```
In [21]:
         import pandas as pd
         import numpy as np
         import imblearn
         from imblearn.under_sampling import NearMiss
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear_model import LassoCV
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.feature selection import SequentialFeatureSelector
         from sklearn.metrics import accuracy_score, classification_report, confusion_metrics
         import matplotlib.pyplot as plt
```

Creating the Dataframe

```
In [2]: | df = pd.read_csv('diabetes.csv')
        undersample = NearMiss(version=1)
        X = df.loc[:, df.columns != 'Diabetes_binary']
        y = df.loc[:, df.columns == 'Diabetes_binary']
        X, y = undersample.fit_resample(X, y)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, rand)
        scaler = StandardScaler()
        scaler.fit(X_train)
        X_train_scaled = scaler.transform(X_train)
        X_test_scaled = scaler.transform(X_test)
        df_undersampled_train = pd.DataFrame(X_train_scaled, columns = X.columns)
        df_undersampled_train['Diabetes_binary'] = y_train
        df_undersampled_train.head()
        df_undersampled_test = pd.DataFrame(X_test_scaled, columns = X.columns)
        df_undersampled_test['Diabetes_binary'] = y_test
        df_undersampled_test.head()
```

_			-	
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	HighBP	HighChol	CholCheck	ВМІ	Smoker	Stroke	HeartDiseaseorAttack	PhysA
0	-1.212894	0.876922	0.074482	-1.061978	1.158253	-0.225623	-0.384172	0.5
1	-1.212894	-1.140353	0.074482	0.377975	1.158253	-0.225623	-0.384172	0.5
2	0.824475	0.876922	0.074482	1.017954	-0.863369	-0.225623	-0.384172	0.5
3	-1.212894	0.876922	0.074482	0.377975	-0.863369	-0.225623	-0.384172	0.5
4	0.824475	-1.140353	0.074482	2.777896	-0.863369	-0.225623	-0.384172	0.5

5 rows × 22 columns

Creating The Wrapper Method With KNN As The Estimator

• Using both forward and backward to see which direction yields better results

```
sfs_forward = SequentialFeatureSelector(KNeighborsClassifier(n_neighbors=3), n
In [3]:
        sfs_forward.fit(X_train_scaled, y_train.values.ravel())
        sfs_backward = SequentialFeatureSelector(KNeighborsClassifier(n_neighbors=3),
        sfs_backward.fit(X_train_scaled, y_train.values.ravel())
        cols_idxs_forward = sfs_forward.get_support(indices=True)
        cols_idxs_forward
        forward_selection_train = df_undersampled_train.iloc[:, cols_idxs_forward]
        print(forward selection train)
        print(cols_idxs_forward)
        cols_idxs_backward = sfs_backward.get_support(indices=True)
        cols_idxs_backward
        backward_selection_train = df_undersampled_train.iloc[:, cols_idxs_backward]
        print(backward_selection_train)
        print(cols_idxs_backward)
        forward_selection_test = df_undersampled_test.iloc[:, cols_idxs_forward]
        backward_selection_test = df_undersampled_test.iloc[:, cols_idxs_backward]
```

```
HeartDiseaseorAttack PhysActivity
                                          Fruits AnyHealthcare
                                                                     GenHlth
\
0
                 -0.384172
                                 0.514775 0.669234
                                                          0.147309 -0.639948
                                                         0.147309 1.255723
1
                   2.603001
                               -1.942597 0.669234
2
                  -0.384172
                               0.514775 -1.494245
                                                         0.147309 -0.639948
3
                 -0.384172
                               0.514775 0.669234
                                                         0.147309 -1.587783
4
                 -0.384172
                               -1.942597 0.669234
                                                         0.147309 -0.639948
                                      . . .
                                                               . . .
                            -1.942597 0.669234
49479
                 -0.384172
                                                         0.147309 0.307887
49480
                 -0.384172
                                0.514775 -1.494245
                                                         0.147309 -0.639948
49481
                 -0.384172
                                                         0.147309 -0.639948
                                0.514775 0.669234
49482
                 -0.384172
                                 0.514775 0.669234
                                                         0.147309 -0.639948
49483
                 -0.384172
                                 0.514775 0.669234
                                                        0.147309 -0.639948
      MentHlth PhysHlth DiffWalk
                                          Sex
      -0.332699 -0.446002 -0.485309 -1.036097
0
1
      -0.332699 -0.446002 2.060543 -1.036097
     -0.332699 -0.446002 -0.485309 0.965161
3
      -0.332699 -0.446002 -0.485309 -1.036097
4
      2.664163 0.116531 -0.485309 -1.036097
                      . . .
49479 -0.332699 -0.446002 -0.485309 0.965161
49480 -0.332699 -0.446002 -0.485309 0.965161
49481 -0.332699 -0.220989 -0.485309 -1.036097
49482 -0.332699 -0.446002 -0.485309 0.965161
49483 -0.332699 -0.446002 -0.485309 0.965161
[49484 rows x 9 columns]
[ 6 7 8 11 13 14 15 16 17]
                              Veggies AnyHealthcare
            BMI PhysActivity
                                                       GenHlth MentHlth \
      -1.221972
                    0.514775 0.418265
                                              0.147309 -0.639948 -0.332699
1
      0.697964
                    -1.942597 -2.390830
                                              0.147309 1.255723 -0.332699
2
                   0.514775 0.418265
                                             0.147309 -0.639948 -0.332699
     -1.061978
3
     -0.581994
                   0.514775 0.418265
                                             0.147309 -1.587783 -0.332699
4
      1.177948
                   -1.942597 -2.390830
                                             0.147309 -0.639948 2.664163
. . .
            . . .
                          . . .
                                    . . .
                                                   . . .
                                                             . . .
                                                                       . . .
49479 -0.262004
                  -1.942597 0.418265
                                              0.147309 0.307887 -0.332699
49480 -0.262004
                    0.514775 0.418265
                                              0.147309 -0.639948 -0.332699
49481 -1.061978
                   0.514775 0.418265
                                             0.147309 -0.639948 -0.332699
49482 0.057985
                                             0.147309 -0.639948 -0.332699
                   0.514775 0.418265
49483 0.857959
                    0.514775 0.418265
                                             0.147309 -0.639948 -0.332699
       PhysHlth
                     Sex
                            Income
0
     -0.446002 -1.036097 0.356032
1
     -0.446002 -1.036097 -2.571665
2
     -0.446002 0.965161 0.843982
3
     -0.446002 -1.036097 0.843982
4
      0.116531 -1.036097 -0.131917
49479 -0.446002 0.965161 -0.619867
49480 -0.446002 0.965161 0.843982
49481 -0.220989 -1.036097 -1.107816
49482 -0.446002 0.965161 0.843982
49483 -0.446002 0.965161 0.843982
```

[49484 rows x 9 columns] [3 7 9 11 13 14 15 17 20]

Creating The Wrapper Method With Random Forest Classifier As the Estimator

• Using both forward and backward to see which direction yields better results

```
sfs_forward_rf = SequentialFeatureSelector(RandomForestClassifier(), n_feature
In [4]:
        sfs_forward_rf.fit(X_train_scaled, y_train.values.ravel())
        sfs_backward_rf = SequentialFeatureSelector(RandomForestClassifier(), n_feature
        sfs_backward_rf.fit(X_train_scaled, y_train.values.ravel())
        cols_idxs_forward_rf = sfs_forward_rf.get_support(indices=True)
        cols_idxs_forward_rf
        forward selection train rf = df undersampled train.iloc[:, cols idxs forward re
        print(forward selection train rf)
        print(cols_idxs_forward_rf)
        cols_idxs_backward_rf = sfs_backward_rf.get_support(indices=True)
        cols idxs backward rf
        backward selection_train_rf = df_undersampled_train.iloc[:, cols_idxs_backward]
        print(backward_selection_train_rf)
        print(cols_idxs_backward_rf)
        forward_selection_test_rf = df_undersampled_test.iloc[:, cols_idxs_forward_rf]
        backward_selection_test_rf = df_undersampled_test.iloc[:, cols_idxs_backward_r
```

```
Stroke HeartDiseaseorAttack PhysActivity
           BMI
                                                           Veggies \
0
     -1.221972 -0.225623
                                    -0.384172
                                                  0.514775 0.418265
                                   2.603001
-0.384172
1
      0.697964 -0.225623
                                                 -1.942597 -2.390830
2
                                                 0.514775 0.418265
     -1.061978 -0.225623
                                   -0.384172
3
     -0.581994 -0.225623
                                                 0.514775 0.418265
     1.177948 -0.225623
                                   -0.384172
                                                -1.942597 -2.390830
                                          ...
                . . .
           . . .
                                                       . . .
                                                                 . . .
49479 -0.262004 -0.225623
                                   -0.384172 -1.942597 0.418265
                                   -0.384172
49480 -0.262004 -0.225623
                                                 0.514775 0.418265
49481 -1.061978 4.432171
                                                 0.514775 0.418265
                                  -0.384172
49482 0.057985 -0.225623
                                   -0.384172
                                                 0.514775 0.418265
49483 0.857959 -0.225623
                                   -0.384172
                                                  0.514775 0.418265
       GenHlth MentHlth PhysHlth
                                   Income
     -0.639948 -0.332699 -0.446002 0.356032
     1.255723 -0.332699 -0.446002 -2.571665
2
     -0.639948 -0.332699 -0.446002 0.843982
     -1.587783 -0.332699 -0.446002 0.843982
     -0.639948 2.664163 0.116531 -0.131917
                    . . .
                             . . .
49479 0.307887 -0.332699 -0.446002 -0.619867
49480 -0.639948 -0.332699 -0.446002 0.843982
49481 -0.639948 -0.332699 -0.220989 -1.107816
49482 -0.639948 -0.332699 -0.446002 0.843982
49483 -0.639948 -0.332699 -0.446002 0.843982
[49484 rows x 9 columns]
[ 3 5 6 7 9 13 14 15 20]
                             Veggies AnyHealthcare GenHlth MentHlth \
        Stroke PhysActivity
     -0.225623
                                           0.147309 -0.639948 -0.332699
                  0.514775 0.418265
1
     -0.225623
                  -1.942597 -2.390830
                                           0.147309 1.255723 -0.332699
2
     -0.225623
                  0.514775 0.418265
                                           0.147309 -0.639948 -0.332699
     3
                                           0.147309 -1.587783 -0.332699
                                           0.147309 -0.639948 2.664163
                         . . .
                 -1.942597 0.418265
49479 -0.225623
                                           0.147309 0.307887 -0.332699
49480 -0.225623
                  0.514775 0.418265
                                           0.147309 -0.639948 -0.332699
49481 4.432171
                  0.514775 0.418265
                                           0.147309 -0.639948 -0.332699
49482 -0.225623
                  0.514775 0.418265
                                           0.147309 -0.639948 -0.332699
49483 -0.225623
                                           0.147309 -0.639948 -0.332699
                   0.514775 0.418265
      PhysHlth DiffWalk
                           Income
     -0.446002 -0.485309 0.356032
     -0.446002 2.060543 -2.571665
2
     -0.446002 -0.485309 0.843982
3
     -0.446002 -0.485309 0.843982
      0.116531 -0.485309 -0.131917
           . . .
                   . . .
49479 -0.446002 -0.485309 -0.619867
49480 -0.446002 -0.485309 0.843982
49481 -0.220989 -0.485309 -1.107816
49482 -0.446002 -0.485309 0.843982
49483 -0.446002 -0.485309 0.843982
[49484 \text{ rows } x 9 \text{ columns}]
[ 5 7 9 11 13 14 15 16 20]
```

Testing The Forward KNN Generated Feature Selection

```
rf_wrapper = RandomForestClassifier(criterion = 'entropy', max_features = 'sqrt
In [22]:
         rf_wrapper.fit(forward_selection_train, y_train.values.ravel())
         rfw_train_pred = rf_wrapper.predict(forward_selection_train)
         rfw_train_score = accuracy_score(y_train, rfw_train_pred)
         rfw_test_pred = rf_wrapper.predict(forward_selection_test)
         rfw_test_score = accuracy_score(y_test, rfw_test_pred)
         rfw_conf_train = confusion_matrix(y_train.values.ravel(), rfw_train_pred)
         rfw_conf_test = confusion_matrix(y_test.values.ravel(), rfw_test_pred)
         print(f'Random Forest Train Accuracy: {np.round(rfw_train_score, 3)} & Test Acc
         print(f'Train Confusion Matrix:\n{rfw_conf_train}\n\nTest Confusion Matrix:\n{
         print(f'Train Classification Report:\n{classification_report(y_train, rfw_train)
         disp = ConfusionMatrixDisplay(rfw_conf_test, display_labels = rf_wrapper.classe
         disp.plot()
         plt.show()
         Random Forest Train Accuracy: 0.855 & Test Accuracy: 0.855
         Train Confusion Matrix:
         [[22893 1852]
```

[[22893 1852] [5305 19434]]

Test Confusion Matrix:

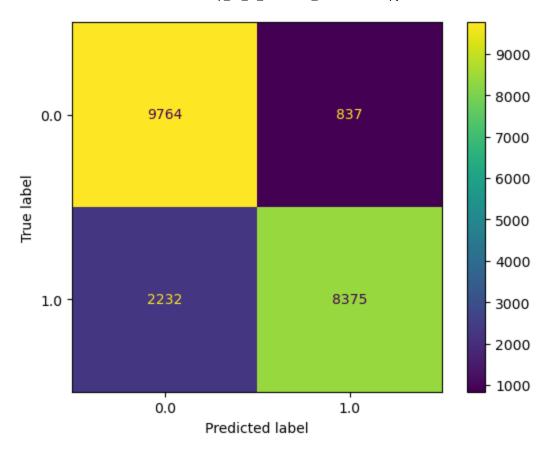
[[9764 837] [2232 8375]]

Train Classification Report:

	precision	recall	f1-score	support
0.0 1.0	0.81 0.91	0.93 0.79	0.86 0.84	24745 24739
accuracy macro avg weighted avg	0.86 0.86	0.86 0.86	0.86 0.85 0.85	49484 49484 49484

Test Classification Report:

0.0 0.81 0.92 0.86	10601
1.0 0.91 0.79 0.85	10607
accuracy 0.86	21208
macro avg 0.86 0.86 0.85	21208
weighted avg 0.86 0.86 0.85	21208



Testing The Backward KNN Generated Feature Selection

Random Forest Train Accuracy: 0.876 & Test Accuracy: 0.87

Train Confusion Matrix:

[[23106 1639] [4487 20252]]

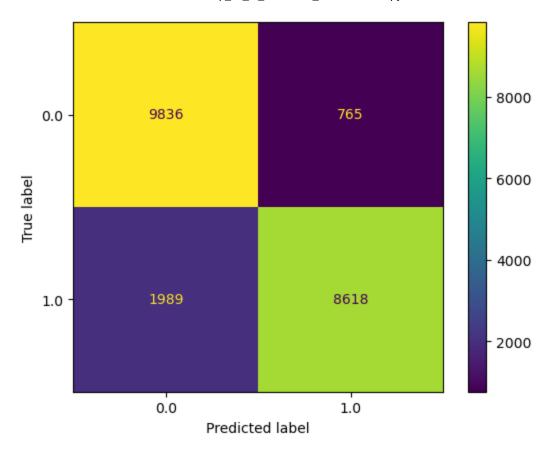
Test Confusion Matrix: [[9836 765] [1989 8618]]

Train Classification Report:

	precision	recall	f1-score	support
0.0 1.0	0.84 0.93	0.93 0.82	0.88 0.87	24745 24739
accuracy macro avg weighted avg	0.88 0.88	0.88 0.88	0.88 0.88 0.88	49484 49484 49484

Test Classification Report:

		precision	recall	f1-score	support
	0.0	0.83	0.93	0.88	10601
	1.0	0.92	0.81	0.86	10607
accur	acy			0.87	21208
macro	•	0.88	0.87	0.87	21208
weighted	avg	0.88	0.87	0.87	21208



Testing The Forward Random Forest Generated Feature Selection

```
rf_wrapper = RandomForestClassifier(criterion = 'entropy', max_features = 'sqrt
In [25]:
         rf_wrapper.fit(forward_selection_train_rf, y_train.values.ravel())
         rfw_train_pred = rf_wrapper.predict(forward_selection_train_rf)
         rfw_train_score = accuracy_score(y_train, rfw_train_pred)
         rfw_test_pred = rf_wrapper.predict(forward_selection_test_rf)
         rfw_test_score = accuracy_score(y_test, rfw_test_pred)
         rfw_conf_train = confusion_matrix(y_train.values.ravel(), rfw_train_pred)
         rfw_conf_test = confusion_matrix(y_test.values.ravel(), rfw_test_pred)
         print(f'Random Forest Train Accuracy: {np.round(rfw_train_score, 3)} & Test Acc
         print(f'Train Confusion Matrix:\n{rfw_conf_train}\n\nTest Confusion Matrix:\n{
         print(f'Train Classification Report:\n{classification_report(y_train, rfw_train)
         disp = ConfusionMatrixDisplay(rfw_conf_test, display_labels = rf_wrapper.classe
         disp.plot()
         plt.show()
         Random Forest Train Accuracy: 0.879 & Test Accuracy: 0.873
         Train Confusion Matrix:
         [[23093 1652]
```

[4342 20397]]

Test Confusion Matrix:

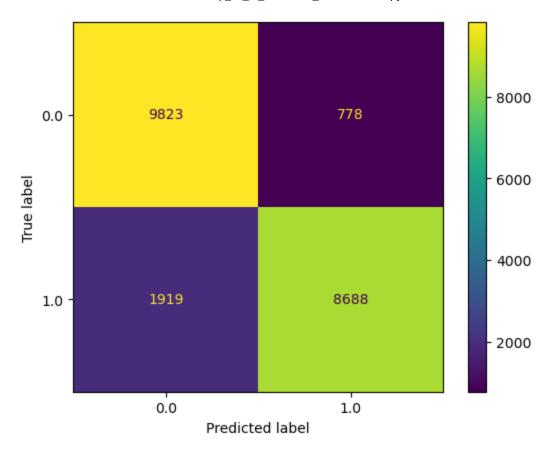
[[9823 778] [1919 8688]]

Train Classification Report:

0.0				
	.84 .93	0.93 0.82	0.89 0.87	24745 24739
).88).88	0.88 0.88	0.88 0.88 0.88	49484 49484 49484

Test Classification Report:

support	f1-score	recall	precision	
10601	0.88	0.93	0.84	0.0
10607	0.87	0.82	0.92	1.0
21208	0.87			accuracy
21208	0.87	0.87	0.88	macro avg
21208	0.87	0.87	0.88	weighted avg



Testing Backward Random Forest Generated Feature Selection

```
rf_wrapper = RandomForestClassifier(criterion = 'entropy', max_features = 'sqrt
In [26]:
         rf_wrapper.fit(backward_selection_train_rf, y_train.values.ravel())
         rfw_train_pred = rf_wrapper.predict(backward_selection_train_rf)
         rfw_train_score = accuracy_score(y_train, rfw_train_pred)
         rfw_test_pred = rf_wrapper.predict(backward_selection_test_rf)
         rfw_test_score = accuracy_score(y_test, rfw_test_pred)
         rfw_conf_train = confusion_matrix(y_train.values.ravel(), rfw_train_pred)
         rfw_conf_test = confusion_matrix(y_test.values.ravel(), rfw_test_pred)
         print(f'Random Forest Train Accuracy: {np.round(rfw_train_score, 3)} & Test Acc
         print(f'Train Confusion Matrix:\n{rfw_conf_train}\n\nTest Confusion Matrix:\n{
         print(f'Train Classification Report:\n{classification_report(y_train, rfw_train)
         disp = ConfusionMatrixDisplay(rfw_conf_test, display_labels = rf_wrapper.classe
         disp.plot()
         plt.show()
         Random Forest Train Accuracy: 0.869 & Test Accuracy: 0.867
         Train Confusion Matrix:
         [[22934 1811]
          [ 4666 20073]]
         Test Confusion Matrix:
         [[9796 805]
```

[2020 8587]]

accuracy macro avg

weighted avg

Train Classification Report:

	precision	recall	f1-score	support
	0.00	0.00		0.47.45
0.0	0.83	0.93	0.88	24745
1.0	0.92	0.81	0.86	24739
accuracy			0.87	49484
macro avg	0.87	0.87	0.87	49484
weighted avg	0.87	0.87	0.87	49484
T + 61 · 6.				
Test Classifi	cation Repor	τ:		
	precision	recall	f1-score	support
	0.00	0.00	2 27	10501
0.0	0.83	0.92	0.87	10601
1.0	0.91	0.81	0.86	10607

0.87

0.87

0.87

0.87

0.87

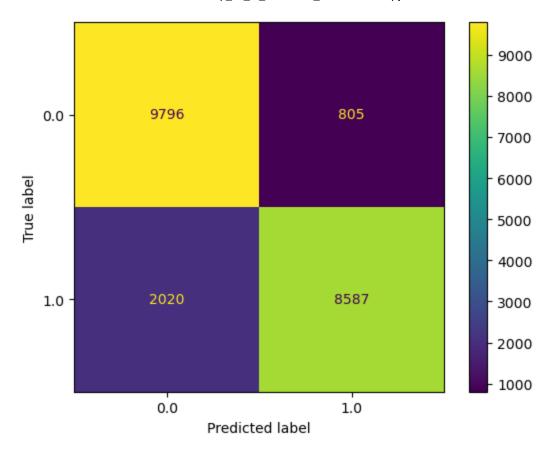
0.87

0.87

21208

21208

21208



Results

- Of all the directions and estimators used the best feature selection was the forward random forest sfs.
 - * The Accuracy of the features using the best model from problem 1:
 - * Training: 0.879 * Testing: 0.873
 - * The 9 Features that were selected are:
 - * BMI
 - * Stroke
 - * HeartDiseaseorAttack
 - * PhysActivity
 - * Veggies
 - * GenHlth
 - * MentHlth
 - * PhysHlth
 - * Income

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411		