In [48]:
```
import pandas as pd
import numpy as np
import imblearn
from imblearn.under_sampling import NearMiss
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, train_tes
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression, Perceptron
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.feature_selection import SelectKBest, f_regression, f_classif, ch
from sklearn.metrics import accuracy_score, classification_report, confusion_ma
import matplotlib.pyplot as plt
```

Recreating the dataset being used for the models

In [3]:
```
#balancing the dataset here:
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)

#splitting the balanced dataset into train and testing samples
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, ranc
scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)

#putting the balanced datasets into individual dataframes for the train and tes
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()
```

Out[3]:

	HighBP	HighChol	CholCheck	BMI	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 Dataframe From The Correlation Selection Method

In [61]:
```
X_selected_train = df_undersampled_train.loc[:, ['Sex', 'HighBP', 'DiffWalk',
                       'Fruits','Income']]
X_selected_test = df_undersampled_test.loc[:, ['Sex', 'HighBP', 'DiffWalk', 'Me
                       'Fruits','Income']]
```

HyperTuning Models Based Of Correlation Feature Selection

Perceptron Hyper Tuning With Correlation Features

In [9]:
```
gs_linear = GridSearchCV(estimator = Perceptron(),
                       param_grid = {'penalty': ['l2', 'l1', 'elasticnet', 'Non
                              'alpha': [0.0001, 0.001, 0.01, 1, 2],
                             'early_stopping': [True, False],
                             'random_state': [42]},
                       cv = 5,
                       scoring='accuracy',
                        verbose = 2,
                        n_jobs = -1)
gs_linear.fit(X_selected_train, y_train.values.ravel())

print(gs_linear.best_params_)
print(gs_linear.best_score_)
```

```
Fitting 5 folds for each of 40 candidates, totalling 200 fits
{'alpha': 0.0001, 'early_stopping': False, 'penalty': 'None', 'random_state':
42}
0.7810608891632318
```

KNN Hyper Tuning With Correlation Features

In [11]:
```
gs = GridSearchCV(estimator=KNeighborsClassifier(),
                  param_grid = {'n_neighbors': range(3, 10, 1),
                                'weights': ['uniform', 'distance'],
                                'algorithm': ['auto', 'ball_tree', 'kd_tree', 'br
                                'p': [1, 2],
                                },
                  cv=5,
                  scoring='accuracy',
                  verbose = 3,
                  n_jobs = -1)
gs.fit(X_selected_train, y_train.values.ravel())

print(gs.best_params_)
print(gs.best_score_)
```

```
Fitting 5 folds for each of 112 candidates, totalling 560 fits
{'algorithm': 'brute', 'n_neighbors': 8, 'p': 1, 'weights': 'distance'}
0.7986219091402971
```

Random Forest Hyper Tuning With Correlation Features

- Unsure why the log_loss parameter was being reported as an error

In [19]:
```python
random_gs = GridSearchCV(estimator=RandomForestClassifier(),
                  param_grid = {'criterion': ['gini', 'entropy', 'log_loss'],
                               'min_samples_split': range(2, 22, 5),
                               'min_samples_leaf': range(2, 22, 5),
                               'max_features': ['sqrt', 'log2', 'auto'],
                               'random_state': [42],
                               'max_depth': range(5, 30, 5)},
                  cv=5,
                  scoring='accuracy',
                  verbose = 3,
                  n_jobs = -1)
random_gs.fit(X_selected_train, y_train.values.ravel())

print(random_gs.best_params_)
print(random_gs.best_score_)
```

```
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
```

Logistic Regression Hyper Tuning With Correlation Features

- Important to note that the errors are a result of GridSearch attempting to pair params that do not work with one another.
  - For instance, solver: newton-cg does not work with penalties that are not l2 or none

In [14]:
```
log_gs = GridSearchCV(estimator = LogisticRegression(),
                      param_grid = {'penalty': ['l1', 'l2', 'elasticnet', 'None
                                   'C': range(1, 10, 1),
                                   'random_state': [42],
                                   'solver': ['lbfgs', 'liblinear', 'newton-cg'
                                   'l1_ratio': [0, 0.5, 1]},
                      cv=5,
                      scoring = 'accuracy',
                      verbose = 3,
                      n_jobs = -1)
log_gs.fit(X_selected_train, y_train)

print(log_gs.best_params_)
print(log_gs.best_score_)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
{'C': 3, 'penalty': 'l2', 'random_state': 42, 'solver': 'liblinear'}
0.812222230934976

C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\model_selection\_valida
tion.py:372: FitFailedWarning:
765 fits failed out of a total of 1080.
The score on these train-test partitions for these parameters will be set t
o nan.
If these failures are not expected, you can try to debug them by setting er
ror_score='raise'.

Below are more details about the failures:
---------------------------------------------------------------------------
-----
45 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\model_selection
\_validation.py", line 680, in _fit_and_score
```

SVM Hyper Tuning With Correlation Features

In [17]:
```
svc_gs = GridSearchCV(estimator = SVC(),
                 param_grid = {'C': [0.1, 1, 5, 10, 15, 20],
                              'kernel': ['linear', 'poly', 'rbf'],
                              'degree': [3, 6, 9],
                              'gamma': ['scale', 'auto']},
                 cv = 5,
                 scoring = 'accuracy',
                     verbose = 3,
                     n_jobs = -1)
svc_gs.fit(X_selected_train, y_train.values.ravel())

print(svc_gs.best_params_)
print(svc_gs.best_score_)
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
{'C': 5, 'degree': 3, 'gamma': 'scale', 'kernel': 'rbf'}
0.8129496648952277
```

Examining Test Scores For All Models With Correlation Data

In [62]:
```
knn = KNeighborsClassifier(algorithm = 'ball_tree', n_neighbors = 9, p = 2, we
knn.fit(X_selected_train, y_train.values.ravel())
knn_train_pred = knn.predict(X_selected_train)
knn_train_score = accuracy_score(y_train, knn_train_pred)
knn_test_pred = knn.predict(X_selected_test)
knn_test_score = accuracy_score(y_test, knn_test_pred)

print(f'KNN Train Accuracy: {np.round(knn_train_score, 3)} & Test Accuracy: {np

rf = RandomForestClassifier(criterion = 'gini',max_features = 'sqrt', max_dept
rf.fit(X_selected_train, y_train.values.ravel())
rf_train_pred = rf.predict(X_selected_train)
rf_train_score = accuracy_score(y_train, rf_train_pred)
rf_test_pred = rf.predict(X_selected_test)
rf_test_score = accuracy_score(y_test, rf_test_pred)

print(f'Random Forest Tree Train Accuracy: {np.round(rf_train_score, 3)} & Tes

line = Perceptron(alpha = 0.0001, early_stopping = False, penalty = None, rand
line.fit(X_selected_train, y_train.values.ravel())
line_train_pred = line.predict(X_selected_train)
line_train_score = accuracy_score(y_train, line_train_pred)
line_test_pred = line.predict(X_selected_test)
line_test_score = accuracy_score(y_test, line_test_pred)

print(f'Linear Classifier/Perceptron Train Accuracy: {np.round(line_train_score

svm = SVC(C = 5, degree = 3, gamma = 'scale', kernel = 'rbf')
svm.fit(X_selected_train, y_train.values.ravel())
svm_train_pred = svm.predict(X_selected_train)
svm_train_score = accuracy_score(y_train, svm_train_pred)
svm_test_pred = svm.predict(X_selected_test)
svm_test_score = accuracy_score(y_test, svm_test_pred)

print(f'SVM Train Accuracy: {np.round(svm_train_score, 3)} & Test Accuracy: {np

log = LogisticRegression(C = 1, penalty = 'l1', random_state=42, solver = 'saga
log.fit(X_selected_train, y_train.values.ravel())
log_train_pred = log.predict(X_selected_train)
log_train_score = accuracy_score(y_train, log_train_pred)
log_test_pred = log.predict(X_selected_test)
log_test_score = accuracy_score(y_test, log_test_pred)

print(f'Logistic Regression Train Accuracy: {np.round(log_train_score, 3)} & Te
```

```
C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\neighbors\_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurt
osis`), the default behavior of `mode` typically preserves the axis it acts a
long. In SciPy 1.11.0, this behavior will change: the default value of `keepd
ims` will become False, the `axis` over which the statistic is taken will be
eliminated, and the value None will no longer be accepted. Set `keepdims` to
True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\neighbors\_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurt
osis`), the default behavior of `mode` typically preserves the axis it acts a
long. In SciPy 1.11.0, this behavior will change: the default value of `keepd
ims` will become False, the `axis` over which the statistic is taken will be
eliminated, and the value None will no longer be accepted. Set `keepdims` to
True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

```
KNN Train Accuracy: 0.793 & Test Accuracy: 0.79
Random Forest Tree Train Accuracy: 0.816 & Test Accuracy: 0.816
Linear Classifier/Perceptron Train Accuracy: 0.695 & Test Accuracy: 0.697
SVM Train Accuracy: 0.814 & Test Accuracy: 0.816
Logistic Regression Train Accuracy: 0.812 & Test Accuracy: 0.813
```

Best Performing Model

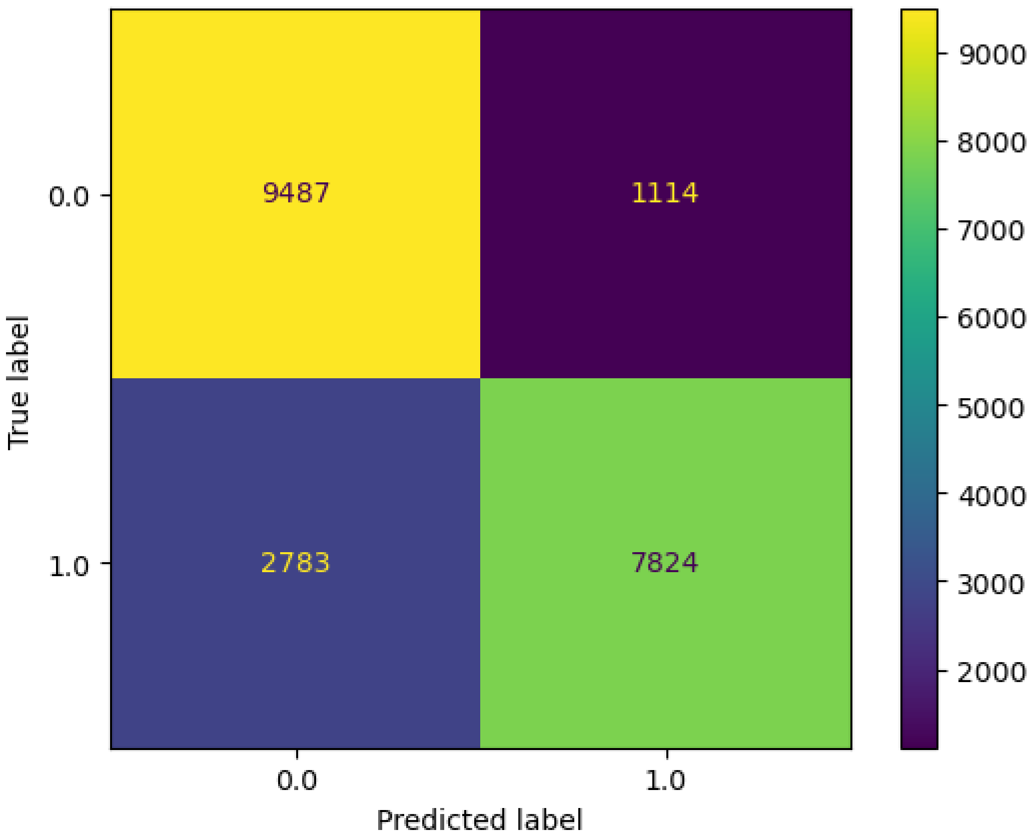
- Before using the wrapper method for feature selection
  - The Best model is Random Forest Tree
    - The accuracy for the model:
      - Train Accuracy: 0.816
      - Test Accuracy: 0.816
    - The params the model used are as follows:
      - criterion = 'gini'
      - max_depth = 10
      - min_samples_split = 18
      - random_state=42
  - The 2 best models following Random Forest Tree are: SVM, and Logistic Regression
    - SVM model accuracy:
      - Train Accuracy: 0.814
      - Test Accuracy: 0.816
    - Logistic Regression accuracy:
      - Train Accuracy: 0.812
      - Test Accuracy: 0.813

Closer Look At The Top 3 Performing Models For Correlation

Random Forest Classifier Performance

In [63]:
```
rf_conf_train = confusion_matrix(y_train, rf_train_pred)
rf_conf_test = confusion_matrix(y_test, rf_test_pred)

print(f'Random Forest Train Accuracy: {np.round(rf_train_score, 3)} & Test Accu

print(f'Train Confusion Matrix:\n{rf_conf_train}\n\nTest Confusion Matrix:\n{r
print(f'Train Classification Report:\n{classification_report(y_train, rf_train_

disp = ConfusionMatrixDisplay(rf_conf_test, display_labels = rf.classes_)
disp.plot()
plt.show()
```

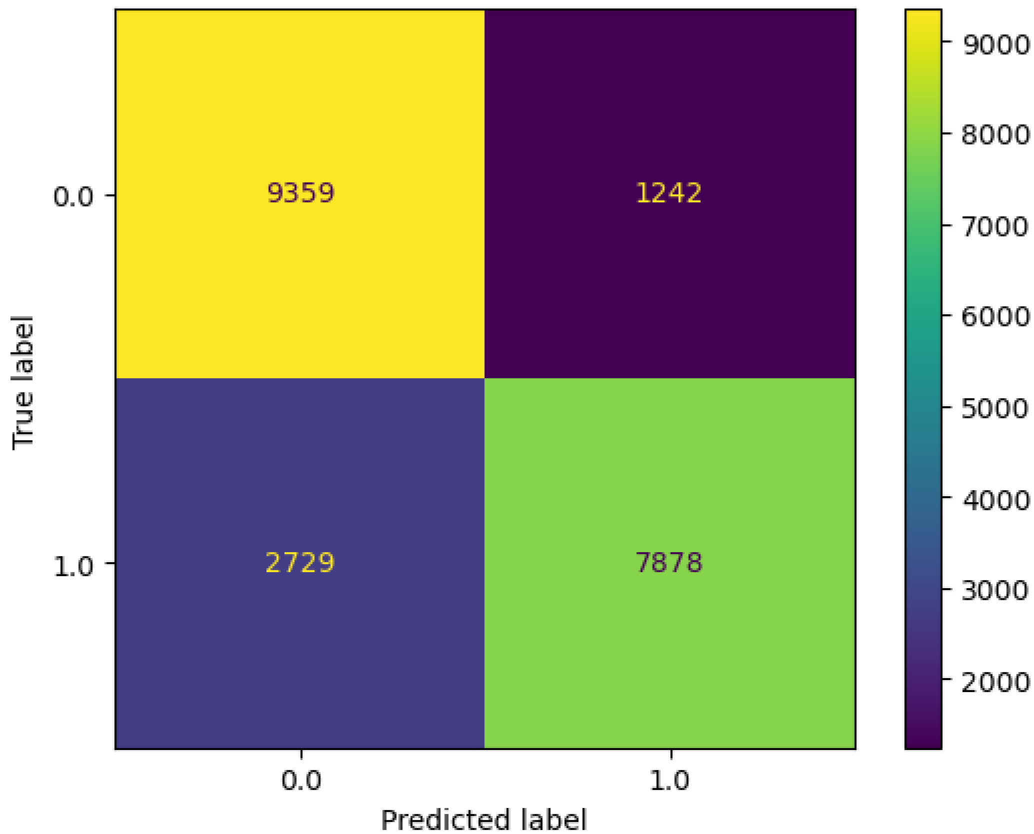
```
Random Forest Train Accuracy: 0.816 & Test Accuracy: 0.816

Train Confusion Matrix:
[[22196  2549]
 [ 6547 18192]]

Test Confusion Matrix:
[[9487 1114]
 [2783 7824]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.90      0.83     24745
         1.0       0.88      0.74      0.80     24739

    accuracy                           0.82     49484
   macro avg       0.82      0.82      0.81     49484
weighted avg       0.82      0.82      0.81     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.89      0.83     10601
         1.0       0.88      0.74      0.80     10607

    accuracy                           0.82     21208
   macro avg       0.82      0.82      0.82     21208
weighted avg       0.82      0.82      0.82     21208
```


9487
1114
2783
7824
0.0
1.0
True label
0.0
1.0
Predicted label
9000
8000
7000
6000
5000
4000
3000
2000

Logistic Regression Model Performance

In [64]:
```
log_conf_train = confusion_matrix(y_train, log_train_pred)
log_conf_test = confusion_matrix(y_test, log_test_pred)

print(f'Logisitc Regression Train Accuracy: {np.round(log_train_score, 3)} & Te

print(f'Train Confusion Matrix:\n{log_conf_train}\n\nTest Confusion Matrix:\n{
print(f'Train Classification Report:\n{classification_report(y_train, log_trai

disp = ConfusionMatrixDisplay(log_conf_test, display_labels = log.classes_)
disp.plot()
plt.show()
```

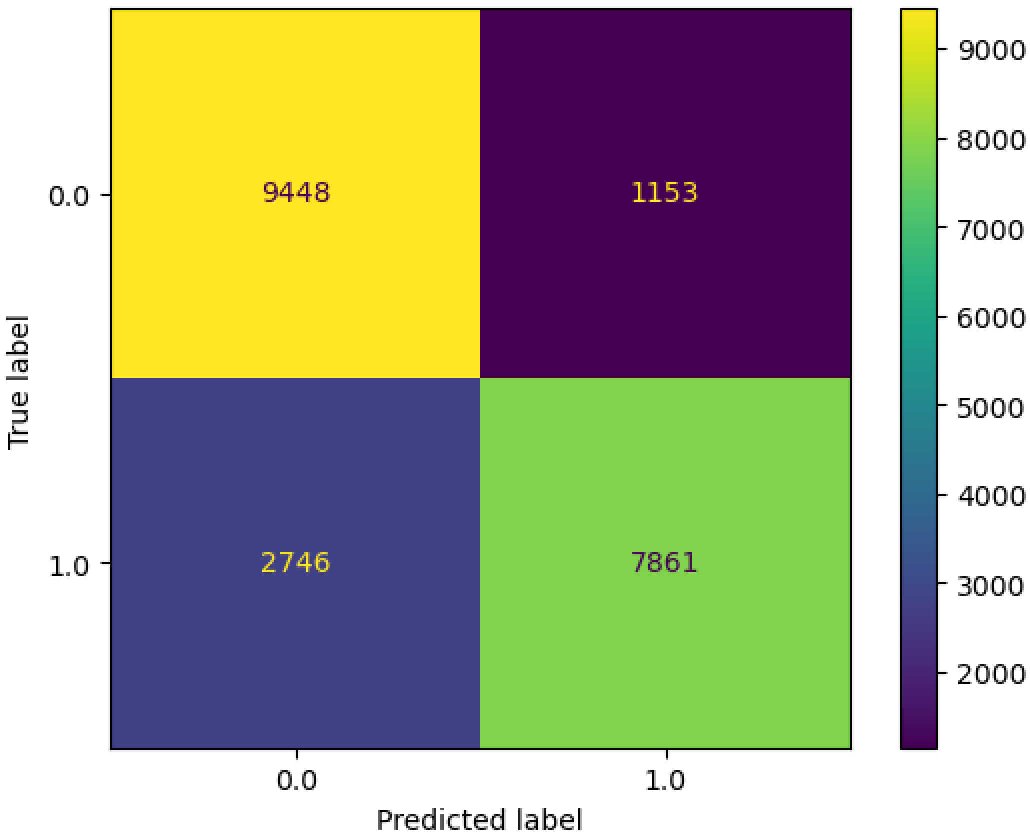
```
Logisitc Regression Train Accuracy: 0.812 & Test Accuracy: 0.813

Train Confusion Matrix:
[[21878  2867]
 [ 6428 18311]]

Test Confusion Matrix:
[[9359 1242]
 [2729 7878]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.88      0.82     24745
         1.0       0.86      0.74      0.80     24739

    accuracy                           0.81     49484
   macro avg       0.82      0.81      0.81     49484
weighted avg       0.82      0.81      0.81     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.88      0.82     10601
         1.0       0.86      0.74      0.80     10607

    accuracy                           0.81     21208
   macro avg       0.82      0.81      0.81     21208
weighted avg       0.82      0.81      0.81     21208
```


9359
1242
2729
7878
0.0
1.0
True label
0.0
1.0
Predicted label
9000
8000
7000
6000
5000
4000
3000
2000

SVM Model Performance

In [65]:
```
svm_conf_train = confusion_matrix(y_train, svm_train_pred)
svm_conf_test = confusion_matrix(y_test, svm_test_pred)

print(f'SVM Train Accuracy: {np.round(svm_train_score, 3)} & Test Accuracy: {np

print(f'Train Confusion Matrix:\n{svm_conf_train}\n\nTest Confusion Matrix:\n{s
print(f'Train Classification Report:\n{classification_report(y_train, svm_trai

disp = ConfusionMatrixDisplay(svm_conf_test, display_labels = svm.classes_)
disp.plot()
plt.show()
```

```
SVM Train Accuracy: 0.814 & Test Accuracy: 0.816

Train Confusion Matrix:
[[22039  2706]
 [ 6474 18265]]

Test Confusion Matrix:
[[9448 1153]
 [2746 7861]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.89      0.83     24745
         1.0       0.87      0.74      0.80     24739

    accuracy                           0.81     49484
   macro avg       0.82      0.81      0.81     49484
weighted avg       0.82      0.81      0.81     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.89      0.83     10601
         1.0       0.87      0.74      0.80     10607

    accuracy                           0.82     21208
   macro avg       0.82      0.82      0.82     21208
weighted avg       0.82      0.82      0.82     21208
```



Creating DataFrame For Lasso Feature

In [34]:
```
X_selected_train = df_undersampled_train.loc[:, ['HighBP', 'BMI', 'Smoker','Hea
                                                 'GenHlth','MentHlth', 'PhysHlt
print(X_selected_train.info())

X_selected_test = df_undersampled_test.loc[:, ['HighBP', 'BMI', 'Smoker','Heart
                                               'GenHlth','MentHlth', 'PhysHlth
print(X_selected_test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49484 entries, 0 to 49483
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   HighBP                49484 non-null  float64
 1   BMI                   49484 non-null  float64
 2   Smoker                49484 non-null  float64
 3   HeartDiseaseorAttack  49484 non-null  float64
 4   HvyAlcoholConsump     49484 non-null  float64
 5   GenHlth               49484 non-null  float64
 6   MentHlth              49484 non-null  float64
 7   PhysHlth              49484 non-null  float64
 8   DiffWalk              49484 non-null  float64
dtypes: float64(9)
memory usage: 3.4 MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21208 entries, 0 to 21207
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   HighBP                21208 non-null  float64
 1   BMI                   21208 non-null  float64
 2   Smoker                21208 non-null  float64
 3   HeartDiseaseorAttack  21208 non-null  float64
 4   HvyAlcoholConsump     21208 non-null  float64
 5   GenHlth               21208 non-null  float64
 6   MentHlth              21208 non-null  float64
 7   PhysHlth              21208 non-null  float64
 8   DiffWalk              21208 non-null  float64
dtypes: float64(9)
memory usage: 1.5 MB
None
```

Hyper Tuning Models Based Off Lasso Selection

Perceptron Hyper Tuning With Lasso Features

In [35]:
```
gs_linear = GridSearchCV(estimator = Perceptron(),
                       param_grid = {'penalty': ['l2', 'l1', 'elasticnet', 'Nor
                                    'alpha': [0.0001, 0.001, 0.01, 1, 2],
                                   'early_stopping': [True, False],
                                   'random_state': [42]},
                       cv = 5,
                       scoring='accuracy',
                        verbose = 2,
                        n_jobs = -1)
gs_linear.fit(X_selected_train, y_train.values.ravel())

print(gs_linear.best_params_)
print(gs_linear.best_score_)
```

```
Fitting 5 folds for each of 40 candidates, totalling 200 fits
{'alpha': 0.0001, 'early_stopping': True, 'penalty': 'None', 'random_state':
42}
0.8209113774872291
```

KNN Hyper Tuning With Lasso Features

In [36]:
```
gs = GridSearchCV(estimator=KNeighborsClassifier(),
                 param_grid = {'n_neighbors': range(3, 10, 1),
                              'weights': ['uniform', 'distance'],
                              'algorithm': ['auto', 'ball_tree', 'kd_tree', 'br
                              'p': [1, 2],
                              },
                 cv=5,
                 scoring='accuracy',
                 verbose = 3,
                 n_jobs = -1)
gs.fit(X_selected_train, y_train.values.ravel())

print(gs.best_params_)
print(gs.best_score_)
```

```
Fitting 5 folds for each of 112 candidates, totalling 560 fits
{'algorithm': 'auto', 'n_neighbors': 9, 'p': 2, 'weights': 'uniform'}
0.840898050649254
```

Random Forest Hyper Tuning With Lasso Features

In [37]:
```
random_gs = GridSearchCV(estimator=RandomForestClassifier(),
                 param_grid = {'criterion': ['gini', 'entropy', 'log_loss'],
                               'min_samples_split': range(2, 22, 5),
                               'min_samples_leaf': range(2, 22, 5),
                               'max_features': ['sqrt', 'log2', 'auto'],
                               'random_state': [42],
                               'max_depth': range(5, 30, 5)},
                 cv=5,
                 scoring='accuracy',
                 verbose = 3,
                 n_jobs = -1)
random_gs.fit(X_selected_train, y_train.values.ravel())

print(random_gs.best_params_)
print(random_gs.best_score_)
```

```
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
        nan         nan         nan         nan         nan         nan
```

SVM Hyper Tuning With Lasso Features

In [41]:
```
svc_gs = GridSearchCV(estimator = SVC(),
                  param_grid = {'C': [0.1, 1, 5, 10],
                               'kernel': ['linear', 'poly', 'rbf'],
                               'degree': [3, 6, 9],
                               'gamma': ['scale', 'auto']},
                  cv = 5,
                  scoring = 'accuracy',
                      verbose = 3,
                      n_jobs = -1)
svc_gs.fit(X_selected_train, y_train.values.ravel())

print(svc_gs.best_params_)
print(svc_gs.best_score_)
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
{'C': 5, 'degree': 3, 'gamma': 'auto', 'kernel': 'rbf'}
0.8524168744045889
```

Logistic Regression Hyper Tuning

In [38]:
```
log_gs = GridSearchCV(estimator = LogisticRegression(),
                      param_grid = {'penalty': ['l1', 'l2', 'elasticnet', 'None
                                    'C': range(1, 10, 1),
                                    'random_state': [42],
                                    'solver': ['lbfgs', 'liblinear', 'newton-cg'
                                    'l1_ratio': [0, 0.5, 1]},
                      cv=5,
                      scoring = 'accuracy',
                      verbose = 3,
                      n_jobs = -1)
log_gs.fit(X_selected_train, y_train)

print(log_gs.best_params_)
print(log_gs.best_score_)
```

```
       nan        nan        nan        nan        nan 0.84683933
       nan        nan        nan        nan        nan        nan
       nan 0.84696058        nan        nan        nan 0.84704141
 0.84683933 0.8467585  0.84683933        nan 0.84687975 0.84683933
       nan        nan        nan        nan        nan 0.84687975
       nan        nan        nan        nan        nan        nan
       nan 0.84696058        nan        nan        nan 0.84704141
 0.84683933 0.8467585  0.84683933        nan 0.84687975 0.84683933
       nan        nan        nan        nan        nan 0.84704141
       nan        nan        nan        nan        nan        nan
       nan 0.84696058        nan        nan        nan 0.84704141
 0.84692017 0.84683933 0.84692017        nan 0.84689996 0.84689996
       nan        nan        nan        nan        nan 0.84689996
       nan        nan        nan        nan        nan        nan
       nan 0.84696058        nan        nan        nan 0.84704141
 0.84692017 0.84683933 0.84692017        nan 0.84689996 0.84689996
       nan        nan        nan        nan        nan 0.84687975
       nan        nan        nan        nan        nan        nan
       nan 0.84696058        nan        nan        nan 0.84704141
 0.84692017 0.84683933 0.84692017        nan 0.84689996 0.84689996
```

Examining Performance of Lasso Models

In [42]:
```
knn = KNeighborsClassifier(algorithm = 'auto', n_neighbors = 9, p = 2, weights
knn.fit(X_selected_train, y_train.values.ravel())
knn_train_pred = knn.predict(X_selected_train)
knn_train_score = accuracy_score(y_train, knn_train_pred)
knn_test_pred = knn.predict(X_selected_test)
knn_test_score = accuracy_score(y_test, knn_test_pred)

print(f'KNN Train Accuracy: {np.round(knn_train_score, 3)} & Test Accuracy: {np

rf = RandomForestClassifier(criterion = 'entropy',max_features = 'sqrt', max_de
rf.fit(X_selected_train, y_train.values.ravel())
rf_train_pred = rf.predict(X_selected_train)
rf_train_score = accuracy_score(y_train, rf_train_pred)
rf_test_pred = rf.predict(X_selected_test)
rf_test_score = accuracy_score(y_test, rf_test_pred)

print(f'Random Forest Tree Train Accuracy: {np.round(rf_train_score, 3)} & Test

line = Perceptron(alpha = 0.0001, early_stopping = True, penalty = None, randor
line.fit(X_selected_train, y_train.values.ravel())
line_train_pred = line.predict(X_selected_train)
line_train_score = accuracy_score(y_train, line_train_pred)
line_test_pred = line.predict(X_selected_test)
line_test_score = accuracy_score(y_test, line_test_pred)

print(f'Linear Classifier/Perceptron Train Accuracy: {np.round(line_train_score

svm = SVC(C = 5, degree = 3, gamma = 'auto', kernel = 'rbf')
svm.fit(X_selected_train, y_train.values.ravel())
svm_train_pred = svm.predict(X_selected_train)
svm_train_score = accuracy_score(y_train, svm_train_pred)
svm_test_pred = svm.predict(X_selected_test)
svm_test_score = accuracy_score(y_test, svm_test_pred)

print(f'SVM Train Accuracy: {np.round(svm_train_score, 3)} & Test Accuracy: {np

log = LogisticRegression(C = 8, l1_ratio = 0, penalty = 'l1', random_state=42,
log.fit(X_selected_train, y_train.values.ravel())
log_train_pred = log.predict(X_selected_train)
log_train_score = accuracy_score(y_train, log_train_pred)
log_test_pred = log.predict(X_selected_test)
log_test_score = accuracy_score(y_test, log_test_pred)

print(f'Logistic Regression Train Accuracy: {np.round(log_train_score, 3)} & Te
```

```
C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\neighbors\_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurt
osis`), the default behavior of `mode` typically preserves the axis it acts a
long. In SciPy 1.11.0, this behavior will change: the default value of `keepd
ims` will become False, the `axis` over which the statistic is taken will be
eliminated, and the value None will no longer be accepted. Set `keepdims` to
True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\neighbors\_classificatio
n.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurt
osis`), the default behavior of `mode` typically preserves the axis it acts a
long. In SciPy 1.11.0, this behavior will change: the default value of `keepd
ims` will become False, the `axis` over which the statistic is taken will be
eliminated, and the value None will no longer be accepted. Set `keepdims` to
True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

```
KNN Train Accuracy: 0.851 & Test Accuracy: 0.841
Random Forest Tree Train Accuracy: 0.857 & Test Accuracy: 0.852
Linear Classifier/Perceptron Train Accuracy: 0.766 & Test Accuracy: 0.763
SVM Train Accuracy: 0.854 & Test Accuracy: 0.85
```

```
C:\Users\Felipe\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:1476: UserWarning: l1_ratio parameter is only used when penalty is 'elastic
net'. Got (penalty=l1)
  warnings.warn(
```

```
Logistic Regression Train Accuracy: 0.847 & Test Accuracy: 0.845
```

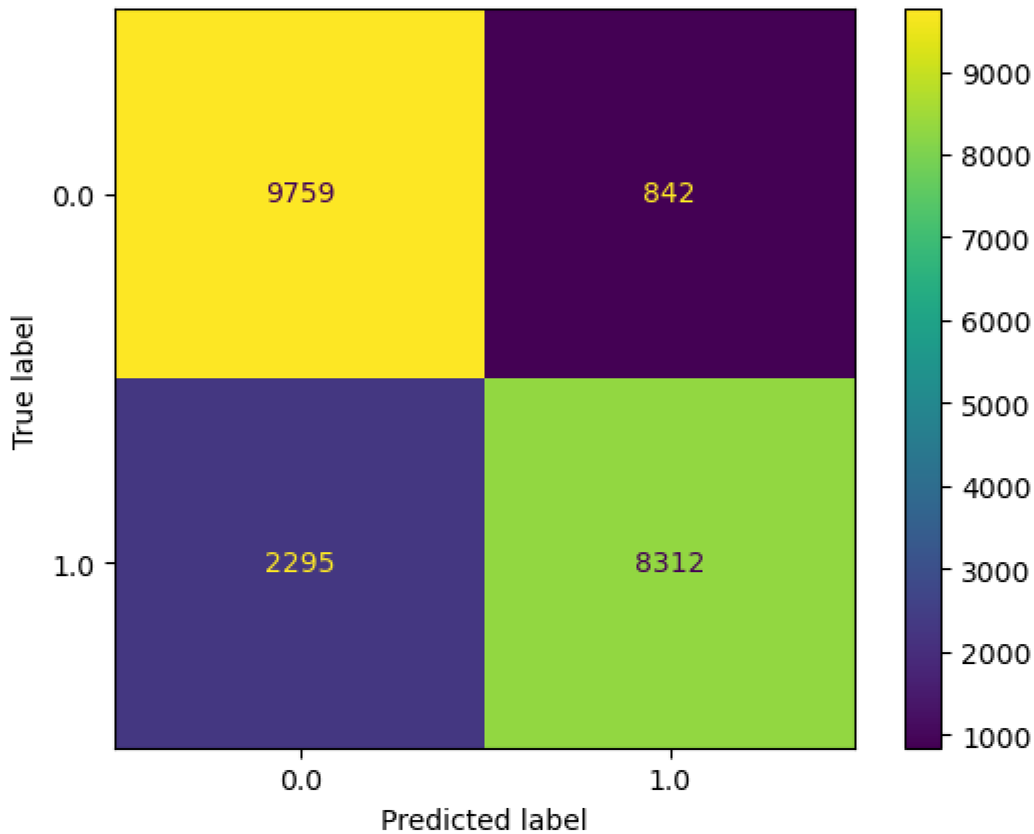
Closer Look At The Top 3 Performing Models For Lasso

Random Forest Model Performance

```
* Created confusion matrix visual for the test data
```

In [51]:
```
rf_conf_train = confusion_matrix(y_train, rf_train_pred)
rf_conf_test = confusion_matrix(y_test, rf_test_pred)

print(f'Random Forest Train Accuracy: {np.round(rf_train_score, 3)} & Test Accu

print(f'Train Confusion Matrix:\n{rf_conf_train}\n\nTest Confusion Matrix:\n{r
print(f'Train Classification Report:\n{classification_report(y_train, rf_train_

disp = ConfusionMatrixDisplay(rf_conf_test, display_labels = rf.classes_)
disp.plot()
plt.show()
```

```
Random Forest Train Accuracy: 0.857 & Test Accuracy: 0.852

Train Confusion Matrix:
[[22938  1807]
 [ 5261 19478]]

Test Confusion Matrix:
[[9759  842]
 [2295 8312]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.93      0.87     24745
         1.0       0.92      0.79      0.85     24739

    accuracy                           0.86     49484
   macro avg       0.86      0.86      0.86     49484
weighted avg       0.86      0.86      0.86     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.92      0.86     10601
         1.0       0.91      0.78      0.84     10607

    accuracy                           0.85     21208
   macro avg       0.86      0.85      0.85     21208
weighted avg       0.86      0.85      0.85     21208
```

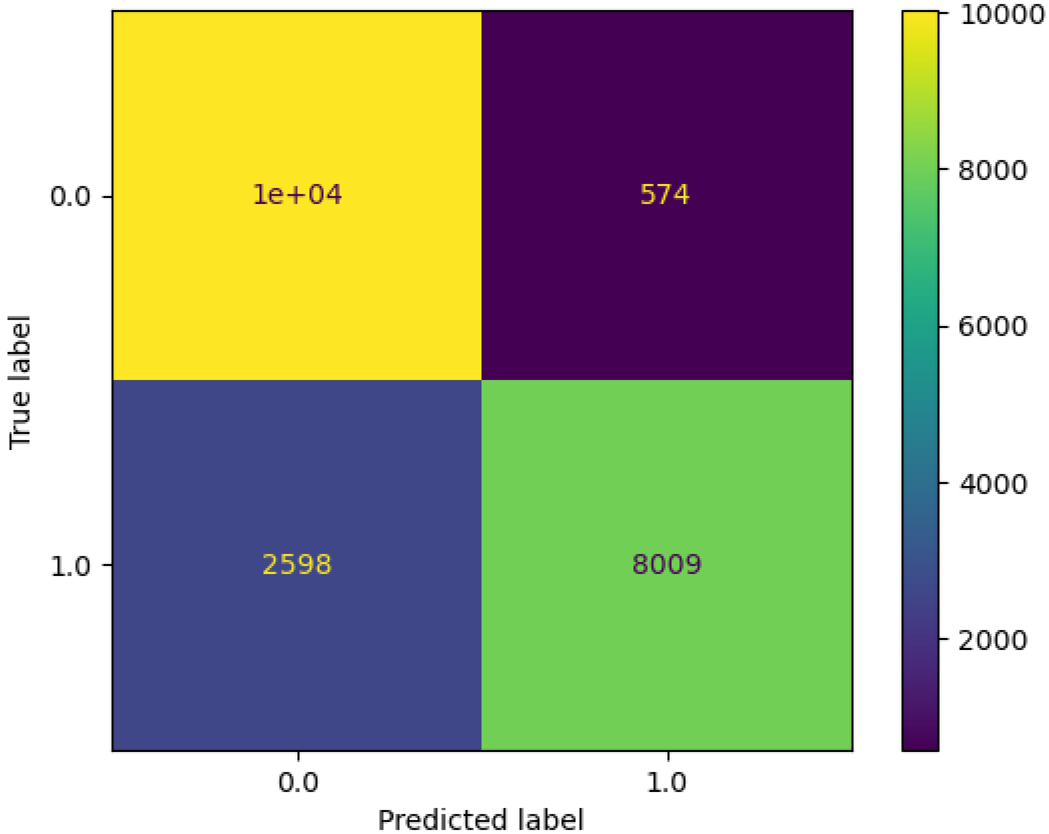


SVM Forest Model Performance

```
* I went ahead and created a better visual for the test datas confusio
n matrix
```

In [50]:
```
svm_conf_train = confusion_matrix(y_train, svm_train_pred)
svm_conf_test = confusion_matrix(y_test, svm_test_pred)

print(f'SVM Train Accuracy: {np.round(svm_train_score, 3)} & Test Accuracy: {n

print(f'Train Confusion Matrix:\n{svm_conf_train}\n\nTest Confusion Matrix:\n{s
print(f'Train Classification Report:\n{classification_report(y_train, svm_trai

disp = ConfusionMatrixDisplay(svm_conf_test, display_labels = svm.classes_)
disp.plot()
plt.show()
```

```
SVM Train Accuracy: 0.854 & Test Accuracy: 0.85

Train Confusion Matrix:
[[23479  1266]
 [ 5951 18788]]

Test Confusion Matrix:
[[10027   574]
 [ 2598  8009]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.95      0.87     24745
         1.0       0.94      0.76      0.84     24739

    accuracy                           0.85     49484
   macro avg       0.87      0.85      0.85     49484
weighted avg       0.87      0.85      0.85     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.79      0.95      0.86     10601
         1.0       0.93      0.76      0.83     10607

    accuracy                           0.85     21208
   macro avg       0.86      0.85      0.85     21208
weighted avg       0.86      0.85      0.85     21208
```

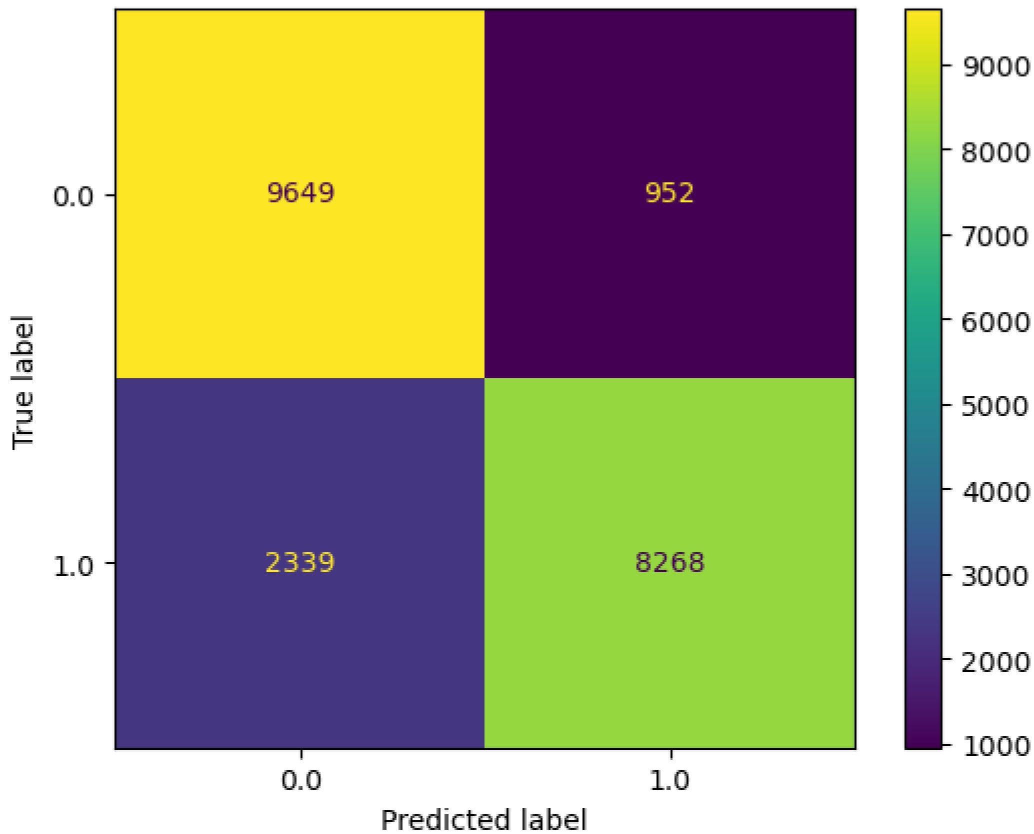


Logistic Regression Model Performance

```
* I went ahead and created a better visual for the test datas confusio
n matrix
```

In [49]:
```
log_conf_train = confusion_matrix(y_train, log_train_pred)
log_conf_test = confusion_matrix(y_test, log_test_pred)

print(f'Logisitc Regression Train Accuracy: {np.round(log_train_score, 3)} & Te

print(f'Train Confusion Matrix:\n{log_conf_train}\n\nTest Confusion Matrix:\n{l
print(f'Train Classification Report:\n{classification_report(y_train, log_trai

disp = ConfusionMatrixDisplay(log_conf_test, display_labels = log.classes_)
disp.plot()
plt.show()
```

```
Logisitc Regression Train Accuracy: 0.847 & Test Accuracy: 0.845

Train Confusion Matrix:
[[22649  2096]
 [ 5475 19264]]

Test Confusion Matrix:
[[9649  952]
 [2339 8268]]

Train Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.92      0.86     24745
         1.0       0.90      0.78      0.84     24739

    accuracy                           0.85     49484
   macro avg       0.85      0.85      0.85     49484
weighted avg       0.85      0.85      0.85     49484

Test Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.91      0.85     10601
         1.0       0.90      0.78      0.83     10607

    accuracy                           0.84     21208
   macro avg       0.85      0.84      0.84     21208
weighted avg       0.85      0.84      0.84     21208
```



Results

- The best performing model was the Random Forest for both feature selection methods
  - Out of the two feature selection methods, LassoCV gave the best results
- With the two different feature selection methods, the top 3 models stayed the same
  - The top three performing models were Random Forest, SVM and Logistic Regression (In that order)
- In addition we can look at both feature selection methods
  - Overall, LassoCV has created the best results for all models
- Model That I am going to use for the remainder of the project is going to be as follows:
  - The LassoCV selection methods as it yielded the best results overall
  - The Random Forest Model as in both selection methods, it performed the best