Analysis of ECG Data to Diagnose Heart Arrhythmias

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About my dataset

My dataset is about heart arrhythmias (irregular heartbeat). Each observation represents a patient, containing ECG values, the name of the patient's arrhythmia, and the heart condition(s) the patient has, if any.
Dataset source: https://figshare.com/collections/ChapmanECG/4560497/2

Research question and learning model

I am trying to use the numeric ECG values of a patient to predict certain arrhythmias and/or heart conditions. Thus, I will use classification models. I will use *Logistic Regression*, *Support Vector Machine (SVM)*, *K-Nearest Neighbors (KNN)*, and *Decision Tree* to predict certain selected heart conditions.

Evaluating the model

I will use a train/test split to train and test the model, then I will look at the accuracy, precision, and recall to evaluate the performance of the model. In medicine we really don't like false negatives, as an undiagnosed heart condition could be life-threatening, so the recall will be especially important. I relate to this personally; despite having multiple ECGs done on me, doctors failed to diagnose me until I had two cardiac arrests in one hour. I was extremely lucky to survive, but if I had been diagnosed earlier we could have avoided that which kills 475,000 Americans yearly.

My prediction

Based on what I've learned about cardiology, the ECG is fairly effective in diagnosing or partially diagnosing many heart conditions. Thus, I expect my models to have at least 80% accuracy at worst, and hopefully very few false negatives, i.e. high recall (although I'm not sure if I will be able to achieve a high enough recall for clinical use).

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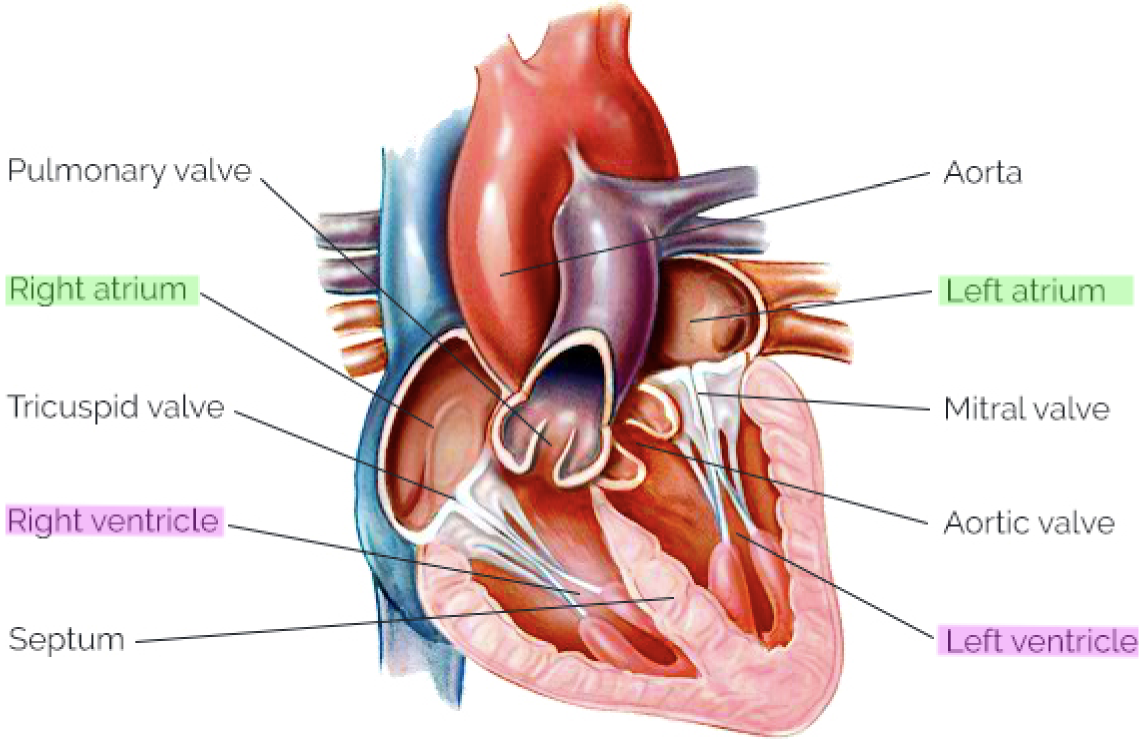
0) Basic anatomy

In this project we are mainly concerned with diagnosing arrhythmogenic conditions related to the atriums (upper chambers) and the ventricles (lower chambers):



[

Source: https://yourheartvalve.com/heart-basics/heart-anatomy/]

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1) Prepare data

In [1]:

```
# Import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, recall_score, classification_report

from itertools import combinations

# Set random state for project (8)
RANDOM_STATE = 8

# Enable inline mode for matplotlib so that Jupyter displays graphs
%matplotlib inline
```

In [2]:

```
# Import dataset of ECG values and diagnostic info for various heart arrhythmias

arrhythmias = pd.read_excel('Diagnostics.xlsx')
arrhythmias
```

Out[2]:

	FileName	Rhythm	Beat	PatientAge	Gender	VentricularRate	Atri

	FileName	Rhythm	Beat	PatientAge	Gender	VentricularRate	Atri
0	MUSE_20180113_171327_27000	AFIB	RBBB TWC	85	MALE	117	
1	MUSE_20180112_073319_29000	SB	TWC	59	FEMALE	52	
2	MUSE_20180111_165520_97000	SA	NONE	20	FEMALE	67	
3	MUSE_20180113_121940_44000	SB	NONE	66	MALE	53	
4	MUSE_20180112_122850_57000	AF	STDD STTC	73	FEMALE	162	
...	...	...	...	...	...	...	
10641	MUSE_20181222_204306_99000	SVT	NONE	80	FEMALE	196	
10642	MUSE_20181222_204309_22000	SVT	NONE	81	FEMALE	162	
10643	MUSE_20181222_204310_31000	SVT	NONE	39	MALE	152	
10644	MUSE_20181222_204312_58000	SVT	NONE	76	MALE	175	
10645	MUSE_20181222_204314_78000	SVT	NONE	75	MALE	117	

10646 rows × 16 columns

In [3]:

```
# Show attribute info

attribute_info = pd.read_excel('AttributesDictionary.xlsx')
attribute_info
```

Out[3]:

	Attributes	Type	ValueRange	Description
0	FileName	String	NaN	ECG data file name(unique ID)
1	Rhythm	String	NaN	Rhythm Label
2	Beat	String	NaN	Other conditions Label
3	PatientAge	Numeric	0-999	Age
4	Gender	String	MALE/FEMAL	Gender
5	VentricularRate	Numeric	0-999	Ventricular rate in BPM
6	AtrialRate	Numeric	0-999	Atrial rate in BPM
7	QRSDuration	Numeric -	0-999	QRS duration in msec
8	QTInterval	Numeric	0-999	QT interval in msec
9	QTCorrected	Numeric	0-999	Corrected QT interval in msec
10	RAxis	Numeric	-179~180	R axis
11	TAxis	Numeric	-179~181	T axis
12	QRSCount	Numeric	0-254	QRS count
13	QOnset	Numeric	16 Bit Unsigned	Q onset(In samples)
14	QOffset	Numeric	17 Bit Unsigned	Q offset(In samples)
15	TOffset	Numeric	18 Bit Unsigned	T offset(In samples)

In [4]:

```
# Check if columns have NaN values

print('Number of NaN values by column:\n')
for col in arrhythmias.columns:
    print(f'{col}: {arrhythmias[col].isnull().sum()}')
```

```
Number of NaN values by column:

FileName: 0
Rhythm: 0
Beat: 0
PatientAge: 0
Gender: 0
VentricularRate: 0
AtrialRate: 0
QRSDuration: 0
QTInterval: 0
QTCorrected: 0
RAxis: 0
TAxis: 0
QRSCount: 0
QOnset: 0
QOffset: 0
TOffset: 0
```

In [5]:

```
# No NaN values, so data is clean
# Drop FileName column

arrhythmias = arrhythmias.drop('FileName', axis=1).reset_index(drop=True)
arrhythmias
```

Out[5]:

	Rhythm	Beat	PatientAge	Gender	VentricularRate	AtrialRate	QRSDuration	QTInterval
0	AFIB	RBBB TWC	85	MALE	117	234	114	356
1	SB	TWC	59	FEMALE	52	52	92	432
2	SA	NONE	20	FEMALE	67	67	82	382
3	SB	NONE	66	MALE	53	53	96	456
4	AF	STDD STTC	73	FEMALE	162	162	114	252
...	...	...	...	...	...	...	...	...
10641	SVT	NONE	80	FEMALE	196	73	168	284
10642	SVT	NONE	81	FEMALE	162	81	162	294
10643	SVT	NONE	39	MALE	152	92	152	340
10644	SVT	NONE	76	MALE	175	178	128	310
10645	SVT	NONE	75	MALE	117	104	140	312

10646 rows × 15 columns

In [6]:

```
# Import dictionary for rhythm names
```

```
rhythm_names_df = pd.read_excel('RhythmNames.xlsx')
rhythm_names_df
```

Out[6]:

	Acronym Name	Full Name
0	SB	Sinus Bradycardia
1	SR	Sinus Rhythm
2	AFIB	Atrial Fibrillation
3	ST	Sinus Tachycardia
4	AF	Atrial Flutter
5	SI	Sinus Irregularity
6	SVT	Supraventricular Tachycardia
7	AT	Atrial Tachycardia
8	AVNRT	Atrioventricular Node Reentrant Tachycardia
9	AVRT	Atrioventricular Reentrant Tachycardia
10	SAAWR	Sinus Atrium to Atrial Wandering Rhythm

In [7]:

```
# Import dictionary for condition names

condition_names_df = pd.read_excel('ConditionNames.xlsx')
condition_names_df
```

Out[7]:

	Acronym Name	Full Name
0	1AVB	1 degree atrioventricular block
1	2AVB	2 degree atrioventricular block
2	2AVB1	2 degree atrioventricular block(Type one)
3	2AVB2	2 degree atrioventricular block(Type two)
4	3AVB	3 degree atrioventricular block
5	ABI	atrial bigeminy
6	ALS	Axis left shift
7	APB	atrial premature beats
8	AQW	abnormal Q wave
9	ARS	Axis right shift
10	AVB	atrioventricular block
11	CCR	countercolockwise rotation
12	CR	colockwise rotation
13	ERV	Early repolarization of the ventricles
14	FQRS	fQRS Wave
15	IDC	Interior differences conduction

	Acronym Name	Full Name
16	IVB	Intraventricular block
17	JEB	junctional escape beat
18	JPS	J point shift
19	JPT	junctional premature beat
20	LBBB	left bundle branch block
21	LBBBB	left back bundle branch block
22	LFBBB	left front bundle branch block
23	LRRI	Long RR interval
24	LVH	left ventricle hypertrophy
25	LVHV	left ventricle high voltage
26	LVQRSAL	lower voltage QRS in all lead
27	LVQRSCL	lower voltage QRS in chest lead
28	LVQRSLL	lower voltage QRS in limb lead
29	MI	myocardial infarction
30	MIBW	myocardial infraction in back wall
31	MIFW	Myocardial infgraction in the front wall
32	MILW	Myocardial infraction in the lower wall
33	MISW	Myocardial infraction in the side wall
34	PRIE	PR interval extension
35	PWC	P wave Change
36	QTIE	QT interval extension
37	RAH	right atrial hypertrophy
38	RAHV	right atrial high voltage
39	RBBB	right bundle branch block
40	RVH	right ventricle hypertrophy
41	STDD	ST drop down
42	STE	ST extension
43	STTC	ST-T Change
44	STTU	ST tilt up
45	TWC	T wave Change
46	TWO	T wave opposite
47	UW	U wave
48	VB	ventricular bigeminy
49	VEB	ventricular escape beat
50	VFW	ventricular fusion wave

	Acronym Name	Full Name
51	VPB	ventricular premature beat
52	VPE	ventricular preexcitation
53	VET	ventricular escape trigeminy
54	WAVN	Wandering in the atrioventricalualr node
55	WPW	WPW

---

2) Atrial Fibrilation (AFib)

AFib is an arrhythmia in which the atriums beat irregularly and rapidly. Usually AFib on its own is not deadly, but it increases the risk of stroke, heart failure, and other complications. It is the most commonly diagnosed arrhythmia and affects millions of Americans.

We will create a new dataframe aimed at predicting AFib from ECG values.

In [8]:

```
# See how many patients have AFib

arrhythmias['Rhythm'].value_counts()
```

Out[8]:

```
SB        3889
SR        1826
AFIB      1780
ST        1568
SVT        587
AF         445
SA         399
AT         121
AVNRT       16
AVRT         8
SAAWR        7
Name: Rhythm, dtype: int64
```

In [9]:

```
# Create new dataframe aimed at predicting AFib

afib_df = arrhythmias.copy()
afib_df = afib_df.rename(columns={'Rhythm': 'AFib'})
afib_df['AFib'] = (afib_df['AFib'] == 'AFIB')

afib_df
```

Out[9]:

	AFib	Beat	PatientAge	Gender	VentricularRate	AtrialRate	QRSDuration	QTInterval	(
0	True	RBBB TWC	85	MALE	117	234	114	356	
1	False	TWC	59	FEMALE	52	52	92	432	
2	False	NONE	20	FEMALE	67	67	82	382	
3	False	NONE	66	MALE	53	53	96	456	

	AFib	Beat	PatientAge	Gender	VentricularRate	AtrialRate	QRSDuration	QTInterval	(
4	False	STDD STTC	73	FEMALE	162	162	114	252	
...	...	...	...	...	...	...	...	...	
10641	False	NONE	80	FEMALE	196	73	168	284	
10642	False	NONE	81	FEMALE	162	81	162	294	
10643	False	NONE	39	MALE	152	92	152	340	
10644	False	NONE	76	MALE	175	178	128	310	
10645	False	NONE	75	MALE	117	104	140	312	

10646 rows × 15 columns

Logistic Regression

In [10]:

```
# Build Logistic Regression model

# Select all numeric ECG values as features
all_features = [
    'VentricularRate',
    'AtrialRate',
    'QRSDuration',
    'QTInterval',
    'QTCorrected',
    'RAxis',
    'TAxis',
    'QRSCount',
    'QOnset',
    'QOffset',
    'TOffset'
]

X = afib_df[all_features]
y = afib_df['AFib']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random

model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

Out[10]:

```
LogisticRegression(max_iter=1000)
```

In [11]:

```
# Prints classification report in a convenient format (strictly for binary targe
def print_report(y_test, y_pred):
    # Accuracy
    print(f"accuracy = {sum(y_pred == y_test) / len(y_test)}")

    # precision = (True Positives) /  (True Positives + False Positives)
    # recall = (True Positives) / (True Positives + False Negatives)
    # F1-score = 2*((precision*recall)/(precision+recall))

    true_pos = false_pos = false_neg = 0
```

```
    for pred, true in zip(y_pred, y_test):
        if true == True and pred == True:
            true_pos += 1
        elif true == False and pred == True:
            false_pos += 1
        elif true == True and pred == False:
            false_neg += 1

    precision = true_pos / (true_pos + false_pos)
    recall = true_pos / (true_pos + false_neg)

    print(f'precision = {precision}')
    print(f'recall = {recall}')
    print(f'F1-score = {2 * ((precision*recall) / (precision+recall))}')
```

In [12]:

```
# Test model

y_pred = model.predict(X_test)
print_report(y_test, y_pred)
```

```
accuracy = 0.8474830954169797
precision = 0.6147540983606558
recall = 0.1728110599078341
F1-score = 0.2697841726618705
```

Interpretation:

The logistic regression model performed very poorly. Even though the model had 84% accuracy, a recall of 0.173 is far too low for any context, let alone a medical one. This means that the model was unable to diagnose most of the patients that actually had AFib. This may partially be due to the fact that, proportionally speaking, there are not many AFib-positive patients in the dataset.

We will try some other classification models to improve our performance.

SVM

In [13]:

```
# Build and test SVM model

model = svm.SVC()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print_report(y_test, y_pred)
```

```
accuracy = 0.8534936138241923
precision = 0.7037037037037037
recall = 0.17511520737327188
F1-score = 0.28044280442804426
```

Interpretation:

This model also performs poorly.

KNN

In [14]:
```
# Build and test KNN model

model = KNeighborsClassifier(n_neighbors=5)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print_report(y_test, y_pred)
```

```
accuracy = 0.8741547708489857
precision = 0.6701030927835051
recall = 0.44930875576036866
F1-score = 0.5379310344827586
```

Interpretation:

This model performs a bit better but still not that well. However, instead of using all the features in the dataset, we can improve our performance by optimizing which features we use, and since KNN performed the best out of the three classifiers, we will try some optimization techniques on it.

Optimize KNN model

Test different combinations of numeric features and see which set of features produces the best model.

In [15]:
```
# Given a certain number of features n_features, this function finds the best se
# n_features that produces the highest accuracy model
def optimize_features(n_features, X, y, model, random_state=RANDOM_STATE):
    all_features = X.columns
    feature_combos = combinations(all_features, n_features)

    best_acc = 0
    best_features = None
    for features in feature_combos:
        features = list(features)

        X_train, X_test, y_train, y_test = train_test_split(X[features], y, test
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        acc = accuracy_score(y_test, y_pred)
        if acc > best_acc:
            best_features = features
            best_acc = acc

    return best_features, best_acc
```

In [16]:
```
# Instantiate new KNN model
knn_model = KNeighborsClassifier(n_neighbors=5)

# Run the optimize_features function using various numbers of features (ranging
# NOTE: There are 11 total features, so this takes some time to run
```

```
for n in range(1, len(all_features) + 1):
    best_features, best_acc = optimize_features(n, X, y, knn_model)
    print(f'Optimal set of {n} feature{"" if n == 1 else "s"} (accuracy={best_ac
    print(best_features)
    print()
```

```
Optimal set of 1 feature (accuracy=0.8377160030052592):
['QOffset']

Optimal set of 2 features (accuracy=0.9380165289256198):
['VentricularRate', 'AtrialRate']

Optimal set of 3 features (accuracy=0.9383921863260706):
['VentricularRate', 'AtrialRate', 'QRSCount']

Optimal set of 4 features (accuracy=0.9256198347107438):
['VentricularRate', 'AtrialRate', 'QRSCount', 'QOnset']

Optimal set of 5 features (accuracy=0.9158527422990232):
['VentricularRate', 'AtrialRate', 'QRSCount', 'QOnset', 'QOffset']

Optimal set of 6 features (accuracy=0.9064613072877535):
['VentricularRate', 'AtrialRate', 'QRSCount', 'QOnset', 'QOffset', 'TOffset']

Optimal set of 7 features (accuracy=0.8996994740796393):
['VentricularRate', 'AtrialRate', 'QTInterval', 'QTCorrected', 'QRSCount', 'QOff
set', 'TOffset']

Optimal set of 8 features (accuracy=0.8974455296769346):
['VentricularRate', 'AtrialRate', 'QTInterval', 'QTCorrected', 'QRSCount', 'QOns
et', 'QOffset', 'TOffset']

Optimal set of 9 features (accuracy=0.886175807663411):
['VentricularRate', 'AtrialRate', 'QRSDuration', 'QTInterval', 'QTCorrected', 'Q
RSCount', 'QOnset', 'QOffset', 'TOffset']

Optimal set of 10 features (accuracy=0.8835462058602555):
['VentricularRate', 'AtrialRate', 'QRSDuration', 'QTInterval', 'QTCorrected', 'T
Axis', 'QRSCount', 'QOnset', 'QOffset', 'TOffset']

Optimal set of 11 features (accuracy=0.8741547708489857):
['VentricularRate', 'AtrialRate', 'QRSDuration', 'QTInterval', 'QTCorrected', 'R
Axis', 'TAxis', 'QRSCount', 'QOnset', 'QOffset', 'TOffset']
```

Based on the results, the optimal model (accuracy=0.938) uses the following 3 features:

- VentricularRate
- AtrialRate
- QRSCount

Now we see how the optimized model performs:

In [17]:

```
best_features = ['VentricularRate', 'AtrialRate', 'QRSCount']

X = afib_df[best_features]
y = afib_df['AFib']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random

knn_model = KNeighborsClassifier(n_neighbors=5)
```

```
knn_model.fit(X_train, y_train)

y_pred = knn_model.predict(X_test)

print_report(y_test, y_pred)
```

```
accuracy = 0.9383921863260706
precision = 0.8214285714285714
recall = 0.7949308755760369
F1-score = 0.8079625292740047
```

Interpretation:

This optimized KNN model is much better than the first three models. The accuracy was improved from 0.874 to 0.938, and more significantly, the recall was improved from 0.449 to 0.795 (the precision is also pretty good). Despite these big improvements in model performance, I don't think this model is quite ready for clinical implementation because it still misses quite a few AFib diagnoses; about 20% of patients with AFib were not diagnosed by this model. It may be a good model when someone's life isn't at risk, but in medicine, the model should be held to a higher standard. In conclusion, it's a fairly strong model but would require more improvement to be deployed in the real world.

---

3) Predicting multiple heart rhythms

So far, I've used classification models to predict a binary target value (has AFib / doesn't have AFib). AFib is not the most concerning arrhythmia. In fact, generally speaking, arrhythmias of the ventricles are more deadly than atrial arrhythmias and can often cause cardiac arrest. For example, while atrial fibrillation often goes unnoticed, ventricular fibrilliation is highly fatal with a mortality rate of 90-95% if not treated immediately (ventricular fibrillation is the type of cardiac arrest I had). Some arrhythmias in this data set, such as supraventricular tachycardia (SVT) can lead to ventricular fibrillation. Thus, it would be useful to build a model that can predict multiple arrhythmias, both atrial and ventricular. For this, I will use a Decision Tree. I will use some optimization techniques such as optimizing the feature set (like before) and testing various max depths for the tree.

Decision Tree

In [18]:

```
# The previous optimize_features function found the optimal set of features give
# features (dimension); this function finds the optimal number of features AND t
# features of that size
def optimize_features_and_dimension(X, y, model, random_state=RANDOM_STATE):
    best_acc = 0
    best_features = None

    for n in range(1, len(X.columns) + 1):
        features, acc = optimize_features(n, X, y, model)
        if acc > best_acc:
            best_features = features
            best_acc = acc
```

```
    return best_features
```

In [19]:

```
# Determine optimal feature set for Decision Tree model
# (takes some time to run)

X = arrhythmias[all_features]
y = arrhythmias['Rhythm']

tree_model = DecisionTreeClassifier(random_state=RANDOM_STATE)

best_features = optimize_features_and_dimension(X, y, tree_model)
best_features
```

Out[19]:

```
['VentricularRate', 'AtrialRate']
```

In [20]:

```
# Build and test Decision Tree model

X_train, X_test, y_train, y_test = train_test_split(X[best_features], y, test_si

# Test various max depths from 2 to 10 and select model with best accuracy
best_acc = 0
best_depth = 2
for depth in range(2, 11):
    tree_model.max_depth = depth
    tree_model.fit(X_train, y_train)

    y_pred = tree_model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)

    if acc > best_acc:
        best_depth = depth
        best_acc = acc

# Build model with optimal max depth
tree_model.max_depth = best_depth
tree_model.fit(X_train, y_train)

y_pred = tree_model.predict(X_test)

print(f'max_depth = {tree_model.max_depth}\n')
print(classification_report(y_test, y_pred, digits=3, zero_division=0))
```

```
max_depth = 9

              precision    recall  f1-score   support

          AF      0.149     0.069     0.095       101
        AFIB      0.785     0.730     0.757       434
          AT      0.000     0.000     0.000        24
       AVNRT      0.000     0.000     0.000         6
        AVRT      0.000     0.000     0.000         1
          SA      0.000     0.000     0.000        89
       SAAWR      0.000     0.000     0.000         2
          SB      0.987     0.990     0.989      1006
          SR      0.750     0.996     0.856       459
          ST      0.905     0.963     0.933       404
         SVT      0.639     0.743     0.687       136
```

```
    accuracy                           0.852      2662
   macro avg      0.383     0.408      0.392      2662
weighted avg      0.806     0.852      0.825      2662
```

Interpretation:

Based on the classification report, it is clear that in many cases the Decision Tree did not do so well, with an accuracy of 0.852, a weighted average recall of 0.832, and bad F1-scores for most rhythms. I'm sure this is partly due to the fact that we have so many different arrhythmias but a relatively small dataset (in some cases we only have a few observations of a particular arrhythmia); notice how the rhythms with higher support (more observations) have better performance. For the last four heart rhythms (SB, SR, ST, SVT) the model was not so bad.

Instead of just looking at how accurate the model was in predicting each unique heart rhythm, I want to see how often the Decision Tree misclassifies an abnormal heart rhythm as normal (false negative). With previous classifiers, I did this by computing the recall score. However, since the Decision Tree is a multiclass classifier, I first need to map the heart rhythms to a binary value (True/False) and then fit the model again. This way, although the Decision Tree won't predict specific heart rhythms, it would at least predict when the heart rhythm is abnormal.

If you look at the rhythm names below, you will see one called "SR" which stands for "Sinus Rhythm". SR is a normal heart rhythm, so we will consider this as "doesn't have arrhythmia", i.e. `False`, and we will consider the other rhythms as "has arrhythmia", i.e `True`. The code below maps "SR" heart rhythms to `False` and all other rhythms to `True`.

In [21]:

```
# See all heart rhythms
rhythm_names_df
```

Out[21]:

	Acronym Name	Full Name
0	SB	Sinus Bradycardia
1	SR	Sinus Rhythm
2	AFIB	Atrial Fibrillation
3	ST	Sinus Tachycardia
4	AF	Atrial Flutter
5	SI	Sinus Irregularity
6	SVT	Supraventricular Tachycardia
7	AT	Atrial Tachycardia
8	AVNRT	Atrioventricular Node Reentrant Tachycardia
9	AVRT	Atrioventricular Reentrant Tachycardia
10	SAAWR	Sinus Atrium to Atrial Wandering Rhythm

In [22]:

```
# Map rhythms to binary outcome
```

```
y_binary = (y != 'SR')
```

In [23]:

```
# Build and test Decision Tree model

binary_tree_model = DecisionTreeClassifier(random_state=RANDOM_STATE)

# Use best_features from before (VentricularRate and AtrialRate)
X_train, X_test, y_train, y_test = train_test_split(X[best_features], y_binary,

# Test various max depths from 2 to 10 and select model with best accuracy
best_acc = 0
best_depth = 2
for depth in range(2, 11):
    binary_tree_model.max_depth = depth
    binary_tree_model.fit(X_train, y_train)

    y_pred = binary_tree_model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)

    if acc > best_acc:
        best_depth = depth
        best_acc = acc

# Build model with optimal max depth
binary_tree_model.max_depth = best_depth
binary_tree_model.fit(X_train, y_train)

y_pred = binary_tree_model.predict(X_test)

print(f'max_depth = {binary_tree_model.max_depth}\n')
print_report(y_test, y_pred)
```

```
max_depth = 10

accuracy = 0.941397445529677
precision = 0.9990248659190639
recall = 0.9300953245574217
F1-score = 0.9633286318758816
```

Interpretation:

Now we have a pretty strong tree model with an accuracy of 0.941 and a recall score of 0.930, compared with those of the multiclass Decision Tree (0.852 for both accuracy and weighted average recall). The recall score of the binary Decision Tree is also much better than the recall score of the KNN model (0.795); so, while the KNN model failed to diagnose about 20% of AFib patients, the binary Decision Tree only failed to recognize about 7% of patients as having abnormal heart rhythms, even if it couldn't always tell exactly which arrhythmia it was. It may be unfair to compare the two models since the KNN model was focused on AFib while the binary Decision Tree clumped all arrhythmias into one group, but in any case the binary Decision Tree performed pretty well (much better than the multiclass Decision Tree).

Now, ideally, I'd want the accuracy to be at least 95% and the recall to be closer to 100% before I can comfortably say it is ready for clinical implementation; however, if any of our models are to be clinically deployed, it is definitely the binary Decision Tree. It performs very well and its numbers would be considered great in many contexts, but I still think it needs a little more improvement before it can be used medically.

I think it's worth noting that usually the benefit of the Decision Tree is that it can predict many different classes, as opposed to just one. We did not take advantage of this in the binary Decision Tree, and instead we made it easier for the model to correctly predict if some abnormality exists. The model is still worth something, but a truly sophisticated model would be able to do both: predict multiple heart rhythms AND perform with very high accuracy and recall.

---

4) Conclusion

To summarize, we developed three promising models:

1. **KNN** - predicts AFib
    - accuracy = 0.938
    - recall = 0.795
    - Performs with high accuracy, but needs a significantly higher recall score to be considered for clinical use.

1. **Multiclass Decision Tree** - predicts multiple heart rhythms
    - accuracy = 0.852
    - weighted average recall = 0.852
    - Overall accuracy is not horrible but should be improved. Performs very poorly for some rhythms, and pretty well for other rhythms; a larger dataset would improve performance for more heart rhythms. Not ready for clinical use, unless we cut out the rhythms for which the model performs poorly.

1. **Binary Decision Tree** - predicts abnormal heart rhythm
    - accuracy = 0.941
    - recall = 0.930
    - Performs with high accuracy and high recall; best candidate for clinical use. Still needs a little improvement in recall score (ideally >95%) to truly be ready for clinical use.

In [25]:

```
knn_model  # predicts AFib
tree_model  # predicts multiple heart rhythms
binary_tree_model  # predicts abnormal heart rhythm

pass
```