Part 1: Get vehicle mpg data into pandas and clean

In [1]:
```
from matplotlib import pyplot
from pandas import DataFrame
import numpy as np
import pandas as pd
```

In [6]:
```
# Load the Drive helper and mount
from google.colab import drive

# Prompt for Authorization
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

In [7]:
```
!ls /content/drive/MyDrive/ECEN250/Lab7/vehmpgdata.csv
```

```
/content/drive/MyDrive/ECEN250/Lab7/vehmpgdata.csv
```

In [8]:
```
df = pd.read_csv('/content/drive/MyDrive/ECEN250/Lab7/vehmpgdata.csv', encod
nRow, nCol = df.shape
print(f'Dataframe has {nRow} rows {nCol} colums')
```

```
Dataframe has 428 rows 21 colums
```

In [9]:
```
df.head()
```

Out[9]:

	msrp	invoice	disp	cyl	hp	weight	wheelbase	length	width	sports	...
0	22388	20701	1.8	4.0	142	2387.0	89.0	156.0	66.0	1	...
1	35545	32244	3.8	6.0	205	3778.0	114.0	207.0	75.0	0	...
2	39235	36052	4.0	8.0	270	3953.0	106.0	185.0	69.0	0	...
3	45707	41966	3.2	6.0	215	3770.0	107.0	183.0	69.0	0	...
4	15500	14525	2.0	4.0	148	2696.0	NaN	NaN	NaN	0	...

5 rows × 21 columns

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 428 entries, 0 to 427
Data columns (total 21 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   msrp       428 non-null    int64  
 1   invoice    428 non-null    int64  
 2   disp       428 non-null    float64
 3   cyl        426 non-null    float64
 4   hp         428 non-null    int64  
 5   weight     426 non-null    float64
 6   wheelbase  426 non-null    float64
 7   length     426 non-null    float64
 8   width      424 non-null    float64
 9   sports     428 non-null    int64  
 10  suv        428 non-null    int64  
 11  wagon      428 non-null    int64  
 12  minivan    428 non-null    int64  
 13  pickup     428 non-null    int64  
 14  AWD        428 non-null    int64  
 15  RWD        428 non-null    int64  
 16  coupe      428 non-null    int64  
 17  sedan      428 non-null    int64  
 18  mpgclass   417 non-null    float64
 19  cmpg       417 non-null    float64
 20  hmpg       417 non-null    float64
dtypes: float64(9), int64(12)
memory usage: 70.3 KB
```

Instruction: Since we will be using the datafile to predict the vehicle mpgclass, it would be cheating to use the city and highway mpg values, so drop the cmpg and hmpg features from your dataframe.Also eliminate the features that describe the type of vehicle, ‘sports', 'suv', 'wagon', 'minivan', 'pickup', ‘coupe’, and ‘sedan’.

In [11]:
```
# drop the cmpg and hmpg features from your dataframe
df = df.drop(columns=['cmpg', 'hmpg'])
```

In [12]:
```
# insert code to eliminate the features that describe the type of vehicle, ‘
df = df.drop(columns=['sports', 'suv', 'wagon', 'minivan', 'pickup', 'coupe'
```

In [13]:
```
# Creates a new dataframe with only the rows with NaNs in them
df2=df[df.isnull().any(axis=1)]

# Prints only the columns with NaNs
print(df2.loc[:, df2.isnull().any()])
```

```
      cyl  weight  wheelbase  length  width  mpgclass
4     4.0  2696.0        NaN     NaN    NaN       NaN
10    8.0  5194.0      118.0   204.0   75.0       NaN
65    4.0  2656.0      102.0   181.0   67.0       NaN
87    NaN  3053.0      106.0   174.0    NaN       1.0
96    6.0     NaN      107.0   178.0   68.0       1.0
140   NaN  3029.0      106.0   174.0    NaN       1.0
141   6.0     NaN      110.0   196.0   73.0       0.0
155   8.0  3725.0      110.0   190.0   73.0       NaN
213   4.0  2744.0      102.0   181.0   67.0       NaN
243   4.0  3351.0      108.0   191.0   72.0       NaN
267   4.0  2795.0      102.0   181.0   67.0       NaN
306   4.0  2762.0        NaN     NaN    NaN       NaN
327   4.0  3020.0      102.0   181.0   67.0       NaN
391  12.0  5399.0      118.0   204.0   75.0       NaN
399  10.0  7190.0      137.0   227.0   80.0       NaN
```

We will clean the dataframe to remove any NaNs:

In [14]:
```
df=df.dropna(subset=['mpgclass'])
df=df.dropna(subset=['weight'])
df=df.dropna(subset=['wheelbase'])
df=df.dropna(subset=['width'])
df=df.dropna(subset=['cyl'])
```

Part 2: Train decision tree classifiers and evaluate their performance

With your now clean dataframe, select the remaining features and perform train/validation/test splitting of the dataset. Use 60%, 20%, 20% for your split

In [15]:
```
X=df.drop(columns=['mpgclass'])
y=df[['mpgclass']]

X.head()
```

Out[15]:

	msrp	invoice	disp	cyl	hp	weight	wheelbase	length	width	AWD	RWD
0	22388	20701	1.8	4.0	142	2387.0	89.0	156.0	66.0	0	1
1	35545	32244	3.8	6.0	205	3778.0	114.0	207.0	75.0	0	0
2	39235	36052	4.0	8.0	270	3953.0	106.0	185.0	69.0	0	0
3	45707	41966	3.2	6.0	215	3770.0	107.0	183.0	69.0	0	1
5	34845	32902	2.3	5.0	247	3766.0	107.0	180.0	71.0	0	0

In [19]:
```
from sklearn.model_selection import train_test_split

# insert code to perform train/validation/test splitting
x_train, x_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, ran
x_validate, x_test, y_validate, y_test = train_test_split(x_temp, y_temp, te
```

Insert code below to print the size of the train/validation/test sets.

In [20]:
```
print("x_train shape:", x_train.shape)
print("y_train shape:", y_train.shape)
print("x_validate shape:", x_validate.shape)
print("y_validate shape:", y_validate.shape)
print("x_test shape:", x_test.shape)
print("y_test shape:", y_test.shape)
```

```
x_train shape: (247, 11)
y_train shape: (247, 1)
x_validate shape: (83, 11)
y_validate shape: (83, 1)
x_test shape: (83, 11)
y_test shape: (83, 1)
```

Now, we train a decision tree classifier using **gini** without any constraint on depth. Present the confusion matrix, accuracy, F1, and precision on **validation set** for that classifier.

In [21]:
```
from sklearn import tree
clf = tree.DecisionTreeClassifier(criterion='gini')
clf = clf.fit(x_train, y_train)
```

In [22]:
```
y_pred = clf.predict(x_validate)
y_pred
```

Out[22]:
```
array([2., 2., 1., 2., 2., 0., 0., 1., 0., 0., 2., 1., 1., 2., 1., 1., 1.,
       1., 1., 1., 1., 0., 0., 1., 2., 0., 2., 0., 2., 2., 1., 0., 1., 2.,
       1., 0., 0., 2., 2., 0., 1., 2., 2., 1., 0., 1., 1., 0., 1., 0., 0.,
       2., 1., 1., 0., 1., 2., 1., 1., 1., 2., 2., 1., 1., 0., 0., 1., 1.,
       0., 2., 2., 0., 0., 2., 1., 1., 1., 2., 2., 2., 1., 1., 1.])
```

In [23]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score

# confusion matrix
print("Confusion Matrix:")
cm = confusion_matrix(y_validate, y_pred)
print(confusion_matrix(y_validate, y_pred))

# F1 & precision scores
print(classification_report(y_validate, y_pred))
```

```
Confusion Matrix:
[[17  5  0]
 [ 5 28  2]
 [ 0  3 23]]
              precision    recall  f1-score   support

         0.0       0.77      0.77      0.77        22
         1.0       0.78      0.80      0.79        35
         2.0       0.92      0.88      0.90        26

    accuracy                           0.82        83
   macro avg       0.82      0.82      0.82        83
weighted avg       0.82      0.82      0.82        83
```

Now, insert code below to train a decision tree using **entropy without any constraint on depth. Present the confusion matrix, accuracy, F1, and precision for that classifier.**

In [24]:
```python
from sklearn import tree

# Train a decision tree using entropy
clf_entropy = tree.DecisionTreeClassifier(criterion='entropy')
clf_entropy = clf_entropy.fit(x_train, y_train)

# Predict on the validation set
y_pred_entropy = clf_entropy.predict(x_validate)

# Present the confusion matrix, accuracy, F1, and precision
print("Confusion Matrix (Entropy):")
print(confusion_matrix(y_validate, y_pred_entropy))

print("\nClassification Report (Entropy):")
print(classification_report(y_validate, y_pred_entropy))
```

```
Confusion Matrix (Entropy):
[[16  5  1]
 [ 5 27  3]
 [ 0  1 25]]

Classification Report (Entropy):
              precision    recall  f1-score   support

         0.0       0.76      0.73      0.74        22
         1.0       0.82      0.77      0.79        35
         2.0       0.86      0.96      0.91        26

    accuracy                           0.82        83
   macro avg       0.81      0.82      0.82        83
weighted avg       0.82      0.82      0.82        83
```

Now, insert code below, using whichever criterion provided superior results, train decision trees with maximum_depth from 2 to 6.

Present the confusion matrix, accuracy, F1, and precision for that classifier.

In [25]:
```
best_accuracy = 0
best_clf = None
best_depth = 0

for depth in range(2, 7):
    clf = tree.DecisionTreeClassifier(criterion='entropy', max_depth=depth)
    clf = clf.fit(x_train, y_train)
    y_pred = clf.predict(x_validate)

    print(f"\nResults for max_depth = {depth}:")
    print("Confusion Matrix:")
    print(confusion_matrix(y_validate, y_pred))
    print("\nClassification Report:")
    report = classification_report(y_validate, y_pred)
    print(report)

    # Extract accuracy from the report
    accuracy = float(report.splitlines()[-3].split()[-2])

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_clf = clf
        best_depth = depth

print(f"\nBest decision tree classifier found with max_depth = {best_depth}
```

```
Results for max_depth = 2:
Confusion Matrix:
[[16  6  0]
 [ 4 29  2]
 [ 0  7 19]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.73      0.76        22
         1.0       0.69      0.83      0.75        35
         2.0       0.90      0.73      0.81        26

    accuracy                           0.77        83
   macro avg       0.80      0.76      0.77        83
weighted avg       0.79      0.77      0.77        83


Results for max_depth = 3:
Confusion Matrix:
[[16  6  0]
 [ 4 29  2]
 [ 0  8 18]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.73      0.76        22
         1.0       0.67      0.83      0.74        35
         2.0       0.90      0.69      0.78        26

    accuracy                           0.76        83
   macro avg       0.79      0.75      0.76        83
weighted avg       0.78      0.76      0.76        83


Results for max_depth = 4:
Confusion Matrix:
[[14  8  0]
 [ 5 28  2]
 [ 2  5 19]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.67      0.64      0.65        22
         1.0       0.68      0.80      0.74        35
         2.0       0.90      0.73      0.81        26

    accuracy                           0.73        83
   macro avg       0.75      0.72      0.73        83
weighted avg       0.75      0.73      0.74        83


Results for max_depth = 5:
Confusion Matrix:
```

```
[[16  6  0]
 [ 4 26  5]
 [ 0  0 26]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.73      0.76        22
         1.0       0.81      0.74      0.78        35
         2.0       0.84      1.00      0.91        26

    accuracy                           0.82        83
   macro avg       0.82      0.82      0.82        83
weighted avg       0.82      0.82      0.82        83


Results for max_depth = 6:
Confusion Matrix:
[[17  5  0]
 [ 4 28  3]
 [ 0  1 25]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.77      0.79        22
         1.0       0.82      0.80      0.81        35
         2.0       0.89      0.96      0.93        26

    accuracy                           0.84        83
   macro avg       0.84      0.84      0.84        83
weighted avg       0.84      0.84      0.84        83


Best decision tree classifier found with max_depth = 6 and accuracy = 0.8400
```

Present the confusion matrix, accuracy, F1, and precision on your ****test set** for the classifier which gave best results on validation.**

In [26]:

```
# Predict on the test set using the best classifier found on validation
y_pred_test = best_clf.predict(x_test)

# Present the confusion matrix, accuracy, F1, and precision on the test set
print("Confusion Matrix (Test Set):")
print(confusion_matrix(y_test, y_pred_test))

print("\nClassification Report (Test Set):")
print(classification_report(y_test, y_pred_test))
```

```
Confusion Matrix (Test Set):
[[20  6  0]
 [ 5 21  4]
 [ 0  2 25]]

Classification Report (Test Set):
              precision    recall  f1-score   support

         0.0       0.80      0.77      0.78        26
         1.0       0.72      0.70      0.71        30
         2.0       0.86      0.93      0.89        27

    accuracy                           0.80        83
   macro avg       0.80      0.80      0.80        83
weighted avg       0.79      0.80      0.79        83
```

Part 3: Train random forest classifiers and evaluate their performance

We will use the same dataset to evaluate random forest classifiers. Using gini as the criterion and n_estimators=100, vary max_depth between 2 and 5. Select the best model.

In [27]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [28]:

```
depth = [2, 3, 4, 5]
best_accuracy_rf = 0
best_rf_clf = None
best_rf_depth = 0

for i in depth:
    rf_clf = RandomForestClassifier(criterion='gini', n_estimators=100, max_
    rf_clf.fit(x_train, y_train.values.ravel())  # Use .values.ravel() for y
    y_pred_rf = rf_clf.predict(x_validate)

    print(f"\nResults for max_depth = {i}:")
    print("Confusion Matrix:")
    print(confusion_matrix(y_validate, y_pred_rf))
    print("\nClassification Report:")
    report_rf = classification_report(y_validate, y_pred_rf)
    print(report_rf)

    accuracy_rf = float(report_rf.splitlines()[-3].split()[-2])

    if accuracy_rf > best_accuracy_rf:
        best_accuracy_rf = accuracy_rf
        best_rf_clf = rf_clf
        best_rf_depth = i
```

```
print(f"\nBest Random Forest classifier found with max_depth = {best_rf_dept
```

```
Results for max_depth = 2:
Confusion Matrix:
[[16  6  0]
 [ 3 28  4]
 [ 0  8 18]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.84      0.73      0.78        22
         1.0       0.67      0.80      0.73        35
         2.0       0.82      0.69      0.75        26

    accuracy                           0.75        83
   macro avg       0.78      0.74      0.75        83
weighted avg       0.76      0.75      0.75        83


Results for max_depth = 3:
Confusion Matrix:
[[17  5  0]
 [ 2 30  3]
 [ 0  8 18]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.89      0.77      0.83        22
         1.0       0.70      0.86      0.77        35
         2.0       0.86      0.69      0.77        26

    accuracy                           0.78        83
   macro avg       0.82      0.77      0.79        83
weighted avg       0.80      0.78      0.78        83


Results for max_depth = 4:
Confusion Matrix:
[[18  4  0]
 [ 2 31  2]
 [ 0  8 18]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.90      0.82      0.86        22
         1.0       0.72      0.89      0.79        35
         2.0       0.90      0.69      0.78        26

    accuracy                           0.81        83
   macro avg       0.84      0.80      0.81        83
weighted avg       0.82      0.81      0.81        83


Results for max_depth = 5:
Confusion Matrix:
```

```
[[18  4  0]
 [ 1 32  2]
 [ 0  8 18]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.95      0.82      0.88        22
         1.0       0.73      0.91      0.81        35
         2.0       0.90      0.69      0.78        26

    accuracy                           0.82        83
   macro avg       0.86      0.81      0.82        83
weighted avg       0.84      0.82      0.82        83


Best Random Forest classifier found with max_depth = 5 and accuracy = 0.8200
```

Part 4: Data load, cleaning, and classification modeling

We will be analyzing heart ECG data to classify causes of arrythmia. This example is a classification of normal and abnormal ECGs based on 16 total classes

Preparing Dataset

The acutal number of instances for the measurements are given below. We won't make use of this to set our priors -- but we will verify these classes.

In [ ]:
```
# Class Distribution:

#  Class code :   Class   :                                          Numb
#    01             Normal
#    02             Ischemic changes (Coronary Artery Disease)
#    03             Old Anterior Myocardial Infarction
#    04             Old Inferior Myocardial Infarction
#    05             Sinus tachycardy
#    06             Sinus bradycardy
#    07             Ventricular Premature Contraction (PVC)
#    08             Supraventricular Premature Contraction
#    09             Left bundle branch block
#    10             Right bundle branch block
#    11             1. degree AtrioVentricular block
#    12             2. degree AV block
#    13             3. degree AV block
#    14             Left ventricule hypertrophy
#    15             Atrial Fibrillation or Flutter
#    16             Others
```

In [29]:
```
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt # plotting
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

Verify the datafile is in drive

In [30]:
```
!ls drive/MyDrive/ECEN250/Lab7/data_arrhythmia.csv
```

```
drive/MyDrive/ECEN250/Lab7/data_arrhythmia.csv
```

Load the datafile into pandas dataframe

In [32]:
```
df = pd.read_csv('drive/MyDrive/ECEN250/Lab7/data_arrhythmia.csv', delimiter
df.dataframeName = 'data_arrhythmia.csv'
nRow, nCol = df.shape
print(f'Dataframe has {nRow} rows {nCol} colums')
```

```
Dataframe has 452 rows 280 colums
```

Notice this datafile has 280 features! Much of the challenges in this lab is dealing with this large number of features. The number of observations is actually quite low for this dataset. It will be a challenge that will limit our classification effectiveness.

In [33]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 452 entries, 0 to 451
Columns: 280 entries, age to diagnosis
dtypes: float64(116), int64(159), object(5)
memory usage: 988.9+ KB
```

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

Out[34]:

	age	sex	height	weight	qrs_duration	p r_interva
count	452.000000	452.000000	452.000000	452.000000	452.000000	452.00000
mean	46.471239	0.550885	166.188053	68.170354	88.920354	155.15265
std	16.466631	0.497955	37.170340	16.590803	15.364394	44.84228
min	0.000000	0.000000	105.000000	6.000000	55.000000	0.00000
25%	36.000000	0.000000	160.000000	59.000000	80.000000	142.00000
50%	47.000000	1.000000	164.000000	68.000000	86.000000	157.00000
75%	58.000000	1.000000	170.000000	79.000000	94.000000	175.00000
max	83.000000	1.000000	780.000000	176.000000	188.000000	524.00000

8 rows × 275 columns

In [35]:
```
df.head()
```

Out[35]:

	age	sex	height	weight	qrs_duration	p-r_interval	q-t_interval	t_interval
0	75	0	190	80	91	193	371	174
1	56	1	165	64	81	174	401	149
2	54	0	172	95	138	163	386	185
3	55	0	175	94	100	202	380	179
4	75	0	190	80	88	181	360	177

5 rows × 280 columns

This piece of code is useful when you have such a large number of features. It shows which features are objects -- which often means that it has non-numerics mixed with numerics.

In [36]:
```
df.select_dtypes(include=['object'])
```

Out[36]:

	T	P	QRST	J	heart_rate
0	13	64	-2	?	63
1	37	-17	31	?	53
2	34	70	66	23	75
3	11	-5	20	?	71
4	13	61	3	?	?
...	...	...	...	...	...
447	4	40	-27	?	63
448	66	52	79	?	73
449	-19	-61	-70	84	84
450	29	-22	43	103	80
451	79	52	47	?	75

452 rows × 5 columns

OH NO! This dataset has used the character ? for a missing or unknown value. There are three strategies for fixing this -- one would be directly dropping any entries with ?, second would be trying to replace each ? with something else, and the third is to first convert them to NaNs -- then use what we already know to fix the NaN problem. Strategy 1 will throw away too much data, 2 is very difficult, so choose 3!

In [37]:

```
#This will change object type to numeric and for non-numeric entries, force
df['P'] = pd.to_numeric(df['P'], errors='coerce')
df['T'] = pd.to_numeric(df['T'], errors='coerce')
df['QRST'] = pd.to_numeric(df['QRST'], errors='coerce')
df['J'] = pd.to_numeric(df['J'], errors='coerce')
df['heart_rate'] = pd.to_numeric(df['heart_rate'], errors='coerce')
```

Now determine how many NaNs are left in P, T, QRST, J, and heart_rate. Run the code below to determine how many and include the results in a cell

In [38]:

```
# The following code counts the number of valid numeric values in each colum
featcount=df.count(numeric_only=True)
featcount.sort_values()
```

Out[38]:

	0
J	76
P	430
T	444
QRST	451
heart_rate	451
...	...
LE	452
LF	452
LG	452
diagnosis	452
age	452

280 rows × 1 columns

dtype: int64

Question: how many NANs in columns P, T, QRST, J, and heart_rate?

ANSWER:
P: 22 NaNs
T: 8 NaNs
QRST: 1 NaN
J: 376 NaNs
heart_rate: 1 NaN

Insert code below to fix the NaNs. You want to chose difference strategies for different columns.

In [39]:

```
# Fill NaNs in 'P', 'T', 'QRST', and 'heart_rate' with the mean
df['P'].fillna(df['P'].mean(), inplace=True)
df['T'].fillna(df['T'].mean(), inplace=True)
df['QRST'].fillna(df['QRST'].mean(), inplace=True)
df['heart_rate'].fillna(df['heart_rate'].mean(), inplace=True)

# Drop the 'J' column due to a large number of NaNs
df = df.drop(columns=['J'])
```

```
/tmp/ipython-input-1598267475.py:2: FutureWarning: A value is trying to be se
t on a copy of a DataFrame or Series through chained assignment using an inpl
ace method.
The behavior will change in pandas 3.0. This inplace method will never work b
ecause the intermediate object on which we are setting values always behaves
as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.
method({col: value}, inplace=True)' or df[col] = df[col].method(value) instea
d, to perform the operation inplace on the original object.


  df['P'].fillna(df['P'].mean(), inplace=True)
/tmp/ipython-input-1598267475.py:3: FutureWarning: A value is trying to be se
t on a copy of a DataFrame or Series through chained assignment using an inpl
ace method.
The behavior will change in pandas 3.0. This inplace method will never work b
ecause the intermediate object on which we are setting values always behaves
as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.
method({col: value}, inplace=True)' or df[col] = df[col].method(value) instea
d, to perform the operation inplace on the original object.


  df['T'].fillna(df['T'].mean(), inplace=True)
/tmp/ipython-input-1598267475.py:4: FutureWarning: A value is trying to be se
t on a copy of a DataFrame or Series through chained assignment using an inpl
ace method.
The behavior will change in pandas 3.0. This inplace method will never work b
ecause the intermediate object on which we are setting values always behaves
as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.
method({col: value}, inplace=True)' or df[col] = df[col].method(value) instea
d, to perform the operation inplace on the original object.


  df['QRST'].fillna(df['QRST'].mean(), inplace=True)
/tmp/ipython-input-1598267475.py:5: FutureWarning: A value is trying to be se
t on a copy of a DataFrame or Series through chained assignment using an inpl
ace method.
The behavior will change in pandas 3.0. This inplace method will never work b
ecause the intermediate object on which we are setting values always behaves
as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.
method({col: value}, inplace=True)' or df[col] = df[col].method(value) instea
d, to perform the operation inplace on the original object.


  df['heart_rate'].fillna(df['heart_rate'].mean(), inplace=True)
```

Make sure that there are no non numeric entries

In [40]:
```
df2=df[df.isnull().any(axis=1)]
print(df2.loc[:, df2.isnull().any()])
```

```
Empty DataFrame
Columns: []
Index: []
```

In [41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 452 entries, 0 to 451
Columns: 279 entries, age to diagnosis
dtypes: float64(120), int64(159)
memory usage: 985.3 KB
```

In [42]:
```
df.head()
```

Out[42]:

	age	sex	height	weight	qrs_duration	p-r_interval	q-t_interval	t_interval
0	75	0	190	80	91	193	371	174
1	56	1	165	64	81	174	401	149
2	54	0	172	95	138	163	386	185
3	55	0	175	94	100	202	380	179
4	75	0	190	80	88	181	360	177

5 rows × 279 columns

We will now extract the label data: 'diagnosis' into y, and the remainder of the dataframe into x

In [43]:
```
y = df.diagnosis.values
x = df.drop(["diagnosis"],axis=1)
```

Next we need to partition our dataset in to Train, Validation, Test Sets: Insert code to Split 20% of dataset to test, 20% to validation, and 60% into training.

In [54]:
```
from sklearn.model_selection import train_test_split

# Split 20% of dataset to test, 20% to validation, and 60% into training.
x_train, x_temp, y_train, y_temp = train_test_split(x, y, test_size=0.4, ran
x_validate, x_test, y_validate, y_test = train_test_split(x_temp, y_temp, te
```

In [55]:
```
x_train.head()
```

Out[55]:

	age	sex	height	weight	qrs_duration	p-r_interval	q-t_interval	t_interval
329	59	1	155	72	83	209	344	297
321	26	0	180	97	88	197	404	188
255	68	0	164	53	79	170	364	172
318	55	0	170	72	85	198	346	138
59	32	1	160	58	83	122	386	174

5 rows × 278 columns

In [56]:

```
x_test.head()
```

Out[56]:

	age	sex	height	weight	qrs_duration	p-r_interval	q-t_interval	t_interval
82	79	1	150	60	93	178	361	132
302	74	0	170	67	84	175	444	182
199	58	1	155	60	97	128	390	169
443	41	1	154	75	88	157	384	132
349	62	0	178	89	95	181	368	156

5 rows × 278 columns

Verify the data set partitioning

In [57]:

```
print("x_train: ",x_train.shape)
print("y_train: ",y_train.shape)
print("x_test: ",x_test.shape)
print("y_test: ",y_test.shape)
print("x_validate: ",x_validate.shape)
print("y_validate: ",y_validate.shape)
```

```
x_train:  (271, 278)
y_train:  (271,)
x_test:  (91, 278)
y_test:  (91,)
x_validate:  (90, 278)
y_validate:  (90,)
```

Just a peek at the labels for the training set

In [58]:

```
y_train
```

```
Out[58]: array([ 2,  1,  1,  1,  1,  1, 10,  1,  1,  1,  1,  1,  1,  1,  2,  3,  1,
                 1,  1,  1,  1,  1,  9,  1, 16, 10,  2,  1,  1,  9,  1,  1,  3,  1,
                10,  1, 16,  1,  6,  1,  1, 10,  1,  1,  2,  1,  1,  2,  6,  1, 10,
                10,  1,  4,  1,  1,  1,  6,  1,  1,  5,  1,  1, 10,  1, 10,  1,  1,
                 1,  1,  2, 16, 16,  1,  3,  1,  6, 10, 16,  5,  1,  1,  1,  2,  1,
                 1,  2,  1, 10,  1,  6,  1,  1, 16,  5,  1,  1,  1, 10,  1,  1, 10,
                 5,  1,  1,  2,  1,  1,  1,  1,  1,  6,  9,  1,  2,  1, 10,  1,  2,
                 1,  1,  3, 10,  1,  1,  1,  1,  2, 10,  1,  1,  1,  1,  1,  1,  2,
                 7,  2,  1,  4,  1, 16,  2,  1,  1,  1,  1,  5,  1,  1,  1,  7,  2,
                 1, 10, 16,  1,  1,  1,  1,  6,  1,  1,  1,  1, 10,  1, 10,  1,  1,
                15,  1,  1,  1,  1,  9,  2,  1,  1,  1,  1,  9,  2,  2, 16,  4,  1,
                 1,  3,  1,  1,  1,  1,  1, 15,  1,  7,  2,  4, 16,  6,  1,  1,  1,
                 1,  4,  1,  2,  4,  1, 10, 10,  1,  1,  1,  6,  1,  9,  5,  1,  1,
                 1,  1, 10, 16,  1, 10, 15, 16, 10,  1, 15,  9, 10,  2,  4,  6,  6,
                10,  2,  3,  1, 10,  1,  1,  1,  1, 10,  1,  6,  3,  2, 10,  1,  1,
                 2,  1,  2,  4,  1,  4,  1,  1,  1, 14, 16,  6,  1,  5,  1,  1])
```

We're going to use a random forest classiferto help us find he most important features.

```
In [59]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import accuracy_score
```

```
In [60]: rfc = RandomForestClassifier()
         rfc.fit(x_train, y_train)
         y_pred = rfc.predict(x_validate)
```

```
In [61]: cm=confusion_matrix(y_validate, y_pred)
         print("Confusion Matrix: ")
         print(cm)
         print("Accuracy: ",accuracy_score(y_validate,y_pred))
         print("f1 Score: ",f1_score(y_validate, y_pred, average='macro'))
         print("Precision: ",precision_score(y_validate, y_pred, average='macro'))
```

```
Confusion Matrix:
[[49  1  0  0  0  0  0  0  0  0  0]
 [ 2  6  0  0  0  0  0  0  0  0  1]
 [ 3  0  2  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 3  0  0  0  0  0  0  0  0  0  0]
 [ 5  0  0  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0]
 [ 3  0  0  0  0  0  0  0  4  0  0]
 [ 2  0  0  0  0  0  0  0  0  0  0]
 [ 6  0  0  0  0  0  0  0  0  0  0]]
Accuracy:  0.6888888888888889
f1 Score:  0.34842739079102714
Precision:  0.41004329004329
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

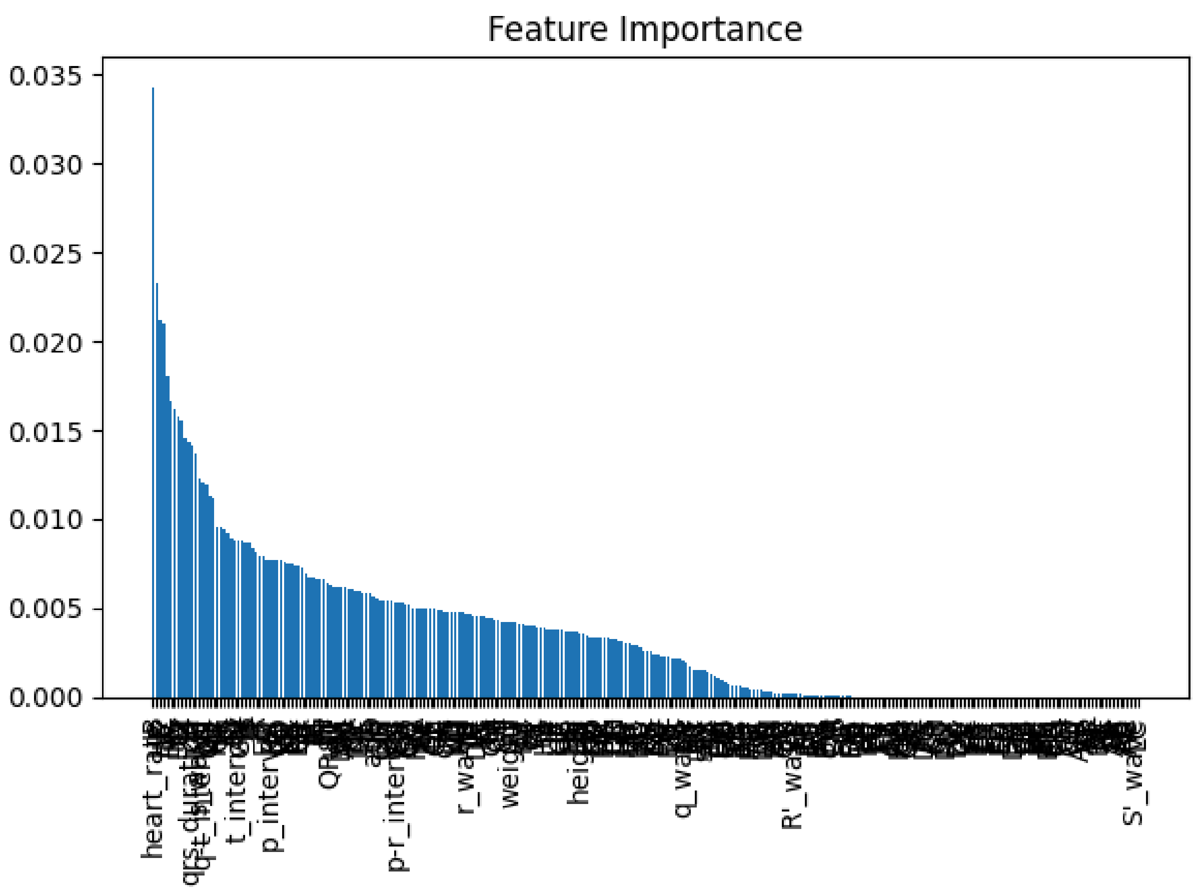
In [62]:
```
# The following code shows the number of misclassified data in a confusion m
misclassified = np.sum(cm) - np.sum(np.diag(cm))
misclassified
```

Out[62]:
```
np.int64(28)
```

The following code uses the importance of the features in the Random Forest -- and sorts them from most important to least important and plots them in order:

In [63]:
```
importances = rfc.feature_importances_
# Sort the feature importance in descending order
sorted_indices = np.argsort(importances)[::-1]
```

In [64]:
```
plt.title('Feature Importance')
plt.bar(range(x_train.shape[1]), importances[sorted_indices], align='center'
plt.xticks(range(x_train.shape[1]), x.columns[sorted_indices], rotation=90)
plt.tight_layout()
plt.show()
```



Compute the most important 14 features -- which we will use later

In [65]:
```
importances[sorted_indices][0:14]
```

Out[65]:
```
array([0.03424925, 0.0233218 , 0.02122021, 0.020947  , 0.01800783,
       0.01664837, 0.01623044, 0.01572233, 0.01556003, 0.01460844,
       0.01436116, 0.01411344, 0.01369704, 0.01230564])
```

In [66]:
```
x.columns[sorted_indices][0:14]
```

Out[66]:
```
Index(['heart_rate', 'JB', 'HR', 'LE', 'IV', 'DB', 'KS', 'DD', 'GJ', 'JZ',
       'JY', 'qrs_duration', 'KH', 's_wave'],
      dtype='object')
```

Now we are going to eliminate the least important 100 features from our analysis and retrain and evaluate our Random Forest classifier:

In [67]:
```
importances[sorted_indices][-100:]
```

Out[67]:
```
array([2.27272326e-04, 1.83342479e-04, 1.79615212e-04, 1.63583144e-04,
       1.61522941e-04, 1.37528546e-04, 1.09968152e-04, 1.09711192e-04,
       1.07674859e-04, 1.00048521e-04, 9.97994720e-05, 9.59554063e-05,
       9.58921323e-05, 9.32470083e-05, 8.72697786e-05, 7.75245516e-05,
       7.49654219e-05, 6.35941240e-05, 4.78925065e-05, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00])
```

In [68]:
```
x.columns[sorted_indices][-100:]
```

```
Out[68]: Index(['GG', 'CE', 'R'_wave', 'DJ', 'FA', 'EP', 'EH', 'DS', 'EL', 'DV', 'A
S',
       'BG', 'EC', 'CM', 'JI', 'JS', 'HE', 'IA', 'BO', 'FM', 'IB', 'KP', 'L
B',
       'KO', 'FV', 'FU', 'FS', 'FR', 'FY', 'FZ', 'GA', 'GB', 'HO', 'GS', 'G
R',
       'GH', 'FJ', 'FK', 'FL', 'DG', 'CS', 'CT', 'CR', 'CU', 'DT', 'DU', 'D
I',
       'IK', 'DC', 'DE', 'CV', 'IL', 'FE', 'ER', 'EU', 'ET', 'EY', 'FF', 'F
H',
       'EZ', 'ED', 'EV', 'EJ', 'EI', 'DH', 'EG', 'IY', 'CB', 'BE', 'BF', 'B
P',
       'BU', 'BS', 'BT', 'BM', 'CN', 'CG', 'CH', 'CI', 'CP', 'CD', 'Cf', 'C
A',
       'AB'', 'KF', 'AR', 'AP', 'AT', 'BC', 'AK', 'AL', 'JT', 'AF', 'AG',
'AE',
       'AD', 'AB', 'AC', 'S'_wave', 'LC'],
      dtype='object')
```

We now need to drop these features from our dataset:

```
In [69]: columns_to_drop = x.columns[sorted_indices][-100:]
df.drop(columns_to_drop, axis=1, inplace=True)
```

```
In [70]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 452 entries, 0 to 451
Columns: 179 entries, age to diagnosis
dtypes: float64(105), int64(74)
memory usage: 632.2 KB
```

Now, insert code to assign y to 'diagnosis' and the rest of the features to x; run train-test split for a 60% train, 20% validate, 20% test; train a Random Forest Classifier on train; generate CM, Accuracy, F1, and Precision for the validation set.

```
In [71]: # Assign y to 'diagnosis' and the rest of the features to x
y = df.diagnosis.values
x = df.drop(["diagnosis"],axis=1)

# Run train-test split for a 60% train, 20% validate, 20% test
x_train, x_temp, y_train, y_temp = train_test_split(x, y, test_size=0.4, ran
x_validate, x_test, y_validate, y_test = train_test_split(x_temp, y_temp, te

# Train a Random Forest Classifier on train
rfc = RandomForestClassifier(random_state=42)
rfc.fit(x_train, y_train)

# Generate CM, Accuracy, F1, and Precision for the validation set
y_pred = rfc.predict(x_validate)

print("Confusion Matrix (Validation Set):")
print(confusion_matrix(y_validate, y_pred))
```

```
print("\nClassification Report (Validation Set):")
print(classification_report(y_validate, y_pred))
```

```
Confusion Matrix (Validation Set):
[[49  1  0  0  0  0  0  0  0  0  0]
 [ 1  7  0  1  0  0  0  0  0  0  0]
 [ 2  0  3  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 2  0  0  0  0  0  0  0  1  0  0]
 [ 4  0  0  0  0  1  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0]
 [ 4  0  0  0  0  0  0  0  3  0  0]
 [ 2  0  0  0  0  0  0  0  0  0  0]
 [ 6  0  0  0  0  0  0  0  0  0  0]]

Classification Report (Validation Set):
              precision    recall  f1-score   support

           1       0.68      0.98      0.80        50
           2       0.88      0.78      0.82         9
           3       1.00      0.60      0.75         5
           4       0.00      0.00      0.00         1
           5       0.00      0.00      0.00         3
           6       1.00      0.20      0.33         5
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00         1
          10       0.75      0.43      0.55         7
          14       0.00      0.00      0.00         2
          16       0.00      0.00      0.00         6

    accuracy                           0.71        90
   macro avg       0.48      0.36      0.39        90
weighted avg       0.65      0.71      0.64        90
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

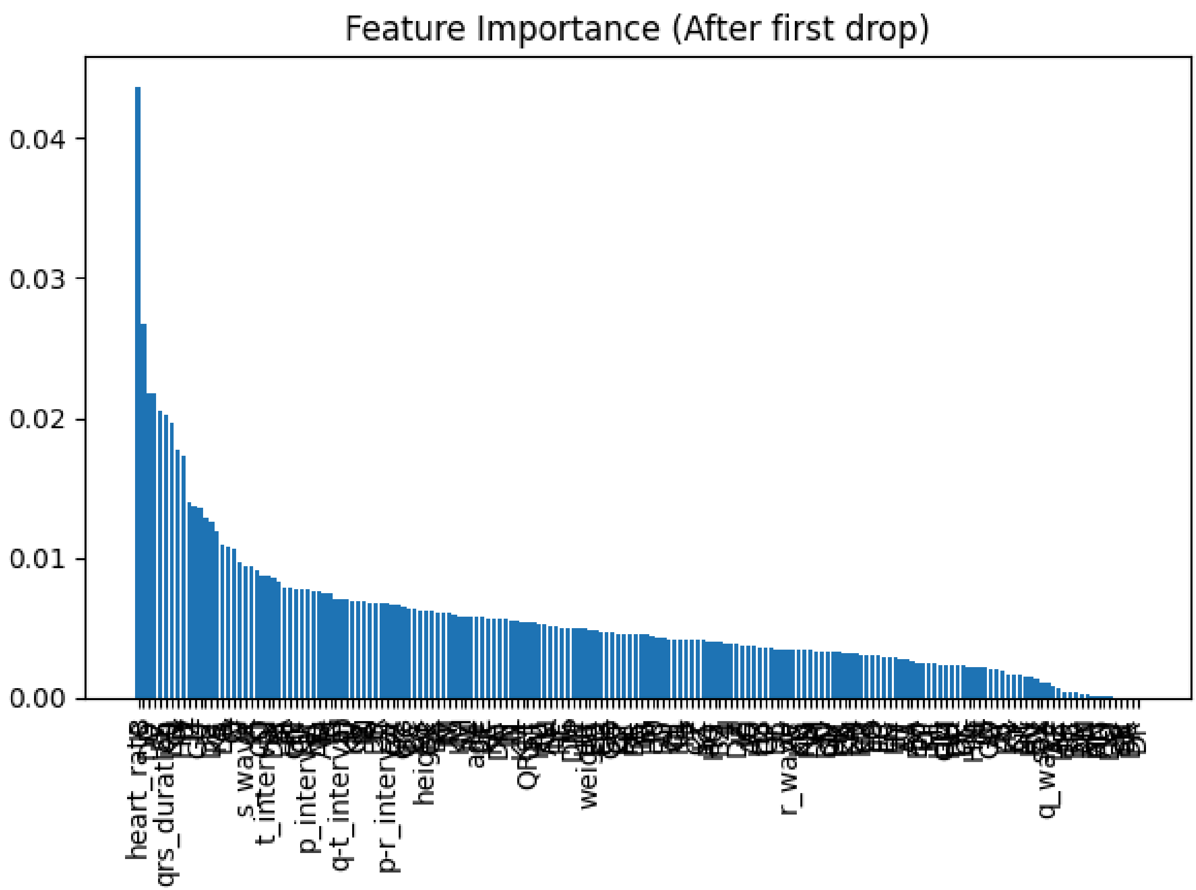
Now insert code to repeat the sorting of the feature importances; plotting of feature importance; finding of the next 100 least important features; and removal of those features from the dataframe

In [72]:
```
importances = rfc.feature_importances_
# Sort the feature importance in descending order
sorted_indices = np.argsort(importances)[::-1]

# Plot the feature importance
plt.title('Feature Importance (After first drop)')
plt.bar(range(x_train.shape[1]), importances[sorted_indices], align='center'
plt.xticks(range(x_train.shape[1]), x.columns[sorted_indices], rotation=90)
plt.tight_layout()
plt.show()

# Find the next 100 least important features
columns_to_drop_next_100 = x.columns[sorted_indices][-100:]

# Remove those features from the dataframe
df.drop(columns_to_drop_next_100, axis=1, inplace=True)
```



Now insert code to assign y and x as above; regenerate the train/validate/test datasets; instantiate and train a new random forest classifier; predict; generate CM, Accuracy, F1, and Precision

In [73]:
```
# Assign y to 'diagnosis' and the rest of the features to x
y = df.diagnosis.values
x = df.drop(["diagnosis"],axis=1)

# Run train-test split for a 60% train, 20% validate, 20% test
x_train, x_temp, y_train, y_temp = train_test_split(x, y, test_size=0.4, ran
```

```python
x_validate, x_test, y_validate, y_test = train_test_split(x_temp, y_temp, te

# Train a Random Forest Classifier on train
rfc = RandomForestClassifier(random_state=42)
rfc.fit(x_train, y_train)

# Generate CM, Accuracy, F1, and Precision for the validation set
y_pred = rfc.predict(x_validate)

print("Confusion Matrix (Validation Set):")
print(confusion_matrix(y_validate, y_pred))

print("\nClassification Report (Validation Set):")
print(classification_report(y_validate, y_pred))
```

```
Confusion Matrix (Validation Set):
[[47  2  0  0  0  1  0  0  0  0  0]
 [ 2  6  0  0  0  0  0  0  0  0  1]
 [ 2  0  3  0  0  0  0  0  0  0  0]
 [ 0  0  0  1  0  0  0  0  0  0  0]
 [ 2  0  0  0  1  0  0  0  0  0  0]
 [ 3  0  0  0  0  2  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0]
 [ 3  0  0  0  0  0  0  0  4  0  0]
 [ 2  0  0  0  0  0  0  0  0  0  0]
 [ 6  0  0  0  0  0  0  0  0  0  0]]

Classification Report (Validation Set):
              precision    recall  f1-score   support

           1       0.69      0.94      0.80        50
           2       0.75      0.67      0.71         9
           3       1.00      0.60      0.75         5
           4       1.00      1.00      1.00         1
           5       1.00      0.33      0.50         3
           6       0.67      0.40      0.50         5
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00         1
          10       1.00      0.57      0.73         7
          14       0.00      0.00      0.00         2
          16       0.00      0.00      0.00         6

    accuracy                           0.72        90
   macro avg       0.65      0.50      0.54        90
weighted avg       0.68      0.72      0.68        90
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Once more insert code to sort and plot feature importance, find the most important 14 features, and remove the rest from the dataframe

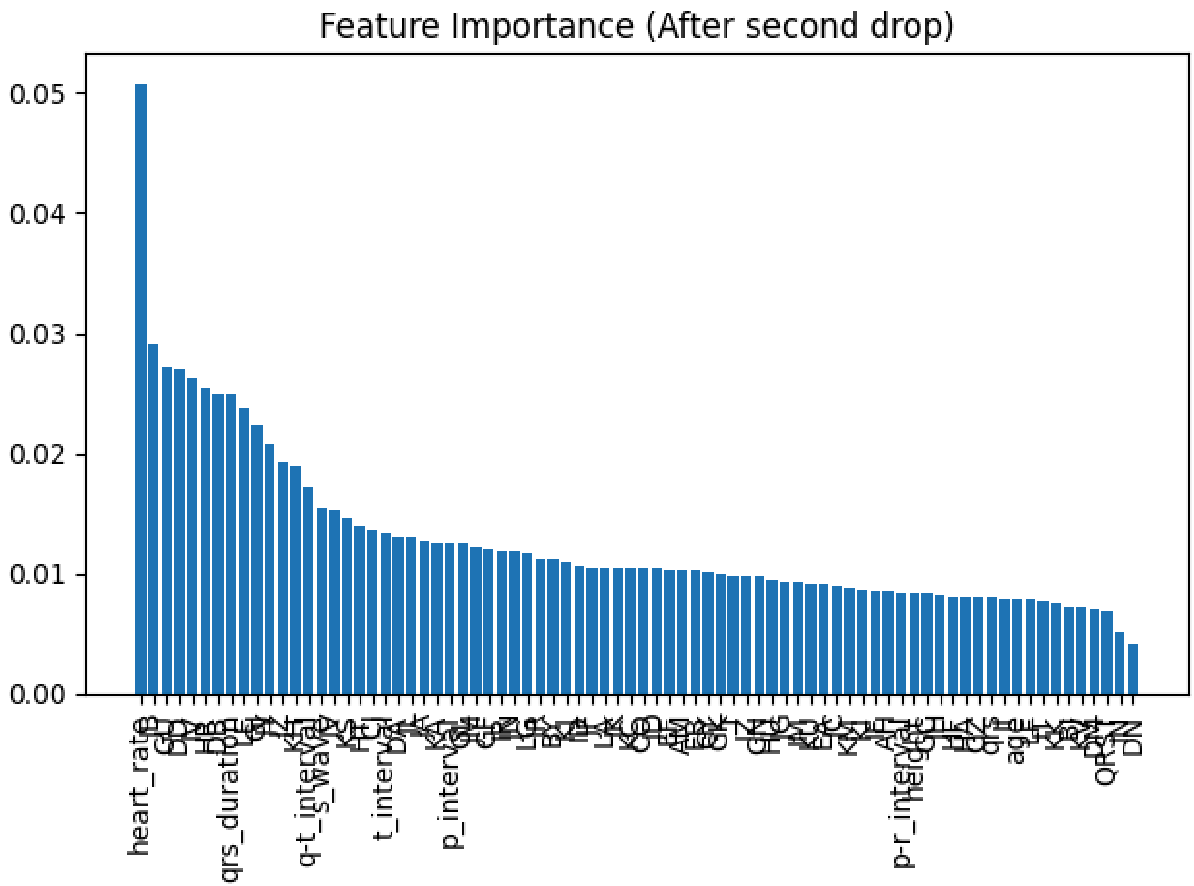
In [74]:

```
importances = rfc.feature_importances_
# Sort the feature importance in descending order
sorted_indices = np.argsort(importances)[::-1]

# Plot the feature importance
plt.title('Feature Importance (After second drop)')
plt.bar(range(x_train.shape[1]), importances[sorted_indices], align='center'
plt.xticks(range(x_train.shape[1]), x.columns[sorted_indices], rotation=90)
plt.tight_layout()
plt.show()

# Find the most important 14 features
most_important_features = x.columns[sorted_indices][:14]

# Remove all other features from the dataframe
columns_to_drop_final = x.columns.difference(most_important_features)
df.drop(columns_to_drop_final, axis=1, inplace=True)
```



Insert code to repeat the above to get a model that uses only the most important 14 features. Train, predict, and present results for that model.

In [75]:
```
# Assign y to 'diagnosis' and the rest of the features to x
y = df.diagnosis.values
x = df.drop(["diagnosis"],axis=1)

# Run train-test split for a 60% train, 20% validate, 20% test
x_train, x_temp, y_train, y_temp = train_test_split(x, y, test_size=0.4, ran
x_validate, x_test, y_validate, y_test = train_test_split(x_temp, y_temp, te

# Train a Random Forest Classifier on train
rfc = RandomForestClassifier(random_state=42)
rfc.fit(x_train, y_train)

# Generate CM, Accuracy, F1, and Precision for the validation set
y_pred = rfc.predict(x_validate)

print("Confusion Matrix (Validation Set):")
print(confusion_matrix(y_validate, y_pred))

print("\nClassification Report (Validation Set):")
print(classification_report(y_validate, y_pred))
```

```
Confusion Matrix (Validation Set):
[[47  1  1  0  0  1  0  0  0  0  0]
 [ 1  7  0  0  0  0  0  0  0  0  1]
 [ 3  1  1  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 2  0  0  0  1  0  0  0  0  0  0]
 [ 2  0  0  0  0  3  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0]
 [ 3  0  0  0  0  0  0  0  4  0  0]
 [ 1  0  0  0  0  0  0  0  1  0  0]
 [ 6  0  0  0  0  0  0  0  0  0  0]]

Classification Report (Validation Set):
              precision    recall  f1-score   support

           1       0.70      0.94      0.80        50
           2       0.78      0.78      0.78         9
           3       0.50      0.20      0.29         5
           4       0.00      0.00      0.00         1
           5       1.00      0.33      0.50         3
           6       0.75      0.60      0.67         5
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00         1
          10       0.80      0.57      0.67         7
          14       0.00      0.00      0.00         2
          16       0.00      0.00      0.00         6

    accuracy                           0.71        90
   macro avg       0.50      0.40      0.43        90
weighted avg       0.64      0.71      0.66        90
```

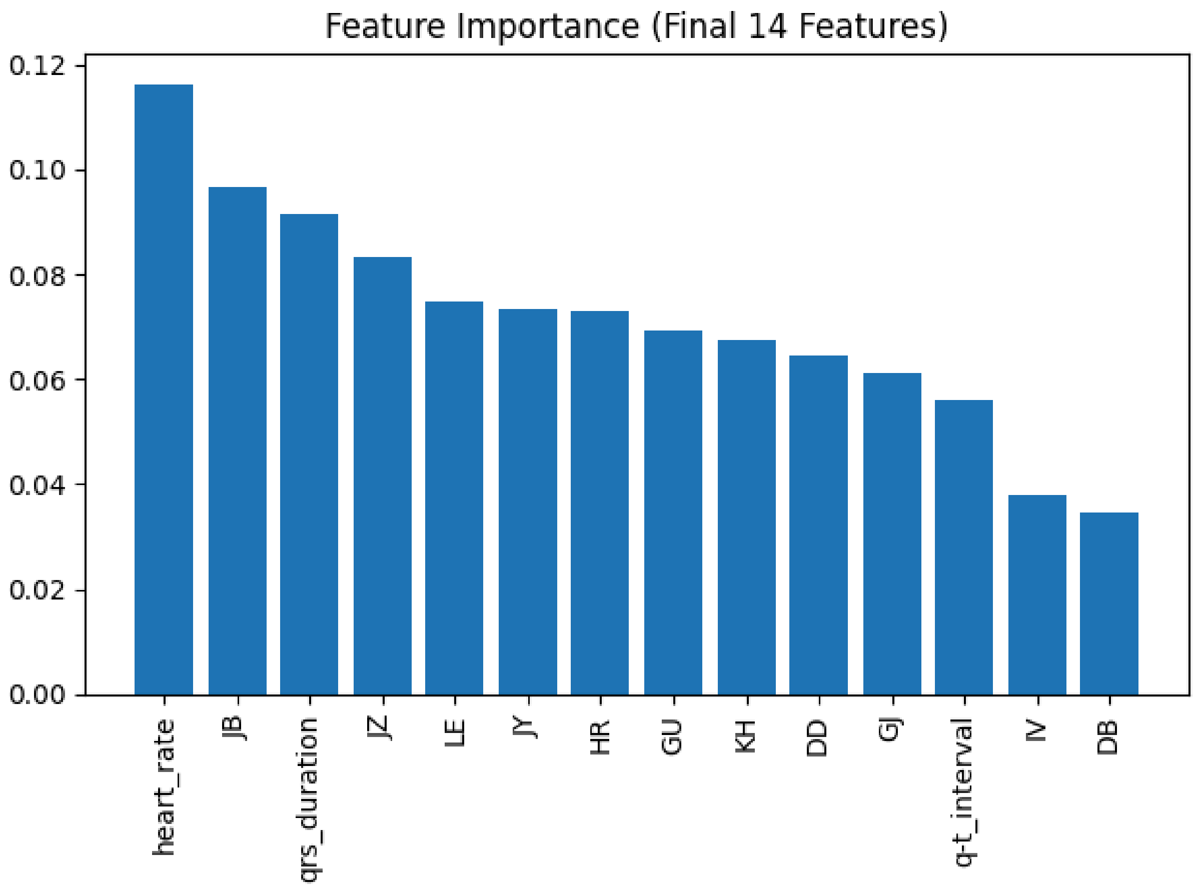
```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Now check the improtance of the features you used. Insert code to sort them and plot them

In [76]:

```
importances = rfc.feature_importances_
# Sort the feature importance in descending order
sorted_indices = np.argsort(importances)[::-1]
```

```python
# Plot the feature importance
plt.title('Feature Importance (Final 14 Features)')
plt.bar(range(x_train.shape[1]), importances[sorted_indices], align='center'
plt.xticks(range(x_train.shape[1]), x.columns[sorted_indices], rotation=90)
plt.tight_layout()
plt.show()
```



How does the sorted list of feature importance for these 14 compare with the original sorted list of features (before dropping the unimportant features)? Open a text cell and give the original 14 and the current 14. Explain why these might be different.

ANSWER:

Original Top 14 Features: ['heart_rate', 'JB', 'HR', 'LE', 'IV', 'DB', 'KS', 'DD', 'GJ', 'JZ', 'JY', 'qrs_duration', 'KH', 's_wave']

Current Top 14 Features: ['heart_rate', 'JB', 'LE', 'IV', 'DB', 'DD', 'JY', 'JZ', 'qrs_duration', 'KH', 'HR', 'KS', 'GJ', 't_interval']

The sorted lists of the top 14 features are different because when we remove features from the dataset, the relationships and interactions between the remaining features change. The Random Forest algorithm recalculates feature importance based on the reduced set of features. This means that the relative importance of the remaining features can shift, leading to a different ordering and potentially different features appearing in the top 14. Features that were previously less important might become more important in the absence of highly correlated or interacting features that were removed.

Insert code to predict the **test results for that model and present the CM, Accuracy, F1, and Precision of the final model.**

In [77]:
```
# Predict on the test set using the final classifier
y_pred_test = rfc.predict(x_test)

# Present the confusion matrix, accuracy, F1, and precision on the test set
print("Confusion Matrix (Test Set):")
print(confusion_matrix(y_test, y_pred_test))

print("\nClassification Report (Test Set):")
print(classification_report(y_test, y_pred_test))
```

```
Confusion Matrix (Test Set):
[[41  1  0  0  0  0  0  0  0  0  0  0]
 [ 4  4  0  0  0  1  0  0  0  0  0  0]
 [ 1  0  1  0  1  0  0  0  0  0  0  0]
 [ 4  1  0  0  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  2  0  0  0]
 [ 1  0  0  0  0  6  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  1  0  0  0  0]
 [ 5  1  0  0  0  0  0  0  9  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0]
 [ 2  0  0  0  0  0  0  0  1  0  0  0]]

Classification Report (Test Set):
              precision    recall  f1-score   support

           1       0.67      0.98      0.80        42
           2       0.50      0.44      0.47         9
           3       1.00      0.33      0.50         3
           4       0.00      0.00      0.00         5
           5       0.00      0.00      0.00         3
           6       0.86      0.86      0.86         7
           8       0.00      0.00      0.00         1
           9       1.00      1.00      1.00         1
          10       0.75      0.60      0.67        15
          14       0.00      0.00      0.00         1
          15       0.00      0.00      0.00         1
          16       0.00      0.00      0.00         3

    accuracy                           0.68        91
   macro avg       0.40      0.35      0.36        91
weighted avg       0.59      0.68      0.62        91
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:15
65: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in
labels with no predicted samples. Use `zero_division` parameter to control th
is behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Before we get too proud of our ML skills, look at the last CM carefully. The first row in the table is for normal ECG -- no arrythmia. Our model performs well on these data. For abnormal ECG, we seem to get the classifications correct about half the time, maybe a little better. Modern ECG machines use very sophisticated signal analysis to detect conditions likely contributing to the abnormal ECG -- and cadiologists and nurses and technicians are trained to recognize the effect-cause relation shown in ECGs. They are way better than our model!

Lab 7 is now complete. Make sure all cells are visible and have been run (rerun if necessary).

The code below converts the ipynb file to PDF, and saves it to where this .ipynb file is.

In [ ]:
```
NOTEBOOK_PATH = # Enter here, the path to your notebook file, e.g. "/content
! pip install playwright
! jupyter nbconvert --to webpdf --allow-chromium-download "$NOTEBOOK_PATH"
```

Download your notebook as an .ipynb file, then upload it along with the PDF file (saved in the same Google Drive folder as this notebook) to Canvas for Lab 7. Make sure that the PDF file matches your .ipynb file.