Parkinson Detection dataset using multiple model

The purpose of the dataset exploration is to detect the outcome of parkinson based on the given attribute as follows:

Name - ASCII subject name and recording number MDVP:Fo(Hz) - Average vocal fundamental frequency MDVP:Fhi(Hz) - Maximum vocal fundamental frequency MDVP:Flo(Hz) - Minimum vocal fundamental frequency

MDVP:Jitter(%),MDVP:Jitter(Abs),MDVP:RAP,MDVP:PPQ,Jitter:DDP - Several measures of variation in fundamental frequency

MDVP:Shimmer,MDVP:Shimmer(dB),Shimmer:APQ3,Shimmer:APQ5,MDVP:APQ,Shimmer:DDA - Several measures of variation in amplitude

NHR,HNR - Two measures of ratio of noise to tonal components in the voice

status - Health status of the subject (one) - Parkinson's, (zero) - healthy

RPDE,D2 - Two nonlinear dynamical complexity measures

DFA - Signal fractal scaling exponent

spread1,spread2,PPE - Three nonlinear measures of fundamental frequency variation

```
import pandas as pd #Dataframe
import numpy as np #array manipulation
import matplotlib.pyplot as plt #visualization
import seaborn as sns #Visualization

from sklearn.model_selection import train_test_split  #Splitting train and test data

#Valuation Metrics
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import roc_auc_score, confusion_matrix, classification_report
```

```
df = pd.read_csv("/content/drive/MyDrive/Python, Data Mining, ETC/Datasets/Parkinsson disease.csv")
df
```

	name	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitt
0	phon_R01_S01_1	119.992	157.302	74.997	0.00784	
1	phon_R01_S01_2	122.400	148.650	113.819	0.00968	
2	phon_R01_S01_3	116.682	131.111	111.555	0.01050	
3	phon_R01_S01_4	116.676	137.871	111.366	0.00997	
4	phon_R01_S01_5	116.014	141.781	110.655	0.01284	
...	...	...	...	...	...	
190	phon_R01_S50_2	174.188	230.978	94.261	0.00459	
191	phon_R01_S50_3	209.516	253.017	89.488	0.00564	
192	phon_R01_S50_4	174.688	240.005	74.287	0.01360	
193	phon_R01_S50_5	198.764	396.961	74.904	0.00740	
194	phon_R01_S50_6	214.289	260.277	77.973	0.00567	

195 rows × 24 columns

```
df.describe
```

```
<bound method NDFrame.describe of               name  MDVP:Fo(Hz)  MDVP:Fhi(Hz)  MDVP:Flo(Hz)  MDVP:Jitter(%)  \
0    phon_R01_S01_1      119.992       157.302        74.997         0.00784
1    phon_R01_S01_2      122.400       148.650       113.819         0.00968
2    phon_R01_S01_3      116.682       131.111       111.555         0.01050
3    phon_R01_S01_4      116.676       137.871       111.366         0.00997
4    phon_R01_S01_5      116.014       141.781       110.655         0.01284
..              ...          ...           ...           ...             ...
190  phon_R01_S50_2      174.188       230.978        94.261         0.00459
191  phon_R01_S50_3      209.516       253.017        89.488         0.00564
```

```
192  phon_R01_S50_4      174.688       240.005        74.287         0.01360
193  phon_R01_S50_5      198.764       396.961        74.904         0.00740
194  phon_R01_S50_6      214.289       260.277        77.973         0.00567

     MDVP:Jitter(Abs)  MDVP:RAP  MDVP:PPQ  Jitter:DDP  MDVP:Shimmer  ...  \
0             0.00007   0.00370   0.00554     0.01109       0.04374  ...
1             0.00008   0.00465   0.00696     0.01394       0.06134  ...
2             0.00009   0.00544   0.00781     0.01633       0.05233  ...
3             0.00009   0.00502   0.00698     0.01505       0.05492  ...
4             0.00011   0.00655   0.00908     0.01966       0.06425  ...
..                ...       ...       ...         ...           ...  ...
190           0.00003   0.00263   0.00259     0.00790       0.04087  ...
191           0.00003   0.00331   0.00292     0.00994       0.02751  ...
192           0.00008   0.00624   0.00564     0.01873       0.02308  ...
193           0.00004   0.00370   0.00390     0.01109       0.02296  ...
194           0.00003   0.00295   0.00317     0.00885       0.01884  ...

     Shimmer:DDA      NHR     HNR  status      RPDE       DFA   spread1  \
0        0.06545  0.02211  21.033       1  0.414783  0.815285 -4.813031
1        0.09403  0.01929  19.085       1  0.458359  0.819521 -4.075192
2        0.08270  0.01309  20.651       1  0.429895  0.825288 -4.443179
3        0.08771  0.01353  20.644       1  0.434969  0.819235 -4.117501
4        0.10470  0.01767  19.649       1  0.417356  0.823484 -3.747787
..           ...      ...     ...     ...       ...       ...       ...
190      0.07008  0.02764  19.517       0  0.448439  0.657899 -6.538586
191      0.04812  0.01810  19.147       0  0.431674  0.683244 -6.195325
192      0.03804  0.10715  17.883       0  0.407567  0.655683 -6.787197
193      0.03794  0.07223  19.020       0  0.451221  0.643956 -6.744577
194      0.03078  0.04398  21.209       0  0.462803  0.664357 -5.724056

      spread2        D2       PPE
0    0.266482  2.301442  0.284654
1    0.335590  2.486855  0.368674
2    0.311173  2.342259  0.332634
3    0.334147  2.405554  0.368975
4    0.234513  2.332180  0.410335
..        ...       ...       ...
190  0.121952  2.657476  0.133050
191  0.129303  2.784312  0.168895
192  0.158453  2.679772  0.131728
193  0.207454  2.138608  0.123306
194  0.190667  2.555477  0.148569

[195 rows x 24 columns]>
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 24 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              195 non-null    object
 1   MDVP:Fo(Hz)       195 non-null    float64
 2   MDVP:Fhi(Hz)      195 non-null    float64
 3   MDVP:Flo(Hz)      195 non-null    float64
 4   MDVP:Jitter(%)    195 non-null    float64
 5   MDVP:Jitter(Abs)  195 non-null    float64
 6   MDVP:RAP          195 non-null    float64
 7   MDVP:PPQ          195 non-null    float64
 8   Jitter:DDP        195 non-null    float64
 9   MDVP:Shimmer      195 non-null    float64
 10  MDVP:Shimmer(dB)  195 non-null    float64
 11  Shimmer:APQ3      195 non-null    float64
 12  Shimmer:APQ5      195 non-null    float64
 13  MDVP:APQ          195 non-null    float64
 14  Shimmer:DDA       195 non-null    float64
 15  NHR               195 non-null    float64
 16  HNR               195 non-null    float64
 17  status            195 non-null    int64
 18  RPDE              195 non-null    float64
 19  DFA               195 non-null    float64
 20  spread1           195 non-null    float64
 21  spread2           195 non-null    float64
 22  D2                195 non-null    float64
 23  PPE               195 non-null    float64
dtypes: float64(22), int64(1), object(1)
memory usage: 36.7+ KB
```

```
df.columns
```

```
Index(['name', 'MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)', 'MDVP:Jitter(%)',
       'MDVP:Jitter(Abs)', 'MDVP:RAP', 'MDVP:PPQ', 'Jitter:DDP',
       'MDVP:Shimmer', 'MDVP:Shimmer(dB)', 'Shimmer:APQ3', 'Shimmer:APQ5',
       'MDVP:APQ', 'Shimmer:DDA', 'NHR', 'HNR', 'status', 'RPDE', 'DFA',
       'spread1', 'spread2', 'D2', 'PPE'],
      dtype='object')
```

```
df = df.drop(columns='name', axis=1)
```

Dropping name column as it doesn't have correlation

```
df
```

	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RA
0	119.992	157.302	74.997	0.00784	0.00007	0.0037
1	122.400	148.650	113.819	0.00968	0.00008	0.0046
2	116.682	131.111	111.555	0.01050	0.00009	0.0054
3	116.676	137.871	111.366	0.00997	0.00009	0.0050
4	116.014	141.781	110.655	0.01284	0.00011	0.0065
...	...	...	...	...	...	.
190	174.188	230.978	94.261	0.00459	0.00003	0.0026
191	209.516	253.017	89.488	0.00564	0.00003	0.0033
192	174.688	240.005	74.287	0.01360	0.00008	0.0062
193	198.764	396.961	74.904	0.00740	0.00004	0.0037
194	214.289	260.277	77.973	0.00567	0.00003	0.0029

195 rows × 23 columns

```
df.rename(columns=({'MDVP:Fo(Hz)':'average_frequency',
           'MDVP:Fhi(Hz)':'max_frequency',
           'MDVP:Flo(Hz)':'min_frequency',
           'MDVP:Jitter(%)':'frequency_%',
           'MDVP:Jitter(Abs)':'frequency_absolute',
           'MDVP:RAP':'frequency_rap',
           'MDVP:PPQ':'frequency_ppq',
           'MDVP:Shimmer':'amp_var1',
           'MDVP:Shimmer(dB)':'amp_var2',
           'Shimmer:APQ3':'amp_var3',
           'Shimmer:APQ5':'amp_var4',
           'MDVP:APQ':'amp_var5',
           'Shimmer:DDA':'amp_var6',
           }), inplace=True)
```

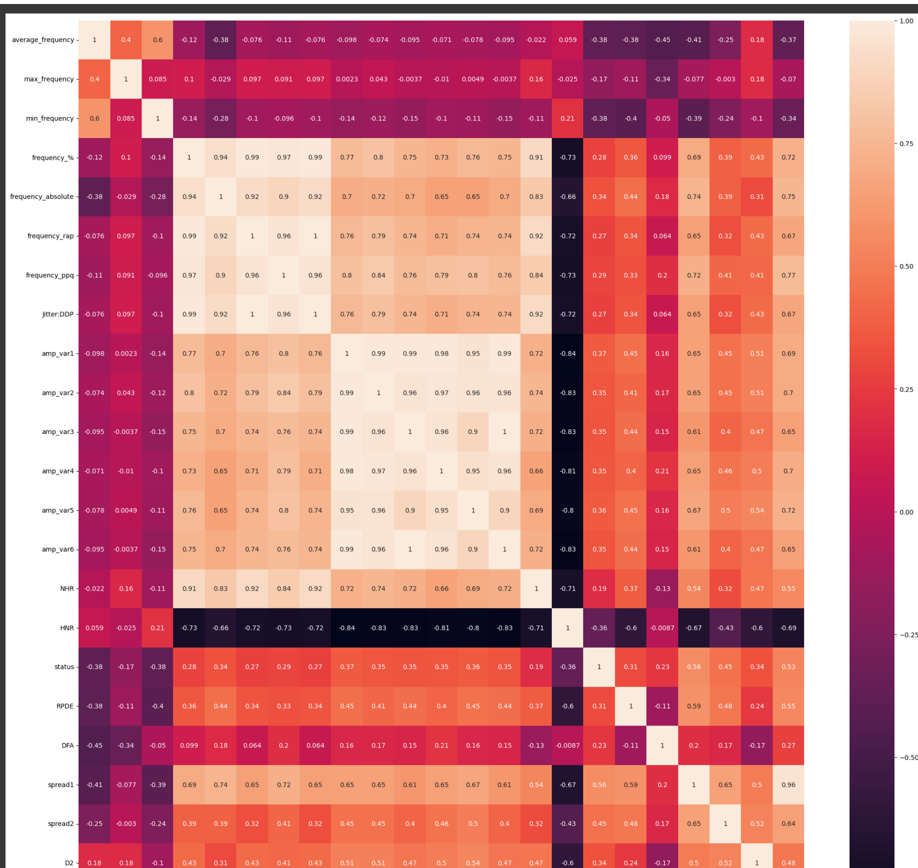
```
df
```

	average_frequency	max_frequency	min_frequency	frequency_%	frequency_absolute
0	119.992	157.302	74.997	0.00784	0.00007
1	122.400	148.650	113.819	0.00968	0.00008
2	116.682	131.111	111.555	0.01050	0.00009
3	116.676	137.871	111.366	0.00997	0.00009
4	116.014	141.781	110.655	0.01284	0.00011
...	...	...	...	...	...
190	174.188	230.978	94.261	0.00459	0.00003

```
# Check null value
df.isna().sum() / len(df) * 100
```

```
average_frequency     0.0
max_frequency         0.0
min_frequency         0.0
frequency_%           0.0
frequency_absolute    0.0
frequency_rap         0.0
frequency_ppq         0.0
Jitter:DDP            0.0
amp_var1              0.0
amp_var2              0.0
amp_var3              0.0
amp_var4              0.0
amp_var5              0.0
amp_var6              0.0
NHR                   0.0
HNR                   0.0
status                0.0
RPDE                  0.0
DFA                   0.0
spread1               0.0
spread2               0.0
D2                    0.0
PPE                   0.0
dtype: float64
```

```
df_corr = df.corr()
plt.figure(figsize=(25,25))
sns.heatmap(df_corr, annot=True)
plt.show()
```



Selecting feature and splitting Train and Test Data

```
X = df.drop(columns='status', axis=1)
y = df.status

X_train, y_train, X_test, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
X.shape
```

    (195, 22)

```
X_train.shape
```

    (156, 22)

```
y_train.shape
```

    (39, 22)

Implementing min max scaler to the dataset

```
#Import min max scaler
from sklearn.preprocessing import MinMaxScaler
```

```
scaler = MinMaxScaler((-1, 1))
```

```
scaler
```

```
▾ MinMaxScaler
```

```
df = scaler.fit_transform(df)
```

```
df
```

```
array([[-0.63138346, -0.77481654, -0.89037042, ...,  0.17153026,
        -0.21867743, -0.0053808 ],
       [-0.6033463 , -0.81013911, -0.4433544 , ...,  0.48267409,
        -0.05370956,  0.34265204],
       [-0.66992292, -0.88174367, -0.46942324, ...,  0.37274182,
        -0.18236124,  0.19336492],
       ...,
       [ 0.00546073, -0.43717403, -0.89854572, ..., -0.31484696,
         0.11793486, -0.63884033],
       [ 0.28578581,  0.20361309, -0.89144127, ..., -0.09423055,
        -0.36355605, -0.67372646],
       [ 0.46654868, -0.35441175, -0.85610326, ..., -0.16981039,
         0.00734563, -0.5690805 ]])
```

```
X_train.head(5)
```

	average_frequency	max_frequency	min_frequency	frequency_%	frequency_absolute
5	120.552	131.162	113.787	0.00968	0.00008
135	110.453	127.611	105.554	0.00494	0.00004
122	138.190	203.522	83.340	0.00704	0.00005
167	260.105	264.919	237.303	0.00339	0.00001
85	180.978	200.125	155.495	0.00406	0.00002

5 rows × 22 columns

I forgot to scale the data, better late than never :D

```
# Fit and transform the entire DataFrame (except the target)
scaled_df = scaler.fit_transform(X)

# Convert the scaled data back to a DataFrame
scaled_df = pd.DataFrame(scaled_df, columns=X.columns)

# Concatenate the scaled features with the target variable
scaled_df_with_target = pd.concat([scaled_df, y.reset_index(drop=True)], axis=1)

# Displaying the scaled DataFrame with target variable
print("Scaled DataFrame with target:")
print(scaled_df_with_target)
```

```
Scaled DataFrame with target:
     average_frequency  max_frequency  min_frequency  frequency_%  \
0            -0.631383      -0.774817      -0.890370    -0.608640
1            -0.603346      -0.810139      -0.443354    -0.491741
2            -0.669923      -0.881744      -0.469423    -0.439644
3            -0.669993      -0.854145      -0.471599    -0.473316
4            -0.677701      -0.838182      -0.479786    -0.290978
..                 ...            ...            ...          ...
190          -0.000361      -0.474028      -0.668555    -0.815121
191           0.410975      -0.384051      -0.723514    -0.748412
192           0.005461      -0.437174      -0.898546    -0.242694
193           0.285786       0.203613      -0.891441    -0.636595
194           0.466549      -0.354412      -0.856103    -0.746506

     frequency_absolute  frequency_rap  frequency_ppq  Jitter:DDP  amp_var1  \
0             -0.501976      -0.709056      -0.504823   -0.709424 -0.375571
1             -0.422925      -0.617534      -0.352626   -0.617916 -0.054227
2             -0.343874      -0.541426      -0.261522   -0.541178 -0.218733
3             -0.343874      -0.581888      -0.350482   -0.582276 -0.171444
4             -0.185771      -0.434489      -0.125402   -0.434259 -0.001095
```

```
..           ...          ...           ...         ...       ...
190      -0.818182    -0.812139     -0.821008   -0.811848 -0.427972
191      -0.818182    -0.746628     -0.785638   -0.746348 -0.671901
192      -0.422925    -0.464355     -0.494105   -0.464119 -0.752784
193      -0.739130    -0.709056     -0.680600   -0.709424 -0.754975
194      -0.818182    -0.781310     -0.758842   -0.781345 -0.830199

     amp_var2  ...  amp_var6       NHR       HNR      RPDE       DFA  \
0   -0.439606  ... -0.334831 -0.863386  0.023490 -0.261689  0.920297
1   -0.110929  ...  0.032097 -0.881338 -0.134845 -0.058339  0.954049
2   -0.347576  ... -0.113365 -0.920807 -0.007559 -0.191168  1.000000
3   -0.290058  ... -0.049044 -0.918006 -0.008128 -0.167490  0.951770
4   -0.179951  ...  0.169085 -0.891651 -0.089003 -0.249682  0.985626
..        ...  ...       ...       ...       ...       ...       ...
190 -0.474117  ... -0.275388 -0.828182 -0.099732 -0.104631 -0.333745
191 -0.707477  ... -0.557324 -0.888914 -0.129806 -0.182866 -0.131798
192 -0.718981  ... -0.686738 -0.322023 -0.232545 -0.295363 -0.351402
193 -0.743632  ... -0.688022 -0.544323 -0.140128 -0.091649 -0.444842
194 -0.827445  ... -0.779946 -0.724162  0.037796 -0.037601 -0.282288

      spread1   spread2        D2       PPE  status
0    0.139750  0.171530 -0.218677 -0.005381       1
1    0.406554  0.482674 -0.053710  0.342652       1
2    0.273489  0.372742 -0.182361  0.193365       1
3    0.391255  0.476177 -0.126046  0.343899       1
4    0.524944  0.027597 -0.191329  0.515223       1
..        ...       ...       ...       ...     ...
190 -0.484213 -0.479185  0.098097 -0.633364       0
191 -0.360089 -0.446089  0.210947 -0.484885       0
192 -0.574111 -0.314847  0.117935 -0.638840       0
193 -0.558699 -0.094231 -0.363556 -0.673726       0
194 -0.189677 -0.169810  0.007346 -0.569081       0

[195 rows x 23 columns]
```

```
df2 = scaled_df_with_target
df2
```

	average_frequency	max_frequency	min_frequency	frequency_%	frequency_absolute
0	-0.631383	-0.774817	-0.890370	-0.608640	-0.501976
1	-0.603346	-0.810139	-0.443354	-0.491741	-0.422925
2	-0.669923	-0.881744	-0.469423	-0.439644	-0.343874
3	-0.669993	-0.854145	-0.471599	-0.473316	-0.343874
4	-0.677701	-0.838182	-0.479786	-0.290978	-0.185771
...	...	...	...	...	...
190	-0.000361	-0.474028	-0.668555	-0.815121	-0.818182
191	0.410975	-0.384051	-0.723514	-0.748412	-0.818182
192	0.005461	-0.437174	-0.898546	-0.242694	-0.422925
193	0.285786	0.203613	-0.891441	-0.636595	-0.739130
194	0.466549	-0.354412	-0.856103	-0.746506	-0.818182

195 rows × 23 columns

```
X = df2.drop(columns='status', axis=1)
y = df2.status

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
print(X_train.shape)
print(y_train.shape)
```

```
(156, 22)
(156,)
```

```
X_train.head()
```

	average_frequency	max_frequency	min_frequency	frequency_%	frequency_absolute
5	-0.624863	-0.881535	-0.443723	-0.491741	-0.422925
135	-0.742449	-0.896033	-0.538522	-0.792884	-0.739130
122	-0.419498	-0.586119	-0.794305	-0.659466	-0.660079
167	1.000000	-0.335460	0.978502	-0.891360	-0.976285
85	0.078697	-0.599988	0.036524	-0.848793	-0.897233

5 rows × 22 columns

For this instance, I'm going to be using Logistic regression, K nearest neighbor, XGBoostClassifier, Suppport Vector Machine (SVM), LGBMClassifier, Logistic regression, and random forest

First lets import all of them

```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

import xgboost as xgb
from xgboost import XGBClassifier

import lightgbm as lgb
from lightgbm import LGBMClassifier
```

```
#Activating the algorithms

lr = LogisticRegression()
KNC = KNeighborsClassifier()
svm = SVC()
rf = RandomForestClassifier()
xgb_clf = XGBClassifier()
lgb_clf = LGBMClassifier()
```

Hyperparameter tuning for our models, I will be using gridsearchCV

The evaluation will be based on accuracy.

```
from sklearn.model_selection import GridSearchCV
```

```
models = {
    'LogisticRegression': LogisticRegression(),
    'KNeighborsClassifier': KNeighborsClassifier(),
    'SVM': SVC(),
    'RandomForestClassifier': RandomForestClassifier(),
    'XGBClassifier': XGBClassifier(),
}
```

```
param_grid = {
    'LogisticRegression': {'C': [0.1, 1, 10, 100], 'penalty': ['l2']},
    'KNeighborsClassifier': {'n_neighbors': [3, 5, 7, 9]},
    'SVM': {'C': [0.1, 1, 10, 100], 'gamma': [0.1, 1, 10], 'kernel': ['rbf', 'linear']},
    'RandomForestClassifier': {'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20]},
    'XGBClassifier': {'n_estimators': [50, 100, 200], 'max_depth': [3, 5, 7]},
}
```

```
#Storing result in a new array
results = {}
for model_name, model in models.items():
  grid_search = GridSearchCV(model, param_grid[model_name], cv=15, scoring='accuracy', error_score='raise
  grid_search.fit(X, y)
  results[model_name] = {
      'best_params' : grid_search.best_params_,
      'best_score' : grid_search.best_score_
      }
```

```
  n_iter_i = _check_optimize_result(
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (stat
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (stat
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
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Please also refer to the documentation for alternative solver options:
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Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
for model_name, result in results.items():
    print(f"Results for {model_name}:")
    print("Best Parameters:", result['best_params'])
    print("Best CV Score:", result['best_score'])
    print()
```

```
Results for LogisticRegression:
Best Parameters: {'C': 0.1, 'penalty': 'l2'}
Best CV Score: 0.841025641025641

Results for KNeighborsClassifier:
Best Parameters: {'n_neighbors': 5}
Best CV Score: 0.8666666666666668

Results for SVM:
Best Parameters: {'C': 10, 'gamma': 1, 'kernel': 'rbf'}
Best CV Score: 0.9128205128205131

Results for RandomForestClassifier:
Best Parameters: {'max_depth': 10, 'n_estimators': 100}
Best CV Score: 0.8820512820512824

Results for XGBClassifier:
Best Parameters: {'max_depth': 5, 'n_estimators': 100}
Best CV Score: 0.9230769230769232
```

XGBClassifier has the best result

Let's put it to the test

```
xgb_clf = XGBClassifier(
    learning_rate=0.1,
    max_depth=3,
    n_estimators=50,
    colsample_bytree=0.8,
    subsample=0.8,
    gamma = 1,
    reg_alpha = 0.1
)
```

```
unique_values_y = np.unique(y)
print(unique_values_y)
```

```
[0 1]
```

```
X_train.describe()
```

	average_frequency	max_frequency	min_frequency	frequency_%	frequency_absolute
count	156.000000	156.000000	156.000000	156.000000	156.000000
mean	-0.235331	-0.632295	-0.391686	-0.718071	-0.714655
std	0.487431	0.353016	0.492344	0.332494	0.293070
min	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
25%	-0.663170	-0.869948	-0.757248	-0.897078	-0.897233
50%	-0.297988	-0.725838	-0.523012	-0.815121	-0.818182
75%	0.109852	-0.516956	-0.127100	-0.664549	-0.660079
max	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 22 columns

```
y_train.describe()
```

```
count    156.000000
mean       0.737179
std        0.441583
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
Name: status, dtype: float64
```

```
X_train_matched = X_train.iloc[:len(y_train)]
```

```
X_train = X_train_matched
```

```
xgb_clf.fit(X_train, y_train)
```

```
▾                              XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=1, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=50, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

```
predict = xgb_clf.predict(X_test)
predict
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1])
```

```
pd.DataFrame({'Actual' : y_test, 'predict': predict},)
```

15	1	1
112	1	1
111	1	1
184	0	1
18	1	1
82	1	1
9	1	1
164	1	1
117	1	1
69	1	1
113	1	1
192	0	0
119	1	1
123	1	1
144	1	1
66	1	1
45	0	0
158	1	1
115	1	1
67	1	1
93	1	1
30	0	0
172	0	0

Classification report

```
from sklearn.metrics import classification_report
```

```
report = classification_report(y_test, predict)

# Print the classification report
print(report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.71      0.83         7
           1       0.94      1.00      0.97        32

    accuracy                           0.95        39
   macro avg       0.97      0.86      0.90        39
weighted avg       0.95      0.95      0.95        39
```

The result of the comparison between each model indicates that XGBClassifier is the best one for this particular dataset.

Now we have to save the model using pickle

```
import pickle
```

```
with open('XGBClassifier_model.pkl', 'wb') as file:
  pickle.dump(xgb_clf, file)
```

```
import os
```

```
os.listdir()
```

```
['.config', 'XGBClassifier_model.pkl', 'drive', 'sample_data']
```