing model (e.g., Random Forest)
final_model = RandomForestClassifier(n_estimators=100,
random_state=42)

# 5. Train the model
final_model.fit(X_train, y_train)

# 6. Make predictions
y_pred = final_model.predict(X_test)

# 7. Evaluate the model
print("□ Final Model Performance:")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
□ Final Model Performance:
Confusion Matrix:
 [[5172 1832]
 [2109 4887]]

Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.74      0.72      7004
           1       0.73      0.70      0.71      6996

    accuracy                           0.72     14000
   macro avg       0.72      0.72      0.72     14000
weighted avg       0.72      0.72      0.72     14000

Accuracy: 0.7185
```