ecg-solution

September 15, 2024

1 Imports

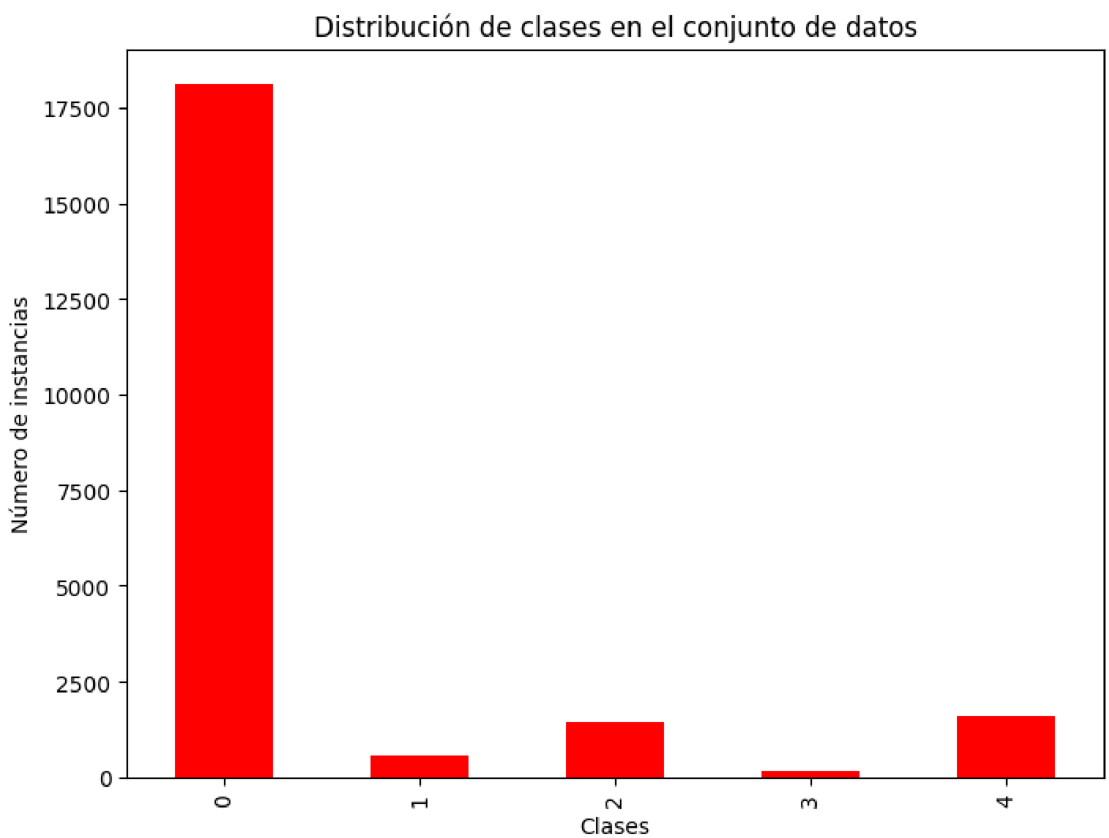
[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, 
    ↪classification_report
from sklearn.model_selection import cross_val_score
from imblearn.under_sampling import RandomUnderSampler
from sklearn.ensemble import RandomForestClassifier, 
    ↪GradientBoostingClassifier, AdaBoostClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import KFold
```

2 Exploración de archivos

[ ]:
```
df = pd.read_csv('sample_data/mitbih_test.csv', header=None)

counts = {i: 0 for i in range(5)}


for _, row in df.iterrows():
    value = int(row[187])
    if 0 <= value <= 5:
        counts[value] += 1

for value, count in counts.items():
    print(f"Clase {value}: {count} ocurrencias")
```

```
counts_series = pd.Series(counts)


plt.figure(figsize=(8, 6))
counts_series.plot(kind='bar', color='red')
plt.title('Distribución de clases en el conjunto de datos')
plt.xlabel('Clases')
plt.ylabel('Número de instancias')
plt.show()
```

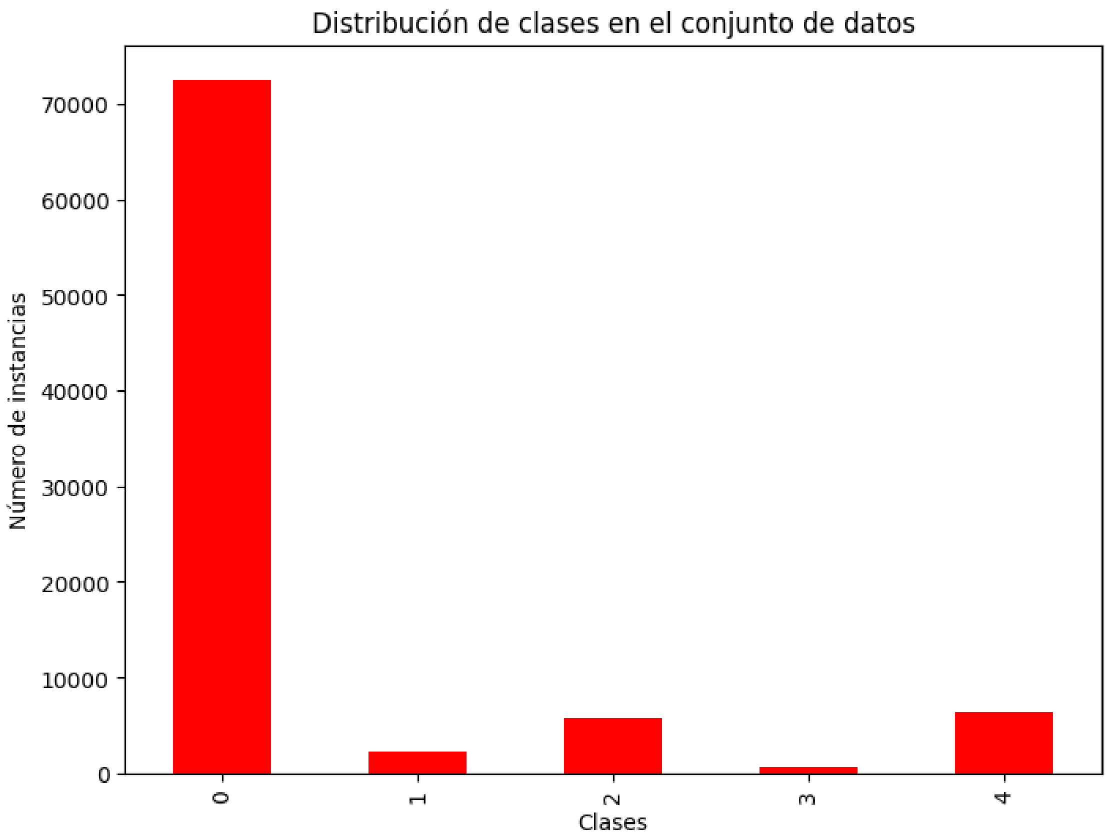
```
Clase 0: 18118 ocurrencias
Clase 1: 556 ocurrencias
Clase 2: 1448 ocurrencias
Clase 3: 162 ocurrencias
Clase 4: 1608 ocurrencias
```



[ ]:
```
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

counts = {i: 0 for i in range(5)}
```

```
for _, row in df.iterrows():
    value = int(row[187])
    if 0 <= value <= 5:
        counts[value] += 1

for value, count in counts.items():
    print(f"Clase {value}: {count} ocurrencias")


counts_series = pd.Series(counts)


plt.figure(figsize=(8, 6))
counts_series.plot(kind='bar', color='red')
plt.title('Distribución de clases en el conjunto de datos')
plt.xlabel('Clases')
plt.ylabel('Número de instancias')
plt.show()
```

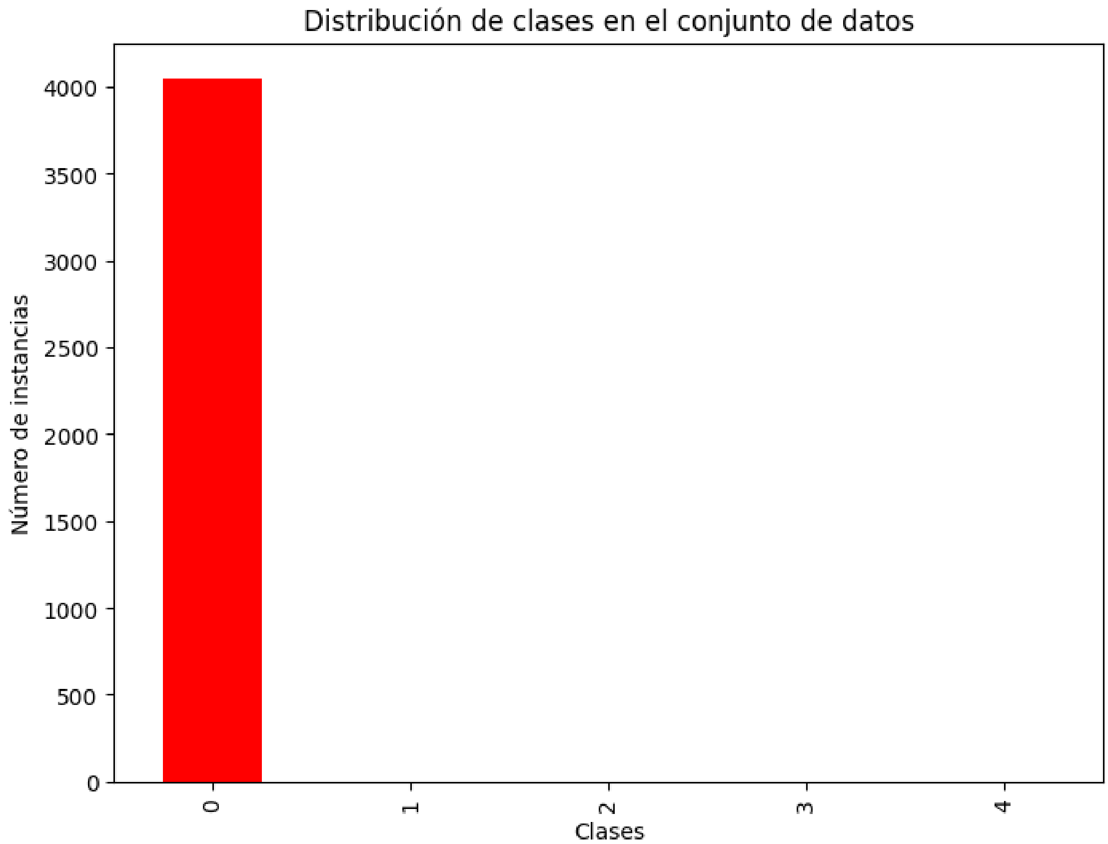
```
Clase 0: 72471 ocurrencias
Clase 1: 2223 ocurrencias
Clase 2: 5788 ocurrencias
Clase 3: 641 ocurrencias
Clase 4: 6431 ocurrencias
```



[ ]:
```
df = pd.read_csv('sample_data/ptbdb_normal.csv', header=None)

counts = {i: 0 for i in range(5)}


for _, row in df.iterrows():
    value = int(row[187])
    if 0 <= value <= 5:
        counts[value] += 1

for value, count in counts.items():
    print(f"Clase {value}: {count} ocurrencias")


counts_series = pd.Series(counts)


plt.figure(figsize=(8, 6))
counts_series.plot(kind='bar', color='red')
plt.title('Distribución de clases en el conjunto de datos')
```

```
plt.xlabel('Clases')
plt.ylabel('Número de instancias')
plt.show()
```

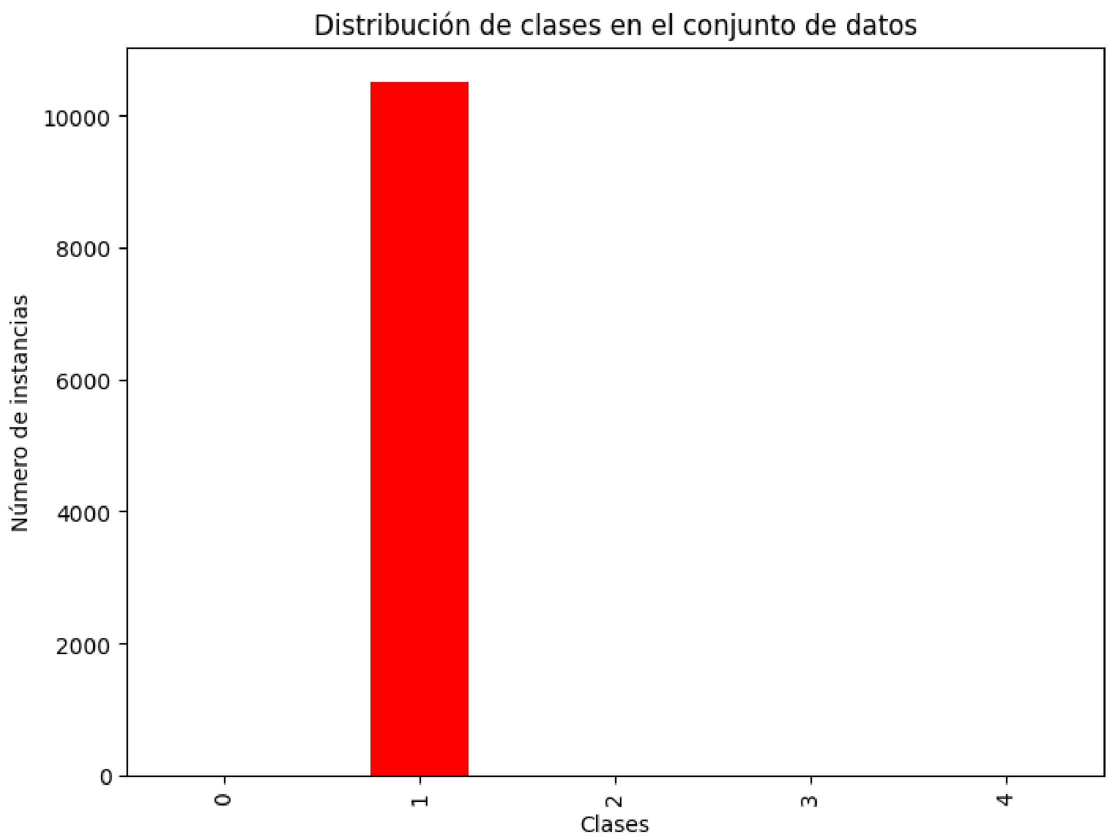
```
Clase 0: 4046 ocurrencias
Clase 1: 0 ocurrencias
Clase 2: 0 ocurrencias
Clase 3: 0 ocurrencias
Clase 4: 0 ocurrencias
```



[ ]:
```
df = pd.read_csv('sample_data/ptbdb_abnormal.csv', header=None)


counts = {i: 0 for i in range(5)}


for _, row in df.iterrows():
    value = int(row[187])
    if 0 <= value <= 5:
        counts[value] += 1
```

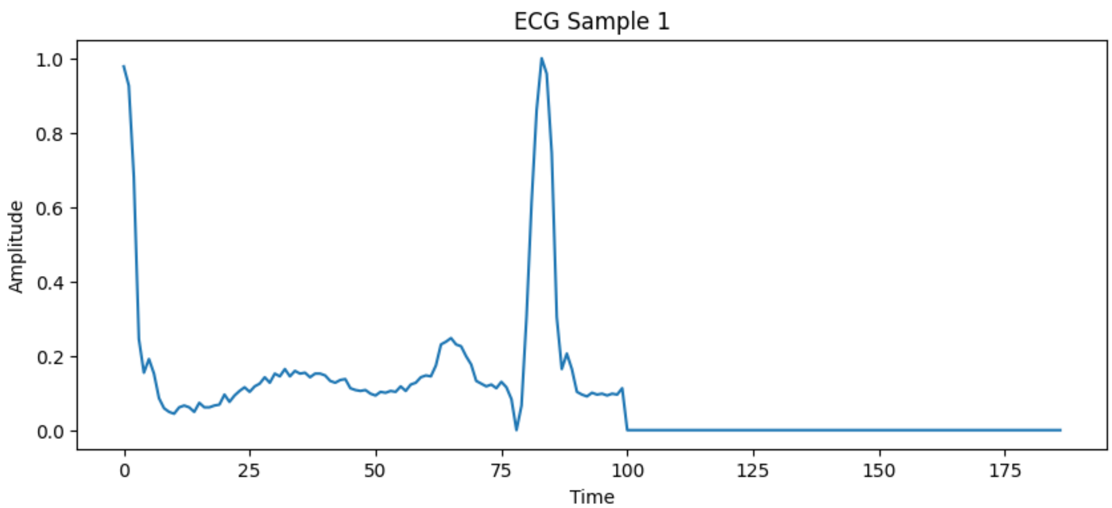
```
for value, count in counts.items():
    print(f"Clase {value}: {count} ocurrencias")


counts_series = pd.Series(counts)


plt.figure(figsize=(8, 6))
counts_series.plot(kind='bar', color='red')
plt.title('Distribución de clases en el conjunto de datos')
plt.xlabel('Clases')
plt.ylabel('Número de instancias')
plt.show()
```

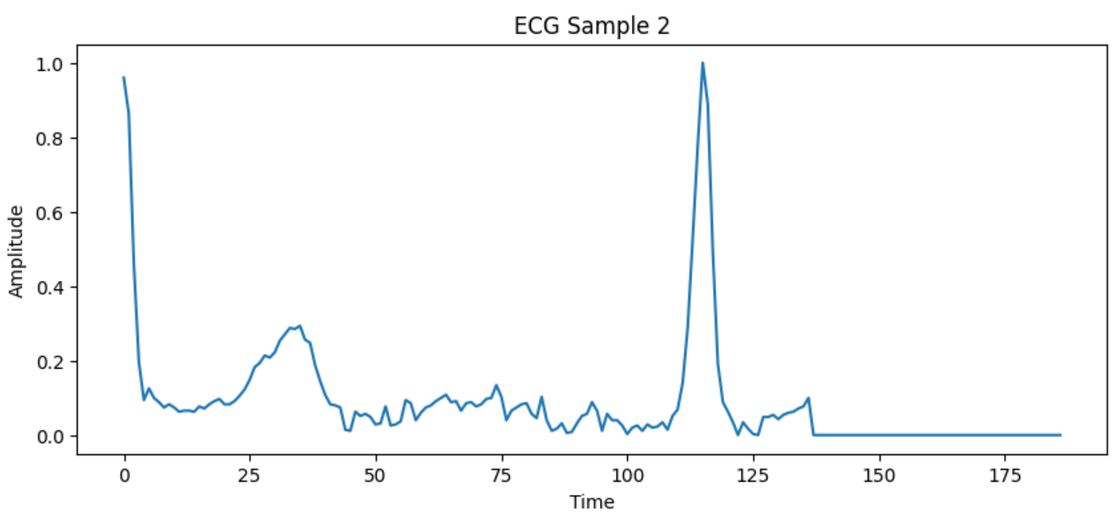
```
Clase 0: 0 ocurrencias
Clase 1: 10506 ocurrencias
Clase 2: 0 ocurrencias
Clase 3: 0 ocurrencias
Clase 4: 0 ocurrencias
```

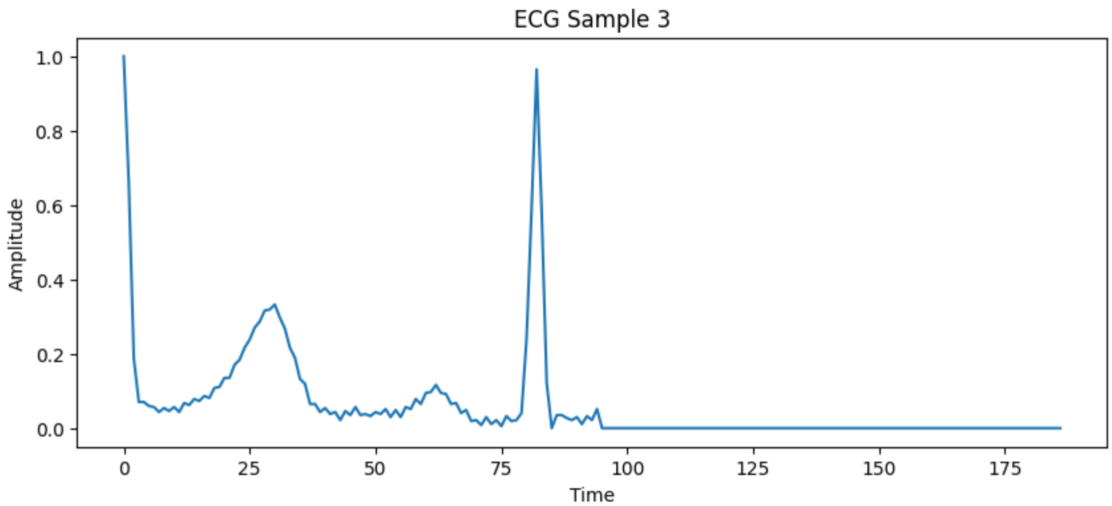


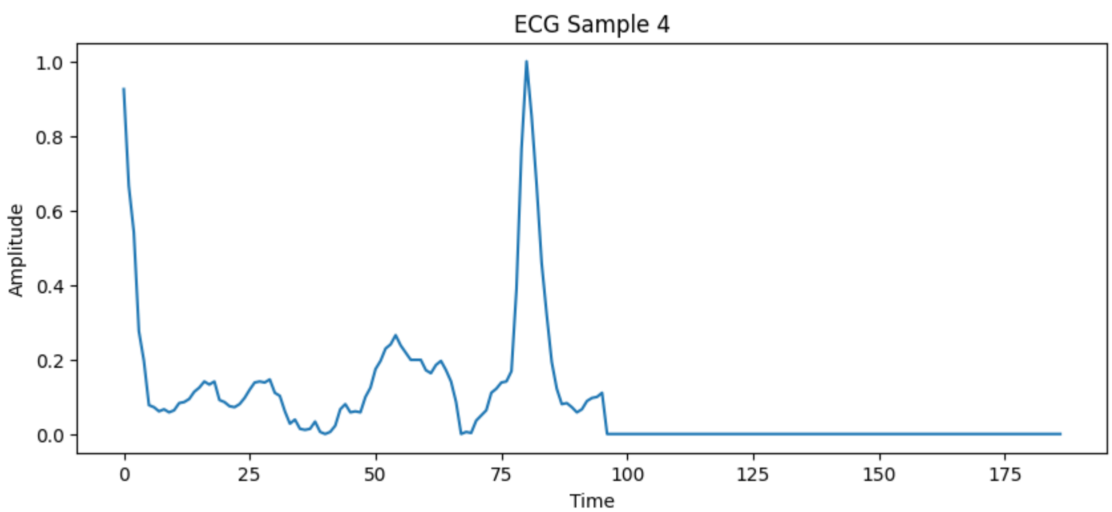
3 Visualización

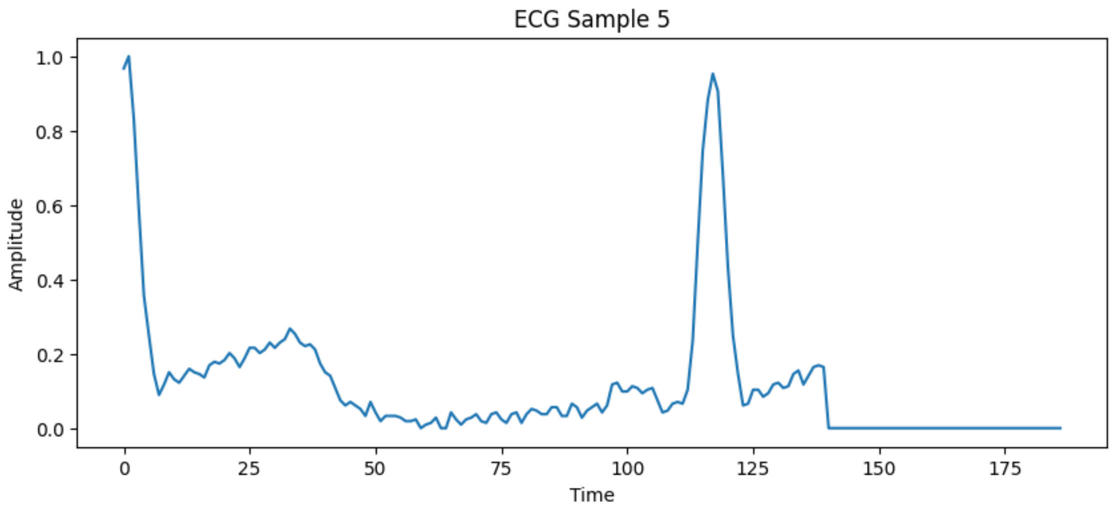
[ ]:
```python
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)


for i in range(5):
    plt.figure(figsize=(10, 4))
    plt.plot(df.iloc[i, :-1])
    plt.title(f'ECG Sample {i+1}')
    plt.xlabel('Time')
    plt.ylabel('Amplitude')
    plt.show()
```






ECG Sample 3
Amplitude
Time
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175


ECG Sample 4
Amplitude
Time
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175



4 Limpieza,Verificación de normalización y datos nulos

[ ]:
```python
df = pd.read_csv('sample_data/mitbih_test.csv', header=None)

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

```
                  0             1             2             3             4    \
count  21892.000000  21892.000000  21892.000000  21892.000000  21892.000000
mean       0.894410      0.761902      0.426627      0.221596      0.201676
std        0.234560      0.218659      0.228572      0.208711      0.177727
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.924260      0.683366      0.251197      0.050505      0.082873
50%        0.990431      0.828996      0.432777      0.167630      0.147642
75%        1.000000      0.912319      0.583991      0.347092      0.259211
max        1.000000      1.000000      1.000000      1.000000      1.000000

                  5             6             7             8             9    \
count  21892.000000  21892.000000  21892.000000  21892.000000  21892.000000
mean       0.209891      0.204805      0.200992      0.197634      0.196022
std        0.172194      0.177946      0.176142      0.170228      0.166707
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.087912      0.072663      0.065997      0.064516      0.068493
50%        0.158111      0.144068      0.144509      0.150422      0.149029
75%        0.287356      0.298453      0.294563      0.289907      0.282956
max        1.000000      1.000000      1.000000      1.000000      0.991429

       …           178           179           180           181  \
count  …  21892.000000  21892.000000  21892.000000  21892.000000
```

```
mean    …       0.004588       0.004327       0.004020       0.003789
std     …       0.043128       0.042187       0.040255       0.039397
min     …       0.000000       0.000000       0.000000       0.000000
25%     …       0.000000       0.000000       0.000000       0.000000
50%     …       0.000000       0.000000       0.000000       0.000000
75%     …       0.000000       0.000000       0.000000       0.000000
max     …       0.980392       1.000000       0.966102       1.000000

                182            183            184            185            186  \
count  21892.000000   21892.000000   21892.000000   21892.000000   21892.000000
mean       0.003638       0.003459       0.003166       0.003000       0.002946
std        0.038535       0.037717       0.035903       0.035522       0.035266
min        0.000000       0.000000       0.000000       0.000000       0.000000
25%        0.000000       0.000000       0.000000       0.000000       0.000000
50%        0.000000       0.000000       0.000000       0.000000       0.000000
75%        0.000000       0.000000       0.000000       0.000000       0.000000
max        1.000000       1.000000       1.000000       0.996053       1.000000

                187
count  21892.000000
mean       0.473689
std        1.143447
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        4.000000

[8 rows x 188 columns]
```

[ ]:
```python
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

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

```
                  0              1              2              3              4  \
count  87554.000000   87554.000000   87554.000000   87554.000000   87554.000000
mean       0.890360       0.758160       0.423972       0.219104       0.201127
std        0.240909       0.221813       0.227305       0.206878       0.177058
min        0.000000       0.000000       0.000000       0.000000       0.000000
25%        0.921922       0.682486       0.250969       0.048458       0.082329
50%        0.991342       0.826013       0.429472       0.166000       0.147878
75%        1.000000       0.910506       0.578767       0.341727       0.258993
max        1.000000       1.000000       1.000000       1.000000       1.000000

                  5              6              7              8              9  \
count  87554.000000   87554.000000   87554.000000   87554.000000   87554.000000
mean       0.210399       0.205808       0.201773       0.198691       0.196757
```

```
std        0.171909       0.178481       0.177240       0.171778       0.168357
min        0.000000       0.000000       0.000000       0.000000       0.000000
25%        0.088416       0.073333       0.066116       0.065000       0.068639
50%        0.158798       0.145324       0.144424       0.150000       0.148734
75%        0.287628       0.298237       0.295391       0.290832       0.283636
max        1.000000       1.000000       1.000000       1.000000       1.000000

       …            178            179            180            181  \
count  …   87554.000000   87554.000000   87554.000000   87554.000000
mean   …       0.005025       0.004628       0.004291       0.003945
std    …       0.044154       0.042089       0.040525       0.038651
min    …       0.000000       0.000000       0.000000       0.000000
25%    …       0.000000       0.000000       0.000000       0.000000
50%    …       0.000000       0.000000       0.000000       0.000000
75%    …       0.000000       0.000000       0.000000       0.000000
max    …       1.000000       1.000000       1.000000       1.000000

                182            183            184            185            186  \
count  87554.000000   87554.000000   87554.000000   87554.000000   87554.000000
mean       0.003681       0.003471       0.003221       0.002945       0.002807
std        0.037193       0.036255       0.034789       0.032865       0.031924
min        0.000000       0.000000       0.000000       0.000000       0.000000
25%        0.000000       0.000000       0.000000       0.000000       0.000000
50%        0.000000       0.000000       0.000000       0.000000       0.000000
75%        0.000000       0.000000       0.000000       0.000000       0.000000
max        1.000000       1.000000       1.000000       1.000000       1.000000

                187
count  87554.000000
mean       0.473376
std        1.143184
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        4.000000

[8 rows x 188 columns]
```

[ ]:
```
df = pd.read_csv('sample_data/ptbdb_normal.csv', header=None)

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

```
                 0             1             2             3             4   \
count  4046.000000   4046.000000   4046.000000   4046.000000   4046.000000
mean      0.979670      0.711486      0.311677      0.119575      0.088608
std       0.029061      0.186376      0.183457      0.110457      0.075760
```

```
min        0.782178     0.121784     0.000000     0.000000     0.000000
25%        0.964468     0.580160     0.164112     0.028731     0.027735
50%        1.000000     0.726449     0.303266     0.092655     0.079476
75%        1.000000     0.863699     0.436091     0.187527     0.134861
max        1.000000     1.000000     0.985955     0.910798     0.846591

                 5            6            7            8            9    …  \
count  4046.000000  4046.000000  4046.000000  4046.000000  4046.000000  …
mean      0.130843     0.159653     0.165608     0.168005     0.170783  …
std       0.081104     0.090131     0.096094     0.102506     0.106190  …
min       0.000000     0.000000     0.000000     0.000000     0.000000  …
25%       0.070776     0.094656     0.098848     0.095594     0.094988  …
50%       0.121144     0.134312     0.142771     0.143002     0.145068  …
75%       0.183746     0.216203     0.217895     0.220572     0.223053  …
max       0.770205     0.754524     0.749095     0.729192     0.700844  …

               178          179          180          181          182  \
count  4046.000000  4046.000000  4046.000000  4046.000000  4046.000000
mean      0.001540     0.001332     0.001304     0.001220     0.000991
std       0.018664     0.016234     0.016668     0.016658     0.015204
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       0.415879     0.361283     0.383522     0.407025     0.446281

               183          184          185     186     187
count  4046.000000  4046.000000  4046.000000  4046.0  4046.0
mean      0.000894     0.000454     0.000474     0.0     0.0
std       0.015311     0.010834     0.011202     0.0     0.0
min       0.000000     0.000000     0.000000     0.0     0.0
25%       0.000000     0.000000     0.000000     0.0     0.0
50%       0.000000     0.000000     0.000000     0.0     0.0
75%       0.000000     0.000000     0.000000     0.0     0.0
max       0.483471     0.371502     0.376668     0.0     0.0

[8 rows x 188 columns]
```

[ ]:
```
df = pd.read_csv('sample_data/ptbdb_abnormal.csv', header=None)


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

```
                  0             1             2             3             4    \
count  10506.000000  10506.000000  10506.000000  10506.000000  10506.000000
mean       0.975468      0.725582      0.438306      0.290384      0.252897
std        0.036354      0.199030      0.262699      0.270977      0.237004
```

```
min        0.624227      0.000000      0.000000      0.000000      0.000000
25%        0.957325      0.586602      0.236455      0.074064      0.088487
50%        1.000000      0.745646      0.404297      0.212845      0.173046
75%        1.000000      0.890043      0.620889      0.427811      0.343089
max        1.000000      1.000000      1.000000      1.000000      1.000000

                  5             6             7             8             9    \
count  10506.000000  10506.000000  10506.000000  10506.000000  10506.000000
mean       0.249423      0.245668      0.247160      0.250203      0.252396
std        0.211751      0.200159      0.194840      0.193160      0.192341
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.101422      0.097175      0.096331      0.098527      0.098041
50%        0.180927      0.182782      0.191793      0.197088      0.200919
75%        0.327582      0.328089      0.347707      0.359378      0.370106
max        1.000000      1.000000      0.985523      0.993213      0.997738

       …           178           179           180           181  \
count  …  10506.000000  10506.000000  10506.000000  10506.000000
mean   …      0.001055      0.001057      0.000744      0.000554
std    …      0.022312      0.022585      0.017557      0.013781
min    …      0.000000      0.000000      0.000000      0.000000
25%    …      0.000000      0.000000      0.000000      0.000000
50%    …      0.000000      0.000000      0.000000      0.000000
75%    …      0.000000      0.000000      0.000000      0.000000
max    …      0.791899      0.773743      0.789804      0.628177

                182           183           184           185      186  \
count  10506.000000  10506.000000  10506.000000  10506.000000  10506.0
mean       0.000533      0.000313      0.000070      0.000074      0.0
std        0.013553      0.010901      0.003754      0.004044      0.0
min        0.000000      0.000000      0.000000      0.000000      0.0
25%        0.000000      0.000000      0.000000      0.000000      0.0
50%        0.000000      0.000000      0.000000      0.000000      0.0
75%        0.000000      0.000000      0.000000      0.000000      0.0
max        0.602033      0.644880      0.265025      0.279310      0.0

           187
count  10506.0
mean       1.0
std        0.0
min        1.0
25%        1.0
50%        1.0
75%        1.0
max        1.0

[8 rows x 188 columns]
```

5 Prueba del primero modelo

5.1 Regresión logistica sin balanceo

[ ]:
```
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

X = df.iloc[:, :187]
y = df[187]
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)


log_reg = LogisticRegression(max_iter=1000, random_state=42)


cv_scores = cross_val_score(log_reg, X_train, y_train, cv=5, scoring='accuracy')


log_reg.fit(X_train, y_train)


y_pred = log_reg.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)
print(f'Precisión del modelo: {accuracy}')


print(f'Precisión promedio con validación cruzada: {cv_scores.mean()}')
print(f'Precisión en cada partición de la validación cruzada: {cv_scores}')
```

```
Precisión del modelo: 0.9139604827349906
Precisión promedio con validación cruzada: 0.9131952967948511
Precisión en cada partición de la validación cruzada: [0.91164953 0.91458639
0.91147915 0.91539528 0.91286612]
```

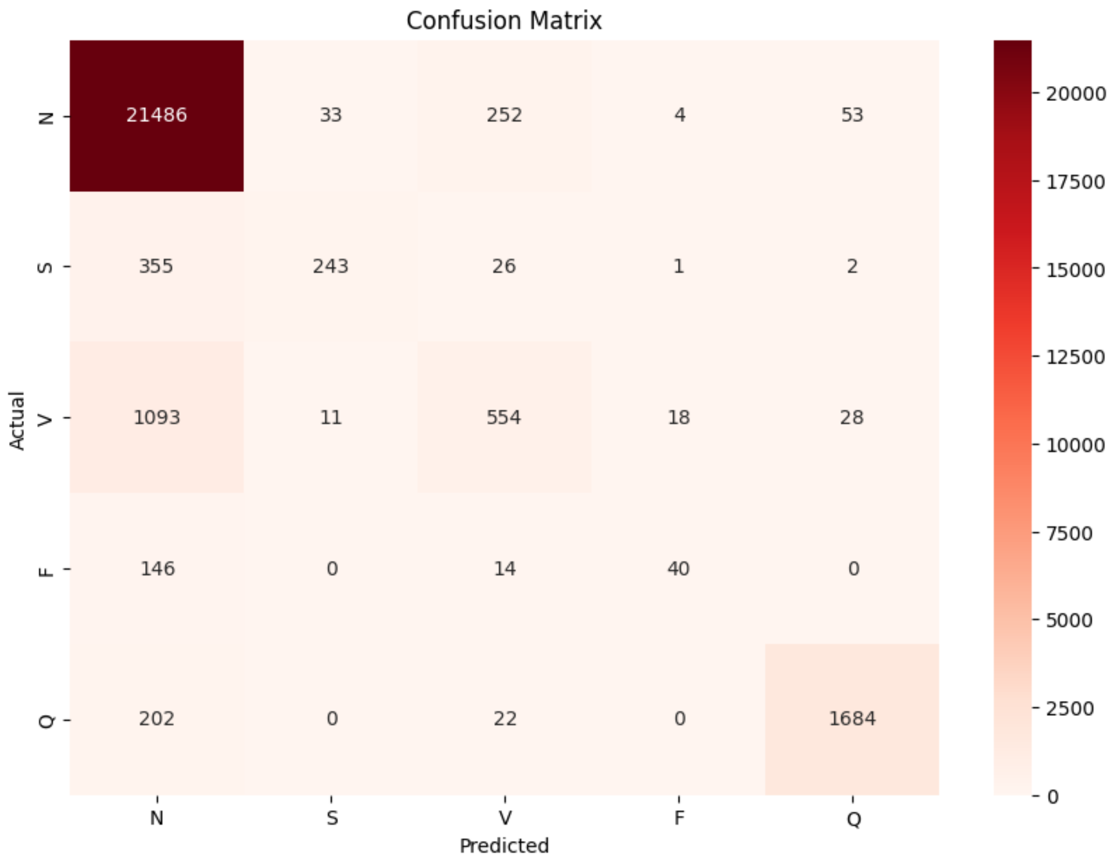
[ ]:
```
report = classification_report(y_test, y_pred)
print("Reporte de clasificación:")
print(report)
```

```
Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.92      0.98      0.95     21828
         1.0       0.85      0.39      0.53       627
         2.0       0.64      0.33      0.43      1704
         3.0       0.63      0.20      0.30       200
```

```
         4.0       0.95      0.88      0.92      1908

    accuracy                           0.91     26267
   macro avg       0.80      0.56      0.63     26267
weighted avg       0.90      0.91      0.90     26267
```

[ ]:
```python
conf_matrix = confusion_matrix(y_test, y_pred)

print("Matriz de confusión:")
print(conf_matrix)


plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Reds', xticklabels=["N",␣
↪"S", "V", "F", "Q"], yticklabels=["N", "S", "V", "F", "Q"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```
Matriz de confusión:
[[21486    33   252     4    53]
 [  355   243    26     1     2]
 [ 1093    11   554    18    28]
 [  146     0    14    40     0]
 [  202     0    22     0  1684]]
```



6 Modelos

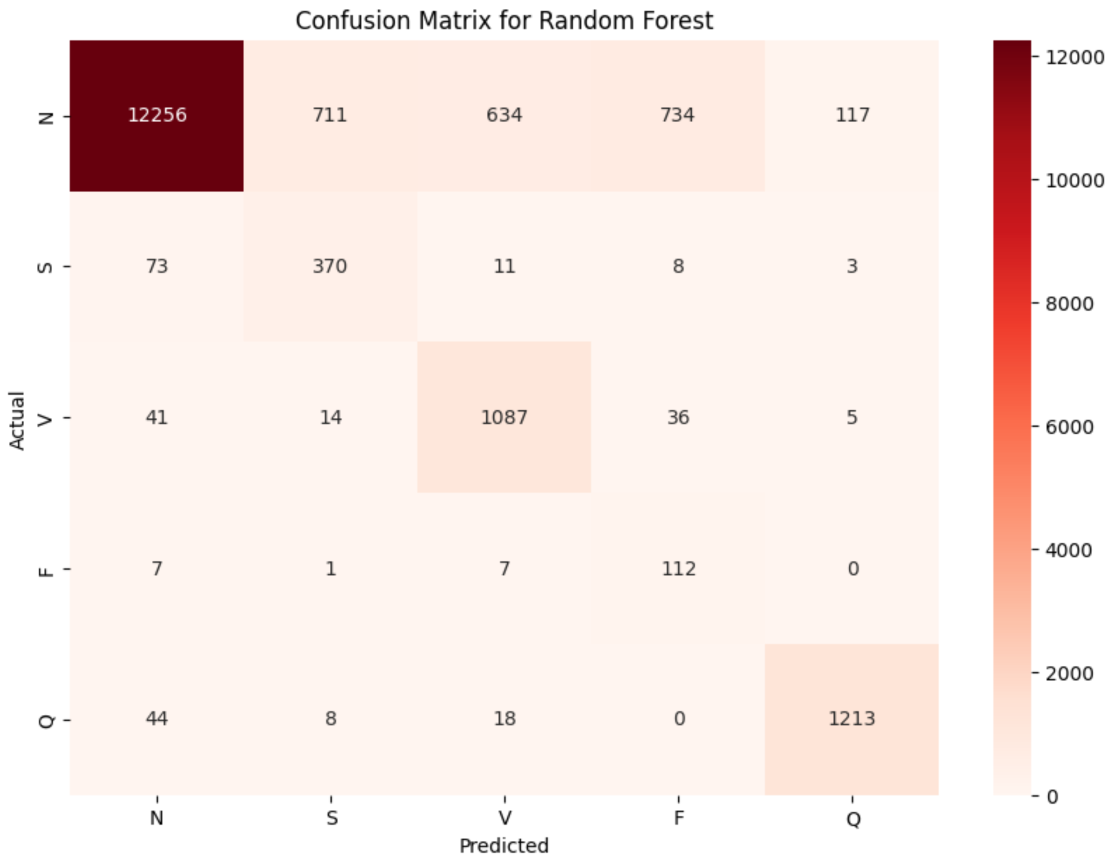
6.1 7 modelos balanceados por RandomUnderSample

[ ]:
```
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

X = df.iloc[:, :187].values
y = df[187].values

n_folds = 5
kf = KFold(n_splits=n_folds, shuffle=True, random_state=42)


models = {
    'Random Forest': RandomForestClassifier(random_state=42),
    'SVM': SVC(random_state=42),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Naive Bayes': GaussianNB(),
```

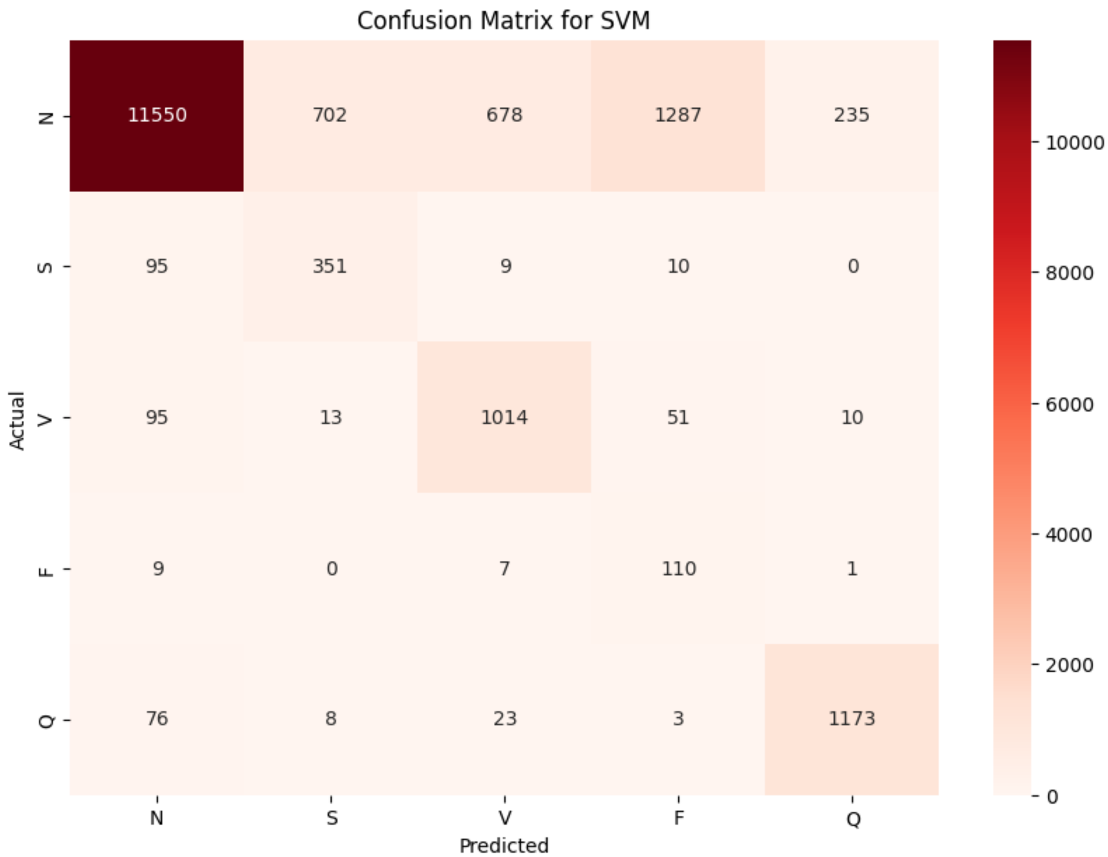
```
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'AdaBoost': AdaBoostClassifier(random_state=42)
}


results = {}


for model_name, model in models.items():
    print(f"Evaluando modelo: {model_name}")

    accuracy_total = 0


    for train_index, test_index in kf.split(X):
        X_train, X_test = X[train_index], X[test_index]
        y_train, y_test = y[train_index], y[test_index]


        undersample = RandomUnderSampler(sampling_strategy='auto',␣
 ↪random_state=42)
        X_res, y_res = undersample.fit_resample(X_train, y_train)


        model.fit(X_res, y_res)


        y_pred = model.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        accuracy_total += accuracy


    accuracy_avg = accuracy_total / n_folds
    results[model_name] = accuracy_avg
    print(f"Precisión promedio para {model_name}: {accuracy_avg:.4f}\n")


    report = classification_report(y_test, y_pred)
    print("Reporte de clasificación:")
    print(report)

    conf_matrix = confusion_matrix(y_test, y_pred)

    plt.figure(figsize=(10, 7))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Reds',␣
 ↪xticklabels=["N", "S", "V", "F", "Q"], yticklabels=["N", "S", "V", "F", "Q"])
    plt.xlabel('Predicted')
```

```
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix for {model_name}')
    plt.show()


best_model_name = max(results, key=results.get)
print(f"\nEl modelo más efectivo es: {best_model_name} con una precisión␣
 ↪promedio de {results[best_model_name]:.4f}")
```

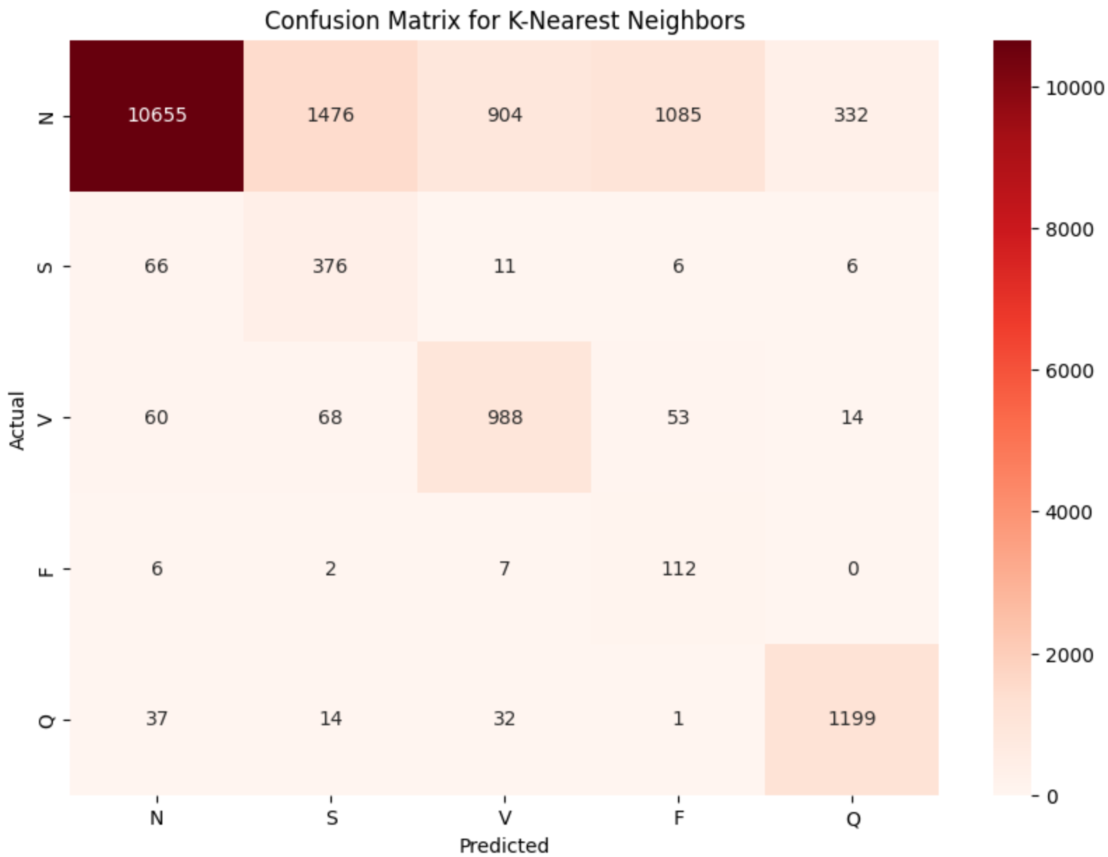
```
Evaluando modelo: Random Forest
Precisión promedio para Random Forest: 0.8511

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.99      0.85      0.91     14452
         1.0       0.34      0.80      0.47       465
         2.0       0.62      0.92      0.74      1183
         3.0       0.13      0.88      0.22       127
         4.0       0.91      0.95      0.93      1283

    accuracy                           0.86     17510
   macro avg       0.59      0.88      0.65     17510
weighted avg       0.93      0.86      0.88     17510
```



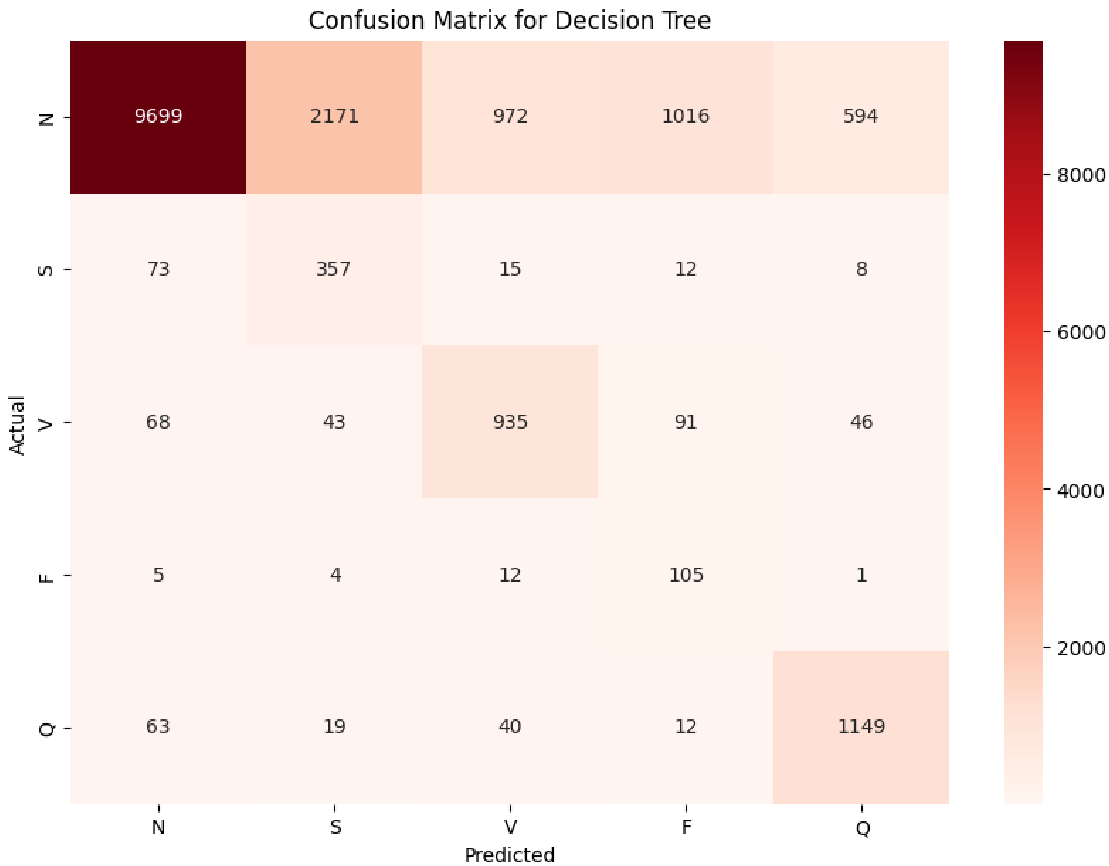

```
Evaluando modelo: SVM
Precisión promedio para SVM: 0.8082

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.98      0.80      0.88     14452
         1.0       0.33      0.75      0.46       465
         2.0       0.59      0.86      0.70      1183
         3.0       0.08      0.87      0.14       127
         4.0       0.83      0.91      0.87      1283

    accuracy                           0.81     17510
   macro avg       0.56      0.84      0.61     17510
weighted avg       0.92      0.81      0.85     17510
```




```
Evaluando modelo: K-Nearest Neighbors
Precisión promedio para K-Nearest Neighbors: 0.7586

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.98      0.74      0.84     14452
         1.0       0.19      0.81      0.31       465
         2.0       0.51      0.84      0.63      1183
         3.0       0.09      0.88      0.16       127
         4.0       0.77      0.93      0.85      1283

    accuracy                           0.76     17510
   macro avg       0.51      0.84      0.56     17510
weighted avg       0.91      0.76      0.81     17510
```

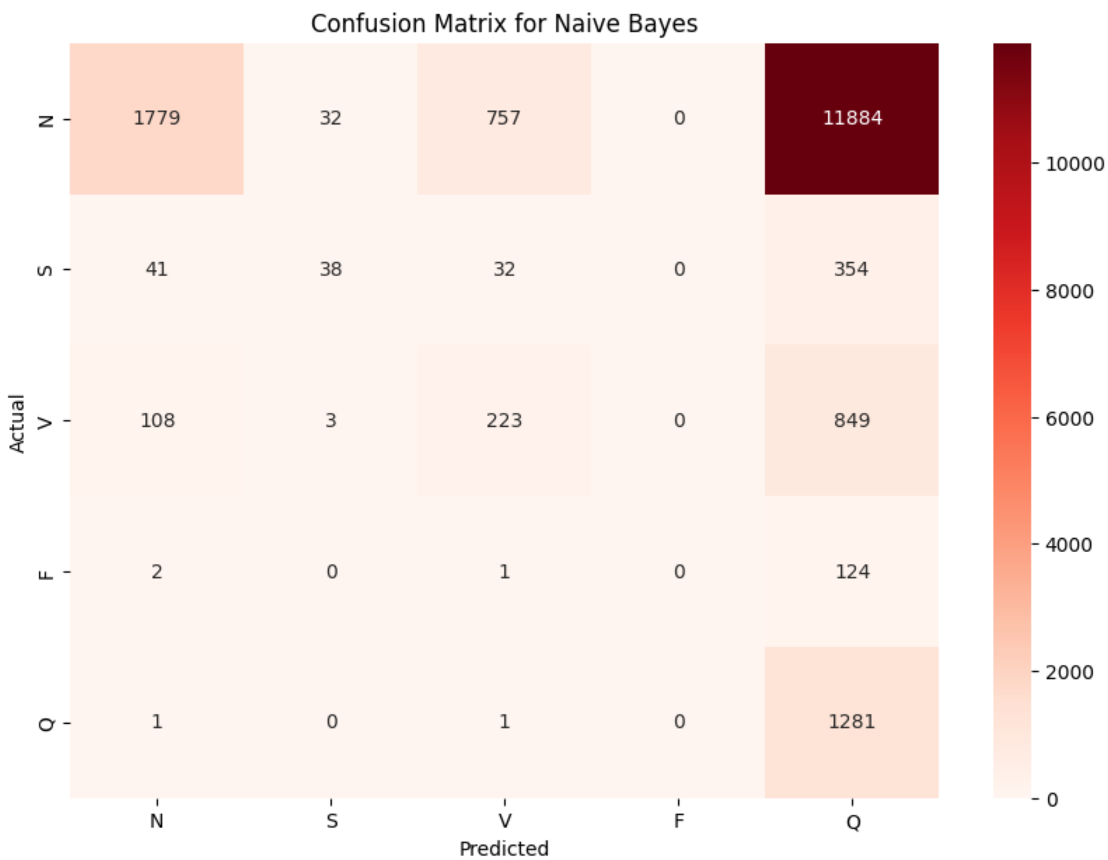



```
Evaluando modelo: Decision Tree
Precisión promedio para Decision Tree: 0.7101

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.98      0.67      0.80     14452
         1.0       0.14      0.77      0.23       465
         2.0       0.47      0.79      0.59      1183
         3.0       0.08      0.83      0.15       127
         4.0       0.64      0.90      0.75      1283

    accuracy                           0.70     17510
   macro avg       0.46      0.79      0.50     17510
weighted avg       0.89      0.70      0.76     17510
```



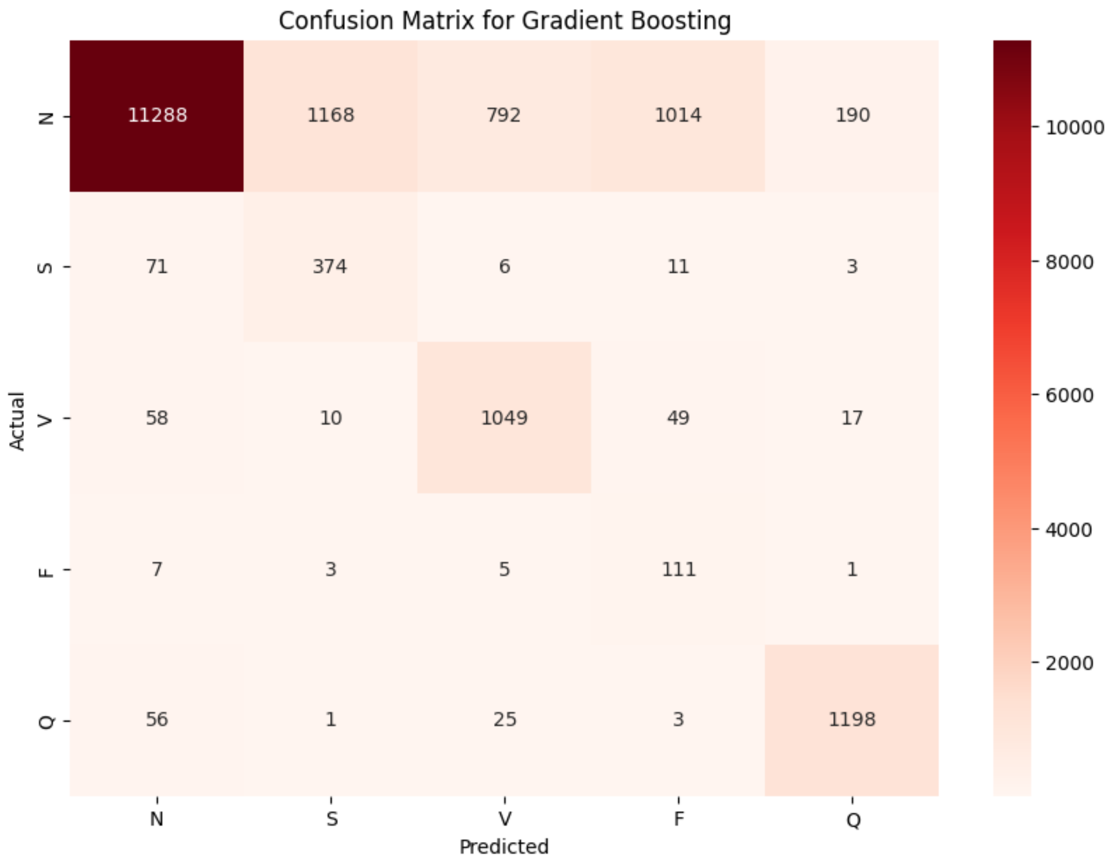

```
Evaluando modelo: Naive Bayes
Precisión promedio para Naive Bayes: 0.1792

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.92      0.12      0.22     14452
         1.0       0.52      0.08      0.14       465
         2.0       0.22      0.19      0.20      1183
         3.0       0.00      0.00      0.00       127
         4.0       0.09      1.00      0.16      1283

    accuracy                           0.19     17510
   macro avg       0.35      0.28      0.14     17510
weighted avg       0.80      0.19      0.21     17510

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1471:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
```

```
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1471:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1471:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




```
Evaluando modelo: Gradient Boosting
Precisión promedio para Gradient Boosting: 0.7945

Reporte de clasificación:
              precision    recall  f1-score   support

         0.0       0.98      0.78      0.87     14452
```

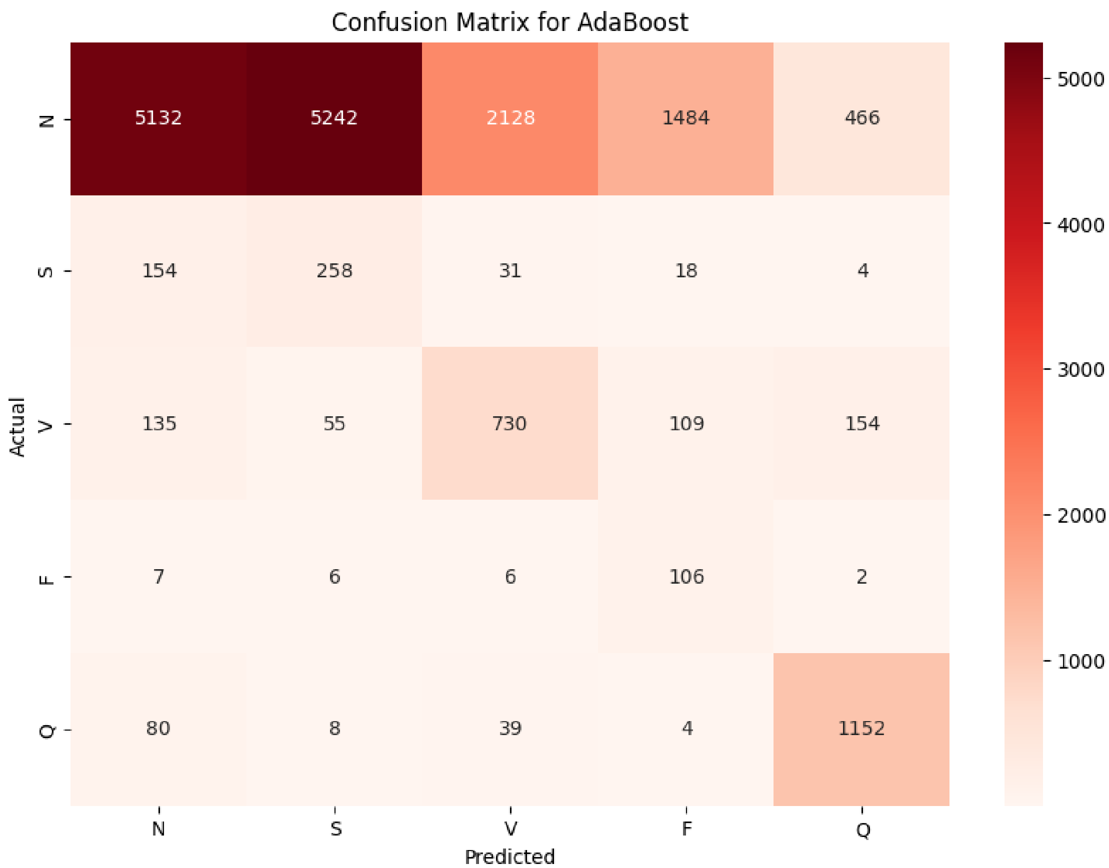
	precision	recall	f1-score	support
1.0	0.24	0.80	0.37	465
2.0	0.56	0.89	0.69	1183
3.0	0.09	0.87	0.17	127
4.0	0.85	0.93	0.89	1283
accuracy			0.80	17510
macro avg	0.55	0.86	0.60	17510
weighted avg	0.92	0.80	0.84	17510




```
Evaluando modelo: AdaBoost
Precisión promedio para AdaBoost: 0.4800

Reporte de clasificación:
```

	precision	recall	f1-score	support
0.0	0.93	0.36	0.51	14452
1.0	0.05	0.55	0.09	465
2.0	0.25	0.62	0.35	1183
3.0	0.06	0.83	0.11	127

```
         4.0       0.65      0.90      0.75      1283

    accuracy                           0.42     17510
   macro avg       0.39      0.65      0.36     17510
weighted avg       0.83      0.42      0.51     17510
```




```
El modelo más efectivo es: Random Forest con una precisión promedio de 0.8511
```

6.2 SMOTE ramdonForest

[ ]:
```python
from imblearn.over_sampling import SMOTE

df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

X = df.iloc[:, :187].values
y = df[187].values

n_folds = 5
```

```python
kf = KFold(n_splits=n_folds, shuffle=True, random_state=42)


model_name = 'Random Forest'
model = RandomForestClassifier(random_state=42)

accuracy_total = 0

for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]


    smote = SMOTE(random_state=42)
    X_res, y_res = smote.fit_resample(X_train, y_train)


    model.fit(X_res, y_res)


    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracy_total += accuracy


accuracy_avg = accuracy_total / n_folds
print(f"Precisión promedio para {model_name}: {accuracy_avg:.4f}\n")


report = classification_report(y_test, y_pred)
print("Reporte de clasificación:")
print(report)

conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Reds', xticklabels=["N",␣
 ↪"S", "V", "F", "Q"], yticklabels=["N", "S", "V", "F", "Q"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for {model_name}')
plt.show()
```

7 Solución

7.1 Modelo 1 = Normal + Abnormal

[ ]:
```python
from sklearn.model_selection import StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report,␣
↪accuracy_score
from imblearn.under_sampling import RandomUnderSampler
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```python
df_normal = pd.read_csv('sample_data/ptbdb_normal.csv', header=None)
df_abnormal = pd.read_csv('sample_data/ptbdb_abnormal.csv', header=None)

df_normal[187] = 0
df_abnormal[187] = 1

df_combined = pd.concat([df_normal, df_abnormal], axis=0).reset_index(drop=True)

X = df_combined.iloc[:, :187]
y = df_combined[187]
```

7.1.1 Balanceo mediante observaciones normales de mitbih_train

[ ]:
```python
df_mitbih = pd.read_csv('sample_data/mitbih_train.csv', header=None)

df_mitbih_normal = df_mitbih[df_mitbih[187] == 0]

normales_faltantes = 2000

df_mitbih_normal_extra = df_mitbih_normal.sample(n=normales_faltantes,␣
↪random_state=42)

df_combined_balanced = pd.concat([df_combined, df_mitbih_normal_extra], axis=0).
↪reset_index(drop=True)

X_balanced = df_combined_balanced.iloc[:, :187]
y_balanced = df_combined_balanced[187]


class_counts_balanced = y_balanced.value_counts()
print("Número de ejemplos por clase después de balancear:")
for cls, count in class_counts_balanced.items():
    print(f"Clase {cls}: {count} ejemplos")
```

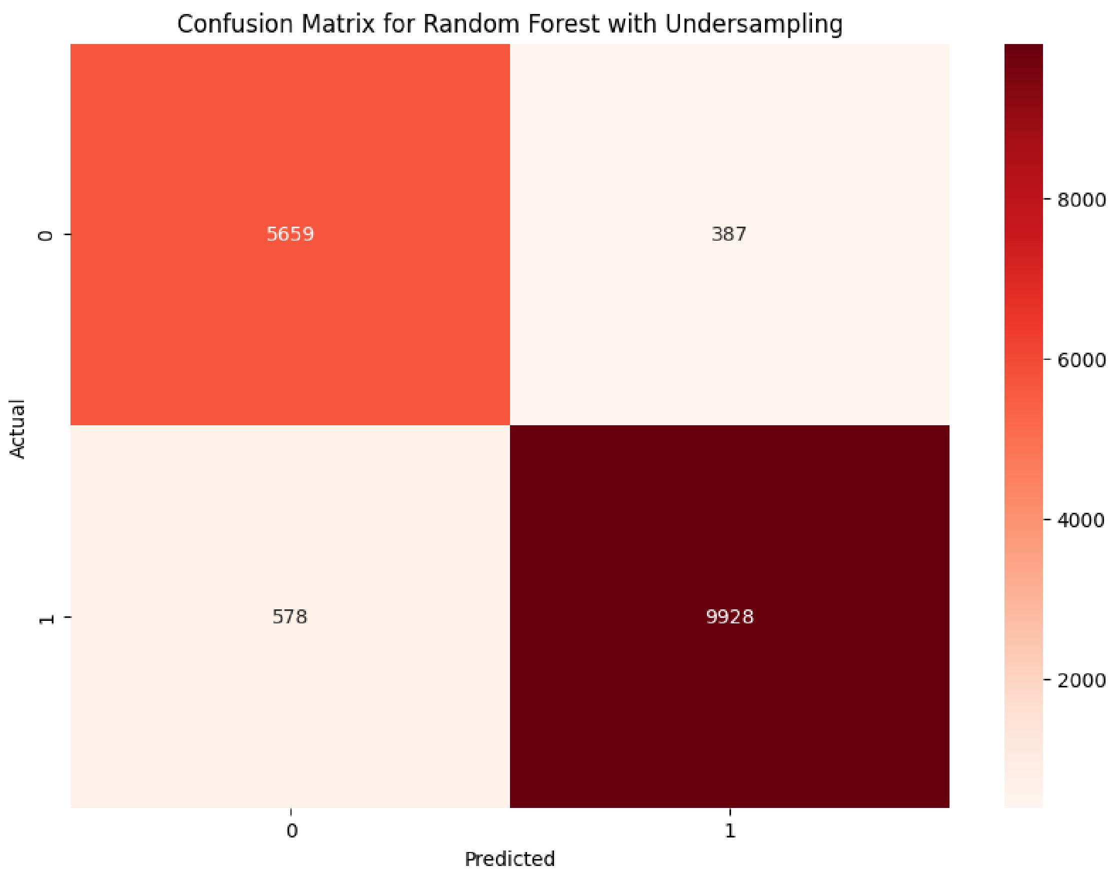
```
Número de ejemplos por clase después de balancear:
Clase 1.0: 10506 ejemplos
```

```
Clase 0.0: 6046 ejemplos
```

7.1.2 Entrenamiento

[ ]:
```python
X_balanced = df_combined_balanced.iloc[:, :187]
y_balanced = df_combined_balanced[187]


under_sampler = RandomUnderSampler(random_state=42)
random_forest_model = RandomForestClassifier(random_state=42)


cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

y_true = []
y_pred = []


for train_index, test_index in cv.split(X_balanced, y_balanced):
    X_train, X_test = X_balanced.iloc[train_index], X_balanced.iloc[test_index]
    y_train, y_test = y_balanced.iloc[train_index], y_balanced.iloc[test_index]


    X_train_under, y_train_under = under_sampler.fit_resample(X_train, y_train)


    random_forest_model.fit(X_train_under, y_train_under)


    y_pred_fold = random_forest_model.predict(X_test)


    y_true.extend(y_test)
    y_pred.extend(y_pred_fold)


y_true = pd.Series(y_true)
y_pred = pd.Series(y_pred)


conf_matrix_rf = confusion_matrix(y_true, y_pred)
report_rf = classification_report(y_true, y_pred)
accuracy_rf = accuracy_score(y_true, y_pred)


plt.figure(figsize=(10, 7))
```

```
sns.heatmap(conf_matrix_rf, annot=True, fmt='d', cmap='Reds', xticklabels=["0",␣
↪"1"], yticklabels=["0", "1"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for Random Forest with Undersampling')
plt.show()


print("\nReporte de Clasificación - Random Forest con Undersampling:")
print(report_rf)
print(f"Exactitud (Accuracy): {accuracy_rf:.2f}")
```

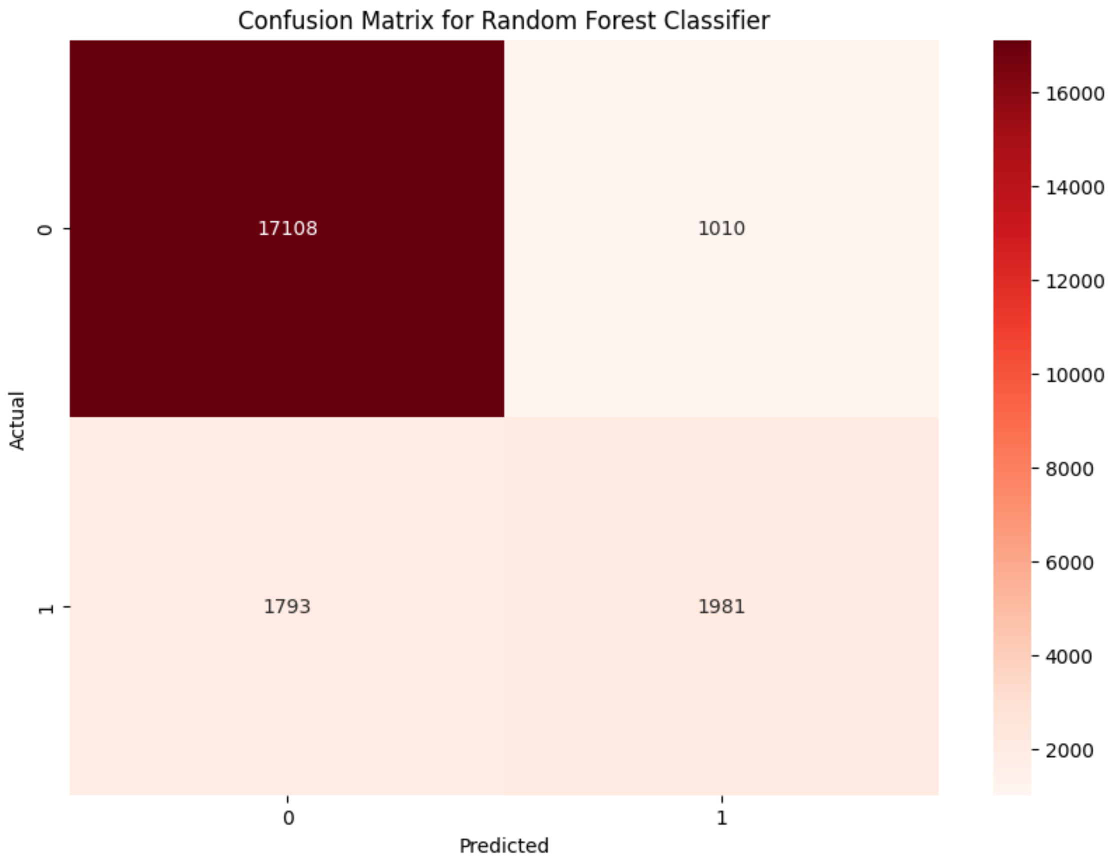



```
Reporte de Clasificación - Random Forest con Undersampling:
              precision    recall  f1-score   support

         0.0       0.91      0.94      0.92      6046
         1.0       0.96      0.94      0.95     10506

    accuracy                           0.94     16552
```

```
   macro avg       0.93      0.94      0.94     16552
weighted avg       0.94      0.94      0.94     16552

Exactitud (Accuracy): 0.94
```

7.1.3 Prueba con mitbih_test

[ ]:
```
df_test = pd.read_csv('sample_data/mitbih_test.csv', header=None)


X_test = df_test.iloc[:, :187]
y_test = df_test[187]


y_test = y_test.replace({2: 1, 3: 1, 4: 1})


random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_balanced, y_balanced)


y_pred_test = random_forest_model.predict(X_test)


conf_matrix_test = confusion_matrix(y_test, y_pred_test)
report_test = classification_report(y_test, y_pred_test)
accuracy_test = accuracy_score(y_test, y_pred_test)


plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_test, annot=True, fmt='d', cmap='Reds',␣
 ↪xticklabels=["0", "1"], yticklabels=["0", "1"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Random Forest Classifier')
plt.show()


print("\nReporte de Clasificación mitbih_test - Random Forest:")
print(report_test)
print(f"Exactitud (Accuracy): {accuracy_test:.2f}")
```




```
Reporte de Clasificación mitbih_test - Random Forest:
              precision    recall  f1-score   support

         0.0       0.91      0.94      0.92     18118
         1.0       0.66      0.52      0.59      3774

    accuracy                           0.87     21892
   macro avg       0.78      0.73      0.75     21892
weighted avg       0.86      0.87      0.87     21892

Exactitud (Accuracy): 0.87
```

7.2 Modelo 2

[ ]:
```
df = pd.read_csv('sample_data/mitbih_train.csv', header=None)

X = df.iloc[:, :187]
y = df[187]
```

[ ]:
```
mask = y != 0
X_filtered = X[mask]
y_filtered = y[mask]


df_abnormal = df[mask]


print(X_filtered.shape)
print(y_filtered.shape)
```

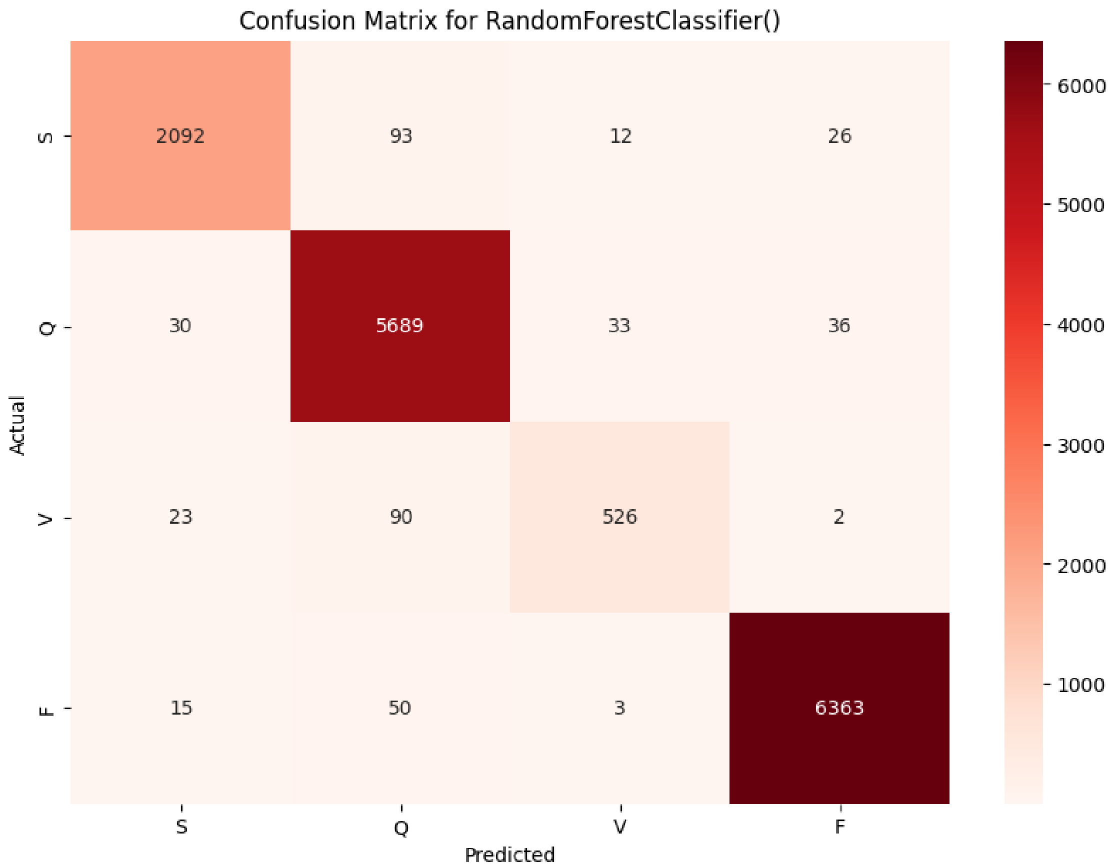
```
(15083, 187)
(15083,)
```

[ ]:
```
X = df_abnormal.iloc[:, :187]
y = df_abnormal[187]
```

7.2.1 Entrenamiento

[ ]:
```
from sklearn.model_selection import cross_val_predict
```

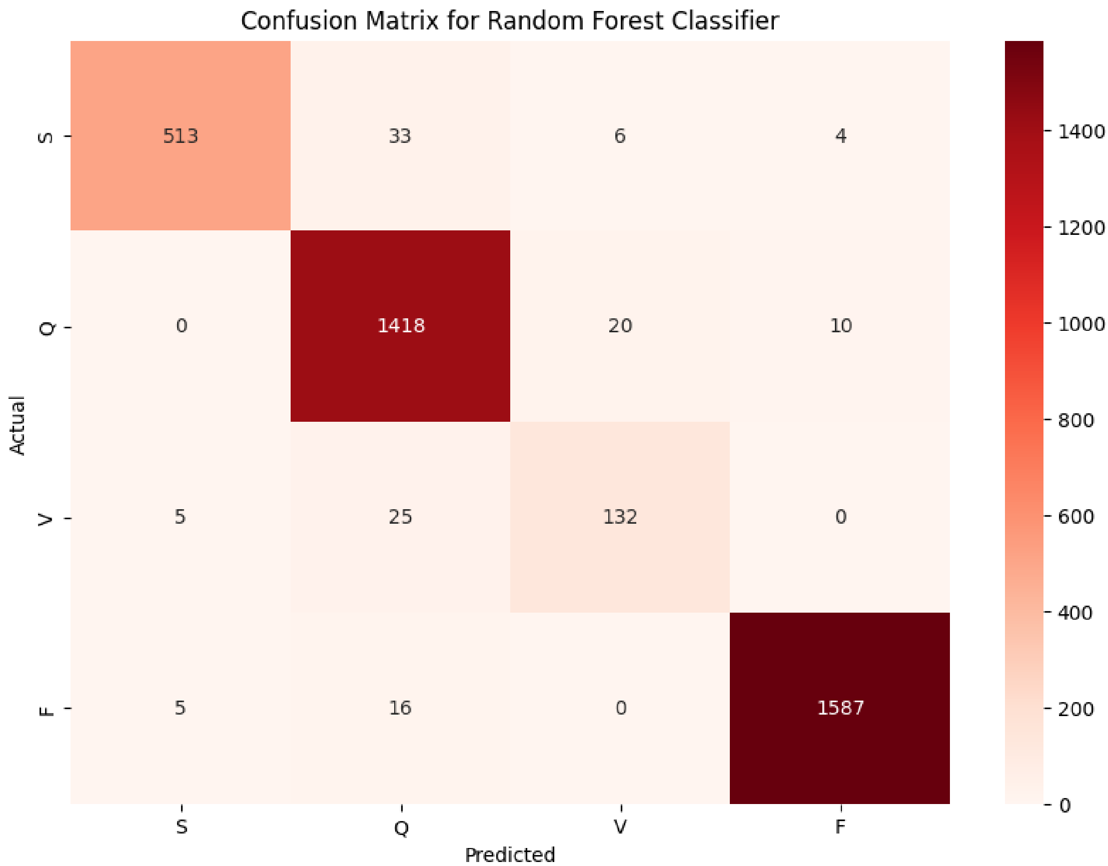
[ ]:
```
random_forest_model = RandomForestClassifier()


y_pred_rf = cross_val_predict(random_forest_model, X, y, cv=5)


conf_matrix_rf = confusion_matrix(y, y_pred_rf)


report_rf = classification_report(y, y_pred_rf)
accuracy_rf = accuracy_score(y, y_pred_rf)

plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_rf, annot=True, fmt='d', cmap='Reds', xticklabels=[␣
↪"S","Q","V","F"], yticklabels=["S","Q","V","F"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for {random_forest_model}')
plt.show()
print("\nReporte de Clasificación - Regresión Logística:")
print(report_rf)
print(f"Exactitud (Accuracy): {accuracy_rf:.2f}")
```




```
Reporte de Clasificación - Regresión Logística:
              precision    recall  f1-score   support

         1.0       0.97      0.94      0.95      2223
         2.0       0.96      0.98      0.97      5788
         3.0       0.92      0.82      0.87       641
         4.0       0.99      0.99      0.99      6431

    accuracy                           0.97     15083
   macro avg       0.96      0.93      0.95     15083
weighted avg       0.97      0.97      0.97     15083

Exactitud (Accuracy): 0.97
```

7.2.2 Prueba con mitbih_test

[ ]:
```
df_test = pd.read_csv('sample_data/mitbih_test.csv', header=None)


X_test = df_test.iloc[:, :187]
y_test = df_test[187]


mask_test = y_test != 0
X_test_filtered = X_test[mask_test]
y_test_filtered = y_test[mask_test]


random_forest_model.fit(X, y)


y_pred_test = random_forest_model.predict(X_test_filtered)


conf_matrix_test = confusion_matrix(y_test_filtered, y_pred_test)
report_test = classification_report(y_test_filtered, y_pred_test)
accuracy_test = accuracy_score(y_test_filtered, y_pred_test)


plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_test, annot=True, fmt='d', cmap='Reds',␣
↪xticklabels=["S", "Q", "V", "F"], yticklabels=["S", "Q", "V", "F"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for Random Forest Classifier')
plt.show()


print("\nReporte de Clasificación - Random Forest:")
print(report_test)
print(f"Exactitud (Accuracy): {accuracy_test:.2f}")
```




```
Reporte de Clasificación - Random Forest:
              precision    recall  f1-score   support

         1.0       0.98      0.92      0.95       556
         2.0       0.95      0.98      0.96      1448
         3.0       0.84      0.81      0.82       162
         4.0       0.99      0.99      0.99      1608

    accuracy                           0.97      3774
   macro avg       0.94      0.93      0.93      3774
weighted avg       0.97      0.97      0.97      3774

Exactitud (Accuracy): 0.97
```

8 Ramdom forest hiperparametros

[ ]:
```
df_mitbih = pd.read_csv('sample_data/mitbih_train.csv', header=None)

df_mitbih_normal = df_mitbih[df_mitbih[187] == 0]

normales_faltantes = 6460

df_mitbih_normal_extra = df_mitbih_normal.sample(n=normales_faltantes,␣
↪random_state=42)

df_combined_balanced = pd.concat([df_combined, df_mitbih_normal_extra], axis=0).
↪reset_index(drop=True)

X_balanced = df_combined_balanced.iloc[:, :187]
y_balanced = df_combined_balanced[187]


from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'bootstrap': [True, False]
}


grid_search = GridSearchCV(estimator=random_forest_model, param_grid=param_grid,
                           cv=3, n_jobs=-1, verbose=1, scoring='accuracy')
grid_search.fit(X_balanced, y_balanced)

best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
print(f"Mejores parámetros: {best_params}")
```

```
Fitting 3 folds for each of 32 candidates, totalling 96 fits
Mejores parámetros: {'bootstrap': False, 'max_depth': 20, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 100}
```

[ ]:
```
y_pred_best_rf_random = cross_val_predict(best_model, X_balanced, y_balanced,␣
↪cv=5)
conf_matrix_best_rf_random = confusion_matrix(y_balanced, y_pred_best_rf_random)
report_best_rf_random = classification_report(y_balanced, y_pred_best_rf_random)
accuracy_best_rf_random = accuracy_score(y_balanced, y_pred_best_rf_random)
```

```python
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_best_rf_random, annot=True, fmt='d', cmap='Reds',␣
 ↪xticklabels=["N","AB"], yticklabels=["N","AB"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for {best_model}')
plt.show()
print("\nReporte de Clasificación - Random Forest con Mejor Parámetro␣
 ↪(Randomized Search):")
print(report_best_rf_random)
print(f"Exactitud (Accuracy): {accuracy_best_rf_random:.2f}")
```

8.1 mas hiperparametros

[ ]:
```python
import pandas as pd


df_normal = pd.read_csv('sample_data/ptbdb_normal.csv', header=None)
df_abnormal = pd.read_csv('sample_data/ptbdb_abnormal.csv', header=None)


df_normal[187] = 0
df_abnormal[187] = 1


df_combined = pd.concat([df_normal, df_abnormal], axis=0).reset_index(drop=True)


X = df_combined.iloc[:, :187]
y = df_combined[187]


class_counts = y.value_counts()

print("Número de ejemplos por clase:")
for cls, count in class_counts.items():
    print(f"Clase {cls}: {count} ejemplos")
```

```
Número de ejemplos por clase:
Clase 1: 10506 ejemplos
Clase 0: 4046 ejemplos
```

[ ]:
```python
df_mitbih = pd.read_csv('sample_data/mitbih_train.csv', header=None)

df_mitbih_normal = df_mitbih[df_mitbih[187] == 0]

normales_faltantes = 6460
```

```
df_mitbih_normal_extra = df_mitbih_normal.sample(n=normales_faltantes,␣
 ↪random_state=42)

df_combined_balanced = pd.concat([df_combined, df_mitbih_normal_extra], axis=0).
 ↪reset_index(drop=True)

X_balanced = df_combined_balanced.iloc[:, :187]
y_balanced = df_combined_balanced[187]
```

8.1.1 No corrio, mucho costo computacional requerido

[ ]:
```
from sklearn.model_selection import GridSearchCV


param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False],
    'class_weight': ['balanced', {0: 1, 1: 4}]
}


rf_model = RandomForestClassifier()


grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy', n_jobs=-1, verbose=2)
grid_search.fit(X_balanced, y_balanced)


print(f"Mejores parámetros encontrados: {grid_search.best_params_}")


best_model = grid_search.best_estimator_
y_pred_test_best = best_model.predict(X_test)


conf_matrix_test_best = confusion_matrix(y_test, y_pred_test_best)
report_test_best = classification_report(y_test, y_pred_test_best)
accuracy_test_best = accuracy_score(y_test, y_pred_test_best)

print("\nReporte de Clasificación con el Mejor Modelo:")
print(report_test_best)
```

```python
print(f"Exactitud (Accuracy) con el Mejor Modelo: {accuracy_test_best:.2f}")
```

```
Fitting 5 folds for each of 432 candidates, totalling 2160 fits
```