Machine Learning with the Equipment Failure Prediction.

Overview

Now I will take the selected/pre-processed/imputed datasets and feed this into different ML models by using cross validation.

Business Problem in machine learning terms:

Given the data points with their respective features, use classification to find out whether the data points belong to surface failure or downhole failure.

Metric to be used:

F2 Score : ((1 + (2)^2) * Precision * Recall) / (((2)^2 * Precision) + Recall)

Datasets:

3 datasets :

1)Median imputed Median dataset.
2)Median imputed Adasyn dataset.
3)Median imputed Smotetomek dataset.

I will feed these 3 datasets into Machine Learning Algorithm.

In [1]:
```
import sqlite3
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.utils.multiclass import unique_labels
```

In [3]:
```
from sklearn import linear_model
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
```

In [4]:
```
from sklearn.linear_model import SGDClassifier
```

In [5]:
```
from sklearn.metrics import fbeta_score
```

In [6]:
```
from sklearn.metrics import make_scorer
import warnings
warnings.simplefilter(action="ignore", category=UserWarning)
from sklearn.model_selection import GridSearchCV
```

In [7]:
```
import os
os.cpu_count()
```

Out[7]:
```
8
```

In [8]:
```
!nvidia-smi
```

```
Mon Nov 23 06:44:06 2020
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 450.80.02    Driver Version: 450.80.02    CUDA Version: 11.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  GeForce MX150       Off  | 00000000:01:00.0 Off |                  N/A |
| N/A   51C    P3    N/A /  N/A |    308MiB /  2002MiB |      6%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A       909      G   /usr/lib/xorg/Xorg                 29MiB |
|    0   N/A  N/A      1427      G   /usr/lib/xorg/Xorg                149MiB |
|    0   N/A  N/A      1595      G   /usr/bin/gnome-shell              123MiB |
+-----------------------------------------------------------------------------+
```

In [9]:
```
!cat /usr/local/cuda/version.txt
```

```
cat: /usr/local/cuda/version.txt: No such file or directory
```

In [10]:
```
!python -V
```

```
/bin/bash: python: command not found
```

For faster tSNE we use the rapids API to run tSNE and PCA on a GPU.
They directly use the GPU cores provided by both Kaggle and google colab instead of the cpus cores.
Huge increase in runtime speed.
Better not to run in kaggle else you will get stuck after a little while.
Instead run in google colab.

#For Google Colab import pynvml pynvml.nvmlInit() handle = pynvml.nvmlDeviceGetHandleByIndex(0) device_name = pynvml.nvmlDeviceGetName(handle) if (device_name != b'Tesla T4') and (device_name != b'Tesla P4') and (device_name != b'Tesla P100-PCIE-16GB'): raise Exception(""" Unfortunately this instance does not have a T4, P4 or P100 GPU.

```
Please make sure you've configured Colab to request a GPU instance type.

Sometimes Colab allocates a Tesla K80 instead of a T4, P4 or P100. Resetting the instance.

If you get a K80 GPU, try Runtime -> Reset all runtimes...
""")
```

else: print('Woo! You got the right kind of GPU!')

%%capture #Use this to stop the huge output messages that come while installing. !git clone [https://github.com/rapidsai/rapidsai-csp-utils.git (https://github.com/rapidsai/rapidsai-csp-utils.git)](https://github.com/rapidsai/rapidsai-csp-utils.git) !bash rapidsai-csp-utils/colab/rapids-colab.sh stable

import sys, os

dist_package_index = sys.path.index('/usr/local/lib/python3.6/dist-packages') sys.path = sys.path[:dist_package_index] + ['/usr/local/lib/python3.6/site-packages'] + sys.path[dist_package_index:] sys.path exec(open('rapidsai-csp-utils/colab/update_modules.py').read(), globals())

import pandas.testing as tm import cudf, cuml from cuml import PCA from cuml.decomposition import PCA from cuml.manifold import TSNE

In [11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

from google.colab import drive drive.mount("/content/gdrive")

Get the data

In [12]:
```
!pwd
```

```
/home/a/Desktop/Data
```

In [13]:
```
new_standard_train_median_all_features_df=pd.read_pickle("new_standard_train_median_all_features_df.pickle")
y_train_median_all_features=pd.read_pickle("y_train_median_all_features.pickle")
new_standard_test_median_all_features_df=pd.read_pickle("new_standard_test_median_all_features_df.pickle")
y_test_median_all_features=pd.read_pickle("y_test_median_all_features.pickle")

new_x_adasyn_df=pd.read_pickle("new_x_adasyn_df.pickle")
y_adasyn=pd.read_pickle("y_adasyn.pickle")
new_standard_test_adasyn_all_features_df=pd.read_pickle("new_standard_test_adasyn_all_features_df.pickle")
y_test_adasyn_all_features=pd.read_pickle("y_test_adasyn_all_features.pickle")

new_x_smotetomek_df=pd.read_pickle("new_x_smotetomek_df.pickle")
y_smotetomek=pd.read_pickle("y_smotetomek.pickle")
new_standard_test_smotetomek_all_features_df=pd.read_pickle("new_standard_test_smotetomek_all_features_df.pi
y_test_smotetomek_all_features=pd.read_pickle("y_test_smotetomek_all_features.pickle")
```

KNN

Using KNN, find the best hyper parameter the gives the best F2 Score

In [10]:
```
#KNN.get_params().keys()
```

In [11]:
```
def run_KNN(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)

    k_list=np.arange(1,100,10)

    parameters = {'n_neighbors': k_list}

    KNN = KNeighborsClassifier(n_jobs=-1)

    grid = GridSearchCV(KNN, parameters, n_jobs=-1, cv=5,scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

KNN on median data

In [ ]:
```
%%time
grid=run_KNN(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

```
CPU times: user 7.25 s, sys: 208 ms, total: 7.46 s
Wall time: 24min 20s
```

Out[15]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(n_jobs=-1), n_jobs=-1,
             param_grid={'n_neighbors': array([ 1, 11, 21, 31, 41, 51, 61, 71, 81, 91])},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[34]:
```
KNeighborsClassifier(n_jobs=-1, n_neighbors=1)
```

In [ ]:
```
grid.best_params_
```

Out[19]:
```
{'n_neighbors': 1}
```

In [ ]:
```
grid.best_score_
```

Out[20]:
```
0.744656005715562
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[24]:

	params	mean_test_score
0	{'n_neighbors': 1}	0.744656
1	{'n_neighbors': 11}	0.599305
2	{'n_neighbors': 21}	0.534970
3	{'n_neighbors': 31}	0.509978
4	{'n_neighbors': 41}	0.470221

In [ ]:
```
k_list_median=list(results["param_n_neighbors"])
cv_f2_score_KNN_median_data=list(results["mean_test_score"])
```

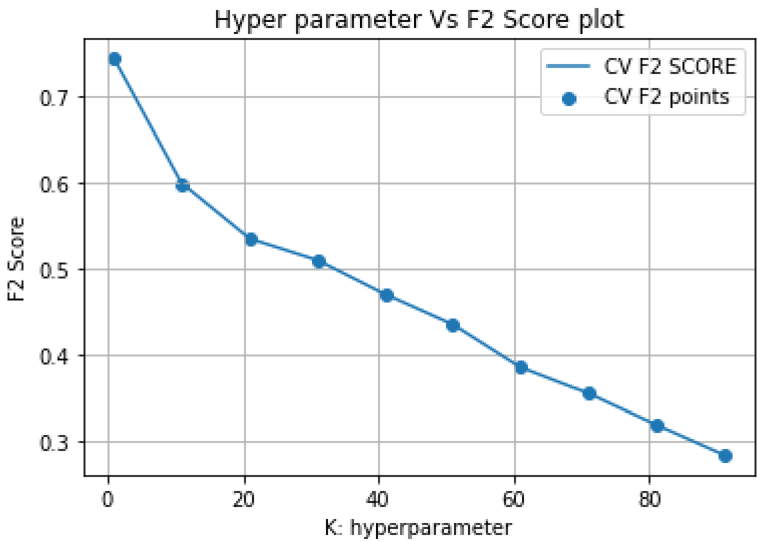
In [ ]:
```
np.save('k_list_median.npy',k_list_median)
#k_list_median=np.load("k_list_median.npy")
```

In [ ]:
```
np.save('cv_f2_score_KNN_median_data.npy',cv_f2_score_KNN_median_data )
#cv_f2_score_KNN_median_data=np.load("cv_f2_score_KNN_median_data.npy")
```

In [ ]:
```
plt.plot(k_list_median,cv_f2_score_KNN_median_data, label='CV F2 SCORE')

plt.scatter(k_list_median,cv_f2_score_KNN_median_data, label='CV F2 points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



KNN on adasyn data

In [ ]:
```
%%time
grid=run_KNN(new_x_adasyn_df,y_adasyn)
grid
```

```
CPU times: user 34.7 s, sys: 233 ms, total: 34.9 s
Wall time: 1h 11min 14s
```

Out[65]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(n_jobs=-1), n_jobs=-1,
             param_grid={'n_neighbors': array([ 1, 11, 21, 31, 41, 51, 61, 71, 81, 91])},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[74]:
```
KNeighborsClassifier(n_jobs=-1, n_neighbors=1)
```

In [ ]:
```
grid.best_params_
```

Out[75]:
```
{'n_neighbors': 1}
```

In [ ]:
```
grid.best_score_
```

Out[76]:
```
0.9831211871253247
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]98078315
```

Out[77]:

	params	mean_test_score
0	{'n_neighbors': 1}	0.983121
1	{'n_neighbors': 11}	0.977702
2	{'n_neighbors': 21}	0.979831
3	{'n_neighbors': 31}	0.980783
4	{'n_neighbors': 41}	0.980780

In [ ]:
```
k_list_adasyn=list(results["param_n_neighbors"])
cv_f2_score_KNN_adasyn_data=list(results["mean_test_score"])
```

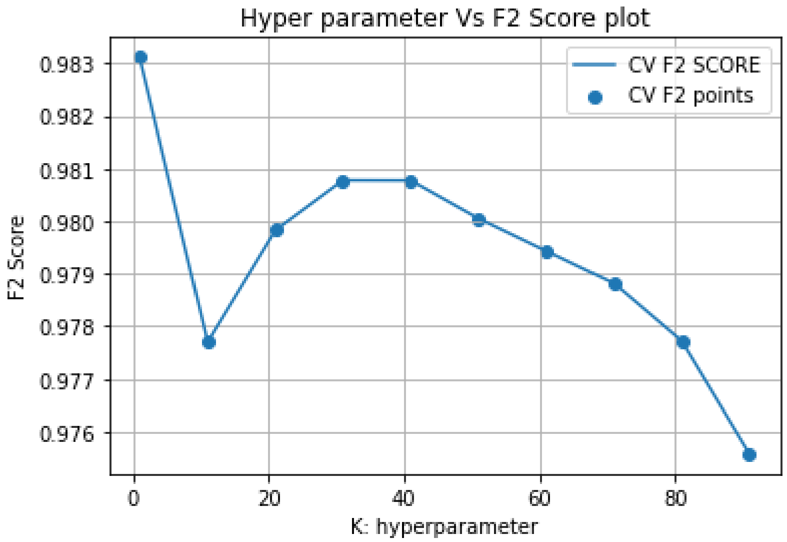
In [ ]:
```
np.save('k_list_adasyn.npy',k_list_adasyn)
#k_list_adasyn=np.load("k_list_adasyn.npy")
```

In [ ]:
```
np.save('cv_f2_score_KNN_adasyn_data.npy',cv_f2_score_KNN_adasyn_data )
#cv_f2_score_KNN_adasyn_data=np.load("cv_f2_score_KNN_adasyn_data.npy")
```

In [ ]:
```
plt.plot(k_list_adasyn,cv_f2_score_KNN_adasyn_data, label='CV F2 SCORE')

plt.scatter(k_list_adasyn,cv_f2_score_KNN_adasyn_data, label='CV F2 points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



KNN on smotetomek data

In [ ]:
```
%%time
grid=run_KNN(new_x_smotetomek_df,y_smotetomek)
grid
```

```
CPU times: user 27.8 s, sys: 252 ms, total: 28.1 s
Wall time: 49min 12s
```

Out[87]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(n_jobs=-1), n_jobs=-1,
             param_grid={'n_neighbors': array([ 1, 11, 21, 31, 41, 51, 61, 71, 81, 91])},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[88]:
```
KNeighborsClassifier(n_jobs=-1, n_neighbors=1)
```

In [ ]:
```
grid.best_params_
```

Out[89]:
```
{'n_neighbors': 1}
```

In [ ]:
```
grid.best_score_
```

Out[90]:
```
0.9980152588027043
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[91]:

	params	mean_test_score
0	{'n_neighbors': 1}	0.998015
1	{'n_neighbors': 11}	0.994369
2	{'n_neighbors': 21}	0.992922
3	{'n_neighbors': 31}	0.992254
4	{'n_neighbors': 41}	0.991534

In [ ]:
```
k_list_smotetomek=list(results["param_n_neighbors"])
cv_f2_score_KNN_smotetomek_data=list(results["mean_test_score"])
```

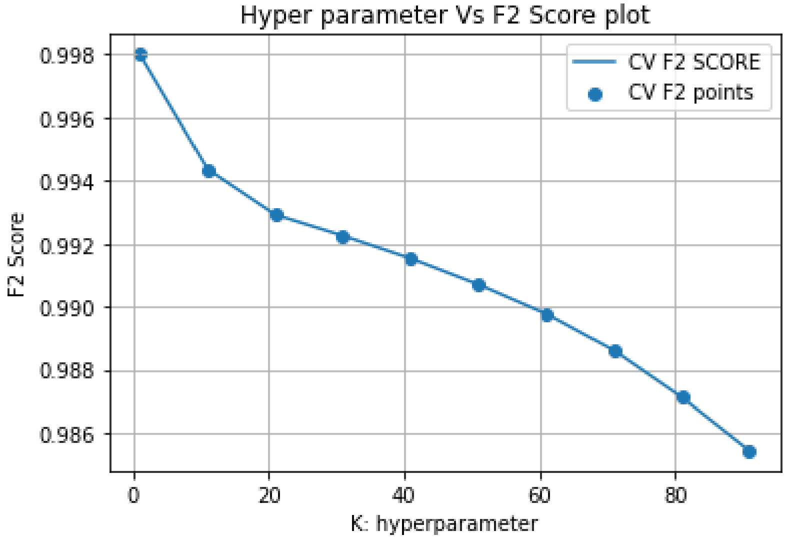
In [ ]:
```
np.save('k_list_smotetomek.npy',k_list_smotetomek)
#k_list_smotetomek=np.load("k_list_smotetomek.npy")
```

In [ ]:
```
np.save('cv_f2_score_KNN_smotetomek_data.npy',cv_f2_score_KNN_smotetomek_data )
#cv_f2_score_KNN_smotetomek_data=np.load("cv_f2_score_KNN_smotetomek_data.npy")
```

In [ ]:
```
plt.plot(k_list_smotetomek,cv_f2_score_KNN_smotetomek_data, label='CV F2 SCORE')

plt.scatter(k_list_smotetomek,cv_f2_score_KNN_smotetomek_data, label='CV F2 points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_KNN_median_data)[::-1]
```

Out[106]:
```
array([0.74465601, 0.5993048 , 0.53496971, 0.50997768, 0.47022117,
       0.43504162, 0.3850689 , 0.35481371, 0.31830202, 0.28341554])
```

In [ ]:
```
np.sort(cv_f2_score_KNN_adasyn_data)[::-1]
```

Out[115]:
```
array([0.98312119, 0.98078315, 0.98077989, 0.98005703, 0.97983065,
       0.97943653, 0.97882069, 0.97772492, 0.97770242, 0.97557984])
```

In [ ]:
```
np.sort(cv_f2_score_KNN_smotetomek_data)[::-1]
```

Out[119]:
```
array([0.99801526, 0.99436885, 0.99292246, 0.99225374, 0.99153402,
       0.99070725, 0.98977714, 0.9886102 , 0.9871287 , 0.98543187])
```

Trying Test Score with median data set.

In [14]:
```
# Utility function to print the confusion matrix
def confusion_matrix(Y_true, Y_pred):

    true = pd.Series(list(Y_true))
    predicted = pd.Series(list(Y_pred))

    return pd.crosstab(true, predicted, rownames=['True'], colnames=['Predicted'])
```

In [15]:
```
KNN = KNeighborsClassifier(11,n_jobs=-1)
#Fit with train data
KNN.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = KNN.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.6263269639065817
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11776   24
1.0           82  118
```

Trying Test Score with adasyn data set.

In [18]:
```
KNN = KNeighborsClassifier(31,n_jobs=-1)
#Fit with train data
KNN.fit(new_x_adasyn_df, y_adasyn)

#Run the prediction with test data.
y_predicted = KNN.predict(new_standard_test_adasyn_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.7014388489208633
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11405  395
1.0            5  195
```

The second highest value after all the 1 NN are the 11 NN . So I will take the 11 NN from the smotetomek dataset.

In [ ]:
```
KNN = KNeighborsClassifier(11,n_jobs=-1)
#Fit with train data
KNN.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with test data.
y_predicted = KNN.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.7821457821457822
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11570  230
1.0            9  191
```

We do not use Multinomial Naive Bayes here as Naive Bayes does not take Negative values.

We have standardized our data so we cannot use the negative values for the Multinomial Naive Bayes.

Logistic Regression

Using Logistic Regression, find the best hyper parameter the gives the best F2 Score

In [20]:
```
def run_Logistic_Regression_LR_Lib(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)

    c_list=[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]

    parameters = {'C': c_list}

    LR = LogisticRegression(penalty='l1',solver = 'liblinear',class_weight='balanced', max_iter=100,n_jobs=-

    grid = GridSearchCV(LR, parameters, n_jobs=-1, cv=5,scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

LR on median data

In [ ]:
```
%%time
grid=run_Logistic_Regression_LR_Lib(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

```
CPU times: user 22.8 s, sys: 310 ms, total: 23.1 s
Wall time: 1h 57min 31s
```

Out[124]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(class_weight='balanced', n_jobs=-1,
                                          penalty='l1', solver='liblinear'),
             n_jobs=-1,
             param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000,
                               10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[125]:
```
LogisticRegression(C=0.1, class_weight='balanced', n_jobs=-1, penalty='l1',
                   solver='liblinear')
```

In [ ]:
```
grid.best_params_
```
Out[126]:
```
{'C': 0.1}
```

In [ ]:
```
grid.best_score_
```
Out[127]:
```
0.7802270537562279
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```
Out[128]:

	params	mean_test_score
0	{'C': 0.0001}	0.277987
1	{'C': 0.001}	0.677371
2	{'C': 0.01}	0.776801
3	{'C': 0.1}	0.780227
4	{'C': 1}	0.769950

In [ ]:
```
c_list_LR_Lib=list(results["param_C"])
cv_f2_score_LR_Lib_median_data=list(results["mean_test_score"])
```

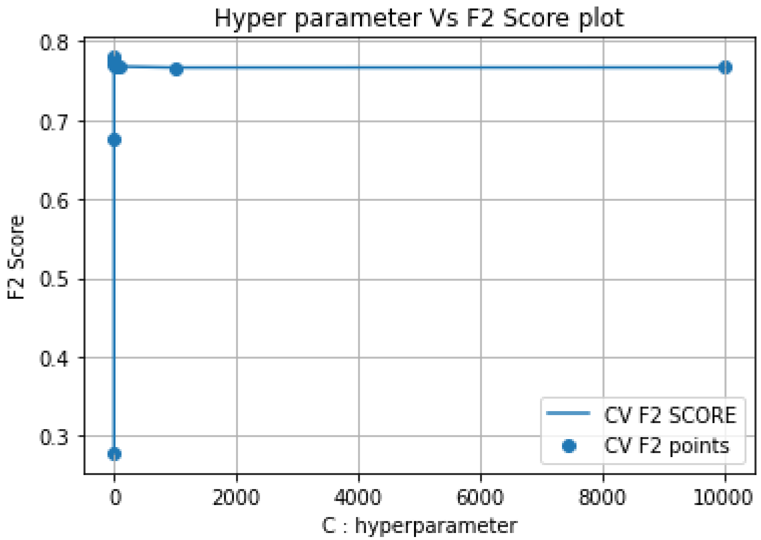
In [ ]:
```
np.save('c_list_LR_Lib.npy',c_list_LR_Lib)
#c_list_LR_Lib=np.load("c_list_LR_Lib.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_Lib_median_data.npy',cv_f2_score_LR_Lib_median_data )
#cv_f2_score_LR_Lib_median_data=np.load("cv_f2_score_LR_Lib_median_data.npy")
```

In [ ]:
```
plt.plot(c_list_LR_Lib,cv_f2_score_LR_Lib_median_data, label='CV F2 SCORE')

plt.scatter(c_list_LR_Lib,cv_f2_score_LR_Lib_median_data, label='CV F2 points')

plt.legend()
plt.xlabel("C : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



LR on adasyn data

In [ ]:
```
%%time
grid=run_Logistic_Regression_LR_Lib(new_x_adasyn_df,y_adasyn)
grid
```

```
CPU times: user 2min 29s, sys: 368 ms, total: 2min 29s
Wall time: 40min 54s
```

Out[144]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(class_weight='balanced', n_jobs=-1,
                                          penalty='l1', solver='liblinear'),
             n_jobs=-1,
             param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000,
                               10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[145]:
```
LogisticRegression(C=100, class_weight='balanced', n_jobs=-1, penalty='l1',
                   solver='liblinear')
```

In [ ]:
```
grid.best_params_
```

Out[146]:
```
{'C': 100}
```

In [ ]:
```
grid.best_score_
```

Out[147]:
```
0.9373459991660015
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[148]:

	params	mean_test_score
0	{'C': 0.0001}	0.912588
1	{'C': 0.001}	0.928675
2	{'C': 0.01}	0.932615
3	{'C': 0.1}	0.935372
4	{'C': 1}	0.937170

In [ ]:
```
c_list_LR_Lib=list(results["param_C"])
cv_f2_score_LR_Lib_adasyn_data=list(results["mean_test_score"])
```

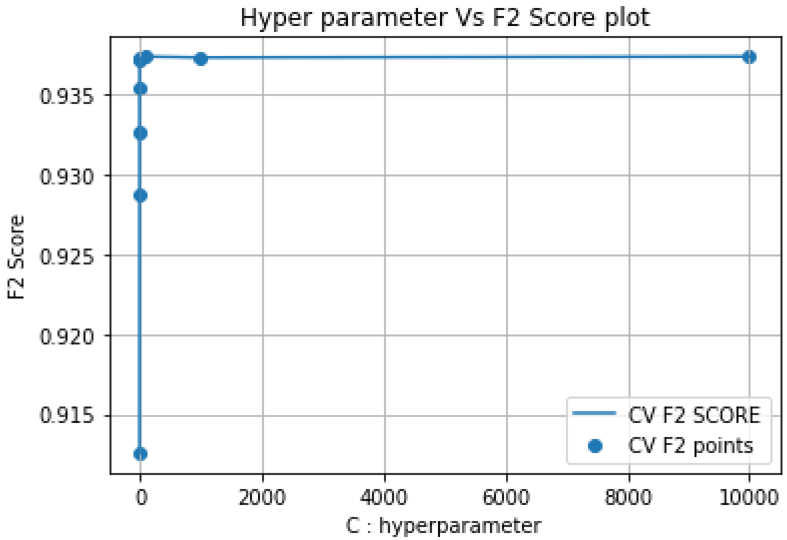
In [ ]:
```
np.save('c_list_LR_Lib.npy',c_list_LR_Lib)
#c_list_LR_Lib=np.load("c_list_LR_Lib.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_Lib_adasyn_data.npy',cv_f2_score_LR_Lib_adasyn_data )
#cv_f2_score_LR_Lib_adasyn_data=np.load("cv_f2_score_LR_Lib_adasyn_data.npy")
```

In [ ]:
```
plt.plot(c_list_LR_Lib,cv_f2_score_LR_Lib_adasyn_data, label='CV F2 SCORE')

plt.scatter(c_list_LR_Lib,cv_f2_score_LR_Lib_adasyn_data, label='CV F2 points')

plt.legend()
plt.xlabel("C : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



LR on smotetomek data

In [ ]:
```
%%time
grid=run_Logistic_Regression_LR_Lib(new_x_smotetomek_df,y_smotetomek)
grid
```

```
CPU times: user 8.7 s, sys: 288 ms, total: 8.99 s
Wall time: 11min 51s
```

Out[153]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(class_weight='balanced', n_jobs=-1,
                                          penalty='l1', solver='liblinear'),
             n_jobs=-1,
             param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000,
                               10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[154]:
```
LogisticRegression(C=100, class_weight='balanced', n_jobs=-1, penalty='l1',
                   solver='liblinear')
```

In [ ]:
```
grid.best_params_
```

Out[155]:
```
{'C': 100}
```

In [ ]:
```
grid.best_score_
```

Out[156]:
```
0.9668803564746792
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[157]:

	params	mean_test_score
0	{'C': 0.0001}	0.949509
1	{'C': 0.001}	0.951743
2	{'C': 0.01}	0.962819
3	{'C': 0.1}	0.966287
4	{'C': 1}	0.966548

In [ ]:
```
c_list_LR_Lib=list(results["param_C"])
cv_f2_score_LR_Lib_smotetomek_data=list(results["mean_test_score"])
```

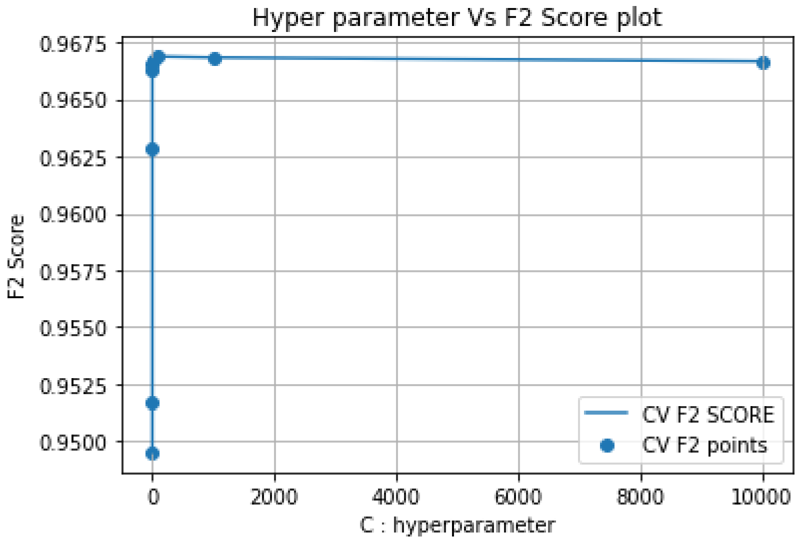
In [ ]:
```
np.save('c_list_LR_Lib.npy',c_list_LR_Lib)
#c_list_LR_Lib=np.load("c_list_LR_Lib.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_Lib_smotetomek_data.npy',cv_f2_score_LR_Lib_smotetomek_data )
#cv_f2_score_LR_Lib_smotetomek_data=np.load("cv_f2_score_LR_Lib_smotetomek_data.npy")
```

In [ ]:
```
plt.plot(c_list_LR_Lib,cv_f2_score_LR_Lib_smotetomek_data, label='CV F2 SCORE')

plt.scatter(c_list_LR_Lib,cv_f2_score_LR_Lib_smotetomek_data, label='CV F2 points')

plt.legend()
plt.xlabel("C : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_LR_Lib_median_data)[::-1][0]
```

Out[167]: 0.7802270537562279

In [ ]:
```
np.sort(cv_f2_score_LR_Lib_adasyn_data)[::-1][0]
```

Out[168]: 0.9373459991660015

In [ ]:
```
np.sort(cv_f2_score_LR_Lib_smotetomek_data)[::-1][0]
```

Out[169]: 0.9668803564746792

In [ ]:
```
c_list_LR_Lib[np.argsort(cv_f2_score_LR_Lib_smotetomek_data)[::-1][0]]
```

Out[170]:
```
100
```

Running LR_Lib on median data with appropriate hyperparameters

In [21]:
```
LR = LogisticRegression(penalty='l1', C=0.1,solver = 'liblinear',class_weight='balanced', max_iter=100,n_job

#Fit with train data
LR.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with cv data.
y_predicted = LR.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with cv data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.7592891760904684
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11550  250
1.0           12  188
```

Running LR_Lib on adasyn data with appropriate hyperparameters

In [22]:
```
LR = LogisticRegression(penalty='l1', C=100,solver = 'liblinear',class_weight='balanced', max_iter=100,n_job

#Fit with train data
LR.fit(new_x_adasyn_df, y_adasyn)

#Run the prediction with cv data.
y_predicted = LR.predict(new_standard_test_adasyn_all_features_df)

#Get the F2 Score with cv data.
f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.6713132795304476
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11420  380
1.0           17  183
```

The best value of cv score is 0.966880 with the c value of 100 with smotetomek data. So I will take this value of c in my algorthim.

In [ ]:
```
LR = LogisticRegression(penalty='l1', C=100,solver = 'liblinear',class_weight='balanced', max_iter=100,n_job

#Fit with train data
LR.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with cv data.
y_predicted = LR.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with cv data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.739549839228296
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11540  260
1.0           16  184
```

Logistic Regression , SGD Library

In [25]:
```
def run_Logistic_Regression_SGD_Lib(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)

    a_list=[10**-6,10**-5,10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]

    parameters = {'alpha': a_list}

    LR = SGDClassifier(loss='log',penalty='l1',n_jobs=-1,class_weight="balanced")

    grid = GridSearchCV(LR, parameters, n_jobs=-1, cv=5,scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

LR on median data

In [ ]:
```
%%time
grid=run_Logistic_Regression_SGD_Lib(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

```
CPU times: user 7.25 s, sys: 40.5 ms, total: 7.29 s
Wall time: 4min 53s
```

Out[56]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', loss='log',
                                     n_jobs=-1, penalty='l1'),
             n_jobs=-1,
             param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                                   10, 100, 1000, 10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[57]:
```
SGDClassifier(alpha=1e-06, class_weight='balanced', loss='log', n_jobs=-1,
              penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[58]:
```
{'alpha': 1e-06}
```

In [ ]:
```
grid.best_score_
```

Out[59]:
```
0.6997559005548746
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[60]:

	params	mean_test_score
0	{'alpha': 1e-06}	0.699756
1	{'alpha': 1e-05}	0.688018
2	{'alpha': 0.0001}	0.629321
3	{'alpha': 0.001}	0.576705
4	{'alpha': 0.01}	0.400172

In [ ]:
```
a_list_LR_SGD=list(results["param_alpha"])
cv_f2_score_LR_SGD_median_data=list(results["mean_test_score"])
```

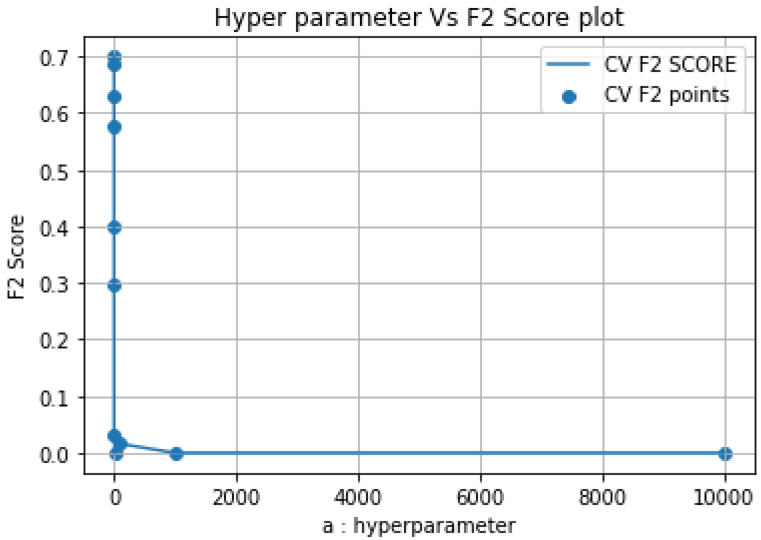
In [ ]:
```
np.save('a_list_LR_SGD.npy',a_list_LR_SGD)
#a_list_LR_SGD=np.load("a_list_LR_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_SGD_median_data.npy',cv_f2_score_LR_SGD_median_data )
#cv_f2_score_LR_SGD_median_data=np.load("cv_f2_score_LR_SGD_median_data.npy")
```

In [ ]:
```
plt.plot(a_list_LR_SGD,cv_f2_score_LR_SGD_median_data, label='CV F2 SCORE')

plt.scatter(a_list_LR_SGD,cv_f2_score_LR_SGD_median_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



LR on adasyn data

In [ ]:
```
%%time
grid=run_Logistic_Regression_SGD_Lib(new_x_adasyn_df,y_adasyn)
grid
```

```
CPU times: user 1min, sys: 155 ms, total: 1min
Wall time: 4min 44s
```

Out[65]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', loss='log',
                                     n_jobs=-1, penalty='l1'),
             n_jobs=-1,
             param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                                   10, 100, 1000, 10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[66]:
```
SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log', n_jobs=-1,
              penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[67]:
```
{'alpha': 1e-05}
```

In [ ]:
```
grid.best_score_
```

Out[68]:
```
0.9302353657989008
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[69]:

	params	mean_test_score
0	{'alpha': 1e-06}	0.926448
1	{'alpha': 1e-05}	0.930235
2	{'alpha': 0.0001}	0.921470
3	{'alpha': 0.001}	0.918137
4	{'alpha': 0.01}	0.920742

In [ ]:
```
a_list_LR_SGD=list(results["param_alpha"])
cv_f2_score_LR_SGD_adasyn_data=list(results["mean_test_score"])
```

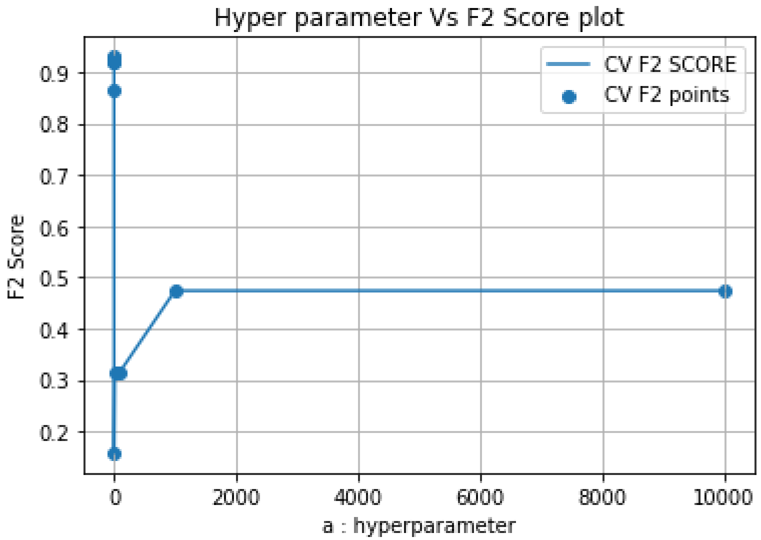
In [ ]:
```
np.save('a_list_LR_SGD.npy',a_list_LR_SGD)
#a_list_LR_SGD=np.load("a_list_LR_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_SGD_adasyn_data.npy',cv_f2_score_LR_SGD_adasyn_data )
#cv_f2_score_LR_SGD_adasyn_data=np.load("cv_f2_score_LR_SGD_adasyn_data.npy")
```

In [ ]:
```
plt.plot(a_list_LR_SGD,cv_f2_score_LR_SGD_adasyn_data, label='CV F2 SCORE')

plt.scatter(a_list_LR_SGD,cv_f2_score_LR_SGD_adasyn_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



LR on smotetomek data

In [ ]:
```
%%time
grid=run_Logistic_Regression_SGD_Lib(new_x_smotetomek_df,y_smotetomek)
grid
```

```
CPU times: user 2min, sys: 123 ms, total: 2min
Wall time: 5min 4s
```

Out[74]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', loss='log',
                                     n_jobs=-1, penalty='l1'),
             n_jobs=-1,
             param_grid={'alpha': [1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                                   10, 100, 1000, 10000]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[75]:
```
SGDClassifier(class_weight='balanced', loss='log', n_jobs=-1, penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[76]:
```
{'alpha': 0.0001}
```

In [ ]:
```
grid.best_score_
```

Out[77]:
```
0.9629510403272501
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[78]:

	params	mean_test_score
0	{'alpha': 1e-06}	0.933178
1	{'alpha': 1e-05}	0.961145
2	{'alpha': 0.0001}	0.962951
3	{'alpha': 0.001}	0.960101
4	{'alpha': 0.01}	0.944096

In [ ]:
```
a_list_LR_SGD=list(results["param_alpha"])
cv_f2_score_LR_SGD_smotetomek_data=list(results["mean_test_score"])
```

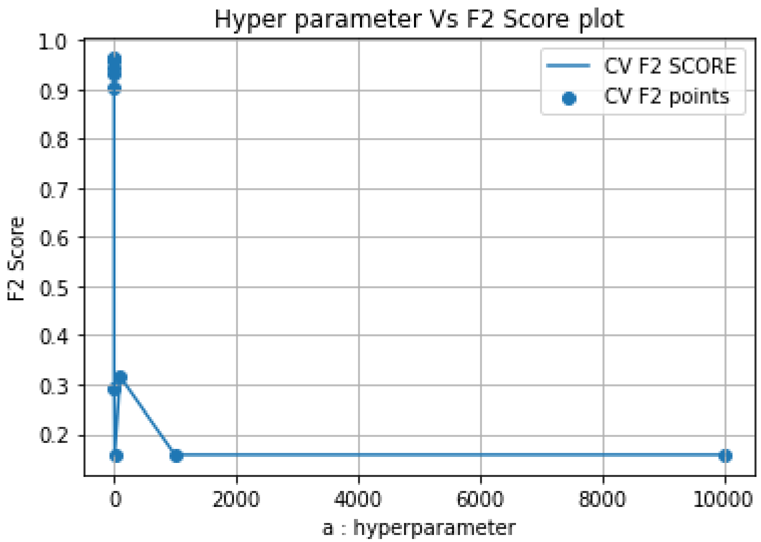
In [ ]:
```
np.save('a_list_LR_SGD.npy',a_list_LR_SGD)
#a_list_LR_SGD=np.load("a_list_LR_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_LR_SGD_smotetomek_data.npy',cv_f2_score_LR_SGD_smotetomek_data )
#cv_f2_score_LR_SGD_smotetomek_data=np.load("cv_f2_score_LR_SGD_smotetomek_data.npy")
```

In [ ]:
```
plt.plot(a_list_LR_SGD,cv_f2_score_LR_SGD_smotetomek_data, label='CV F2 SCORE')

plt.scatter(a_list_LR_SGD,cv_f2_score_LR_SGD_smotetomek_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_LR_SGD_median_data)[::-1][0]
```

Out[83]:
```
0.6997559005548746
```

In [ ]:
```
np.sort(cv_f2_score_LR_SGD_adasyn_data)[::-1][0]
```

Out[84]:
```
0.9302353657989008
```

In [ ]:
```
np.sort(cv_f2_score_LR_SGD_smotetomek_data)[::-1][0]
```

Out[85]:
```
0.9629510403272501
```

In [ ]:
```
a_list_LR_SGD[np.argsort(cv_f2_score_LR_SGD_smotetomek_data)[::-1][0]]
```

Out[86]:
```
0.0001
```

Running LR_SGD on median data with appropriate hyperparameters

In [29]:
```
LR = SGDClassifier(loss='log',penalty='l1',alpha=1e-06,n_jobs=-1,class_weight="balanced")

#Fit with train data
LR.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = LR.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.6845238095238096
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11440  360
1.0           16  184
```

Running LR_SGD on adasyn data with appropriate hyperparameters

In [30]:
```
LR = SGDClassifier(loss='log',penalty='l1',alpha=1e-05,n_jobs=-1,class_weight="balanced")

#Fit with train data
LR.fit(new_x_adasyn_df, y_adasyn)

#Run the prediction with test data.
y_predicted = LR.predict(new_standard_test_adasyn_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.5662805662805662
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11222  578
1.0           24  176
```

The best value of cv score is 0.962951 with the c value of 0.0001 with smotetomek data. So I will take this value of a in my algorthim.

In [ ]:
```
LR = SGDClassifier(loss='log',penalty='l1',alpha=0.0001,n_jobs=-1,class_weight="balanced")

#Fit with train data
LR.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with test data.
y_predicted = LR.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.6642066420664208
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11425  375
1.0           20  180
```

Support Vector Machine

Using Support Vector Machine, find the best hyper parameter the gives the best F2 Score

In [32]:
```
def run_Support_Vector_Machine_SGD(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)

    alpha_list=[10**-4,10**-3,10**-2,10**-1,10**0,10**1]

    parameters = {'alpha': alpha_list}

    clf = SGDClassifier(loss='hinge',penalty='l1',n_jobs=-1,class_weight="balanced")

    grid = GridSearchCV(clf, parameters, cv=5,n_jobs=-1, scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

SVM on median data

In [ ]:
```
%%time
grid=run_Support_Vector_Machine_SGD(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

Out[21]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', n_jobs=-1,
                                     penalty='l1'),
             n_jobs=-1, param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[22]:
```
SGDClassifier(class_weight='balanced', n_jobs=-1, penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[23]:
```
{'alpha': 0.0001}
```

In [ ]:
```
grid.best_score_
```

Out[24]: 0.6320824038784691

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[25]:

	params	mean_test_score
0	{'alpha': 0.0001}	0.632082
1	{'alpha': 0.001}	0.486661
2	{'alpha': 0.01}	0.346751
3	{'alpha': 0.1}	0.514569
4	{'alpha': 1}	0.557906

In [ ]:
```
a_list_SVM_SGD=list(results["param_alpha"])
cv_f2_score_SVM_SGD_median_data=list(results["mean_test_score"])
```

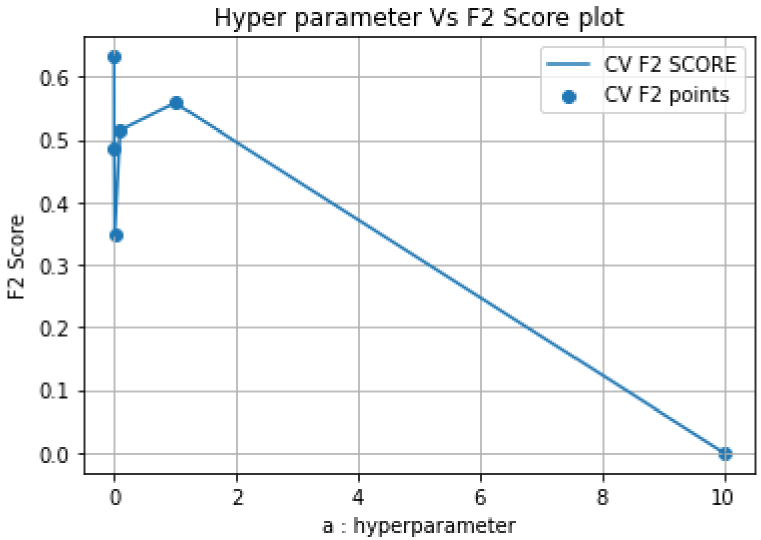
In [ ]:
```
np.save('a_list_SVM_SGD.npy',a_list_SVM_SGD)
#a_list_SVM_SGD=np.load("a_list_SVM_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_SVM_SGD_median_data.npy',cv_f2_score_SVM_SGD_median_data )
#cv_f2_score_SVM_SGD_median_data=np.load("cv_f2_score_SVM_SGD_median_data.npy")
```

In [ ]:
```
plt.plot(a_list_SVM_SGD,cv_f2_score_SVM_SGD_median_data, label='CV F2 SCORE')

plt.scatter(a_list_SVM_SGD,cv_f2_score_SVM_SGD_median_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



SVM on adasyn data

In [ ]:
```
%%time
grid=run_Support_Vector_Machine_SGD(new_x_adasyn_df, y_adasyn)
grid
```

```
CPU times: user 25.2 s, sys: 232 ms, total: 25.4 s
Wall time: 3min 15s
```

Out[30]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', n_jobs=-1,
                                     penalty='l1'),
             n_jobs=-1, param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[35]:
```
SGDClassifier(alpha=0.001, class_weight='balanced', n_jobs=-1, penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[36]:
```
{'alpha': 0.001}
```

In [ ]:
```
grid.best_score_
```

Out[37]:
```
0.9284350232943241
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[38]:

	params	mean_test_score
0	{'alpha': 0.0001}	0.921475
1	{'alpha': 0.001}	0.928435
2	{'alpha': 0.01}	0.923823
3	{'alpha': 0.1}	0.898941
4	{'alpha': 1}	0.667395

In [ ]:
```
a_list_SVM_SGD=list(results["param_alpha"])
cv_f2_score_SVM_SGD_adasyn_data=list(results["mean_test_score"])
```

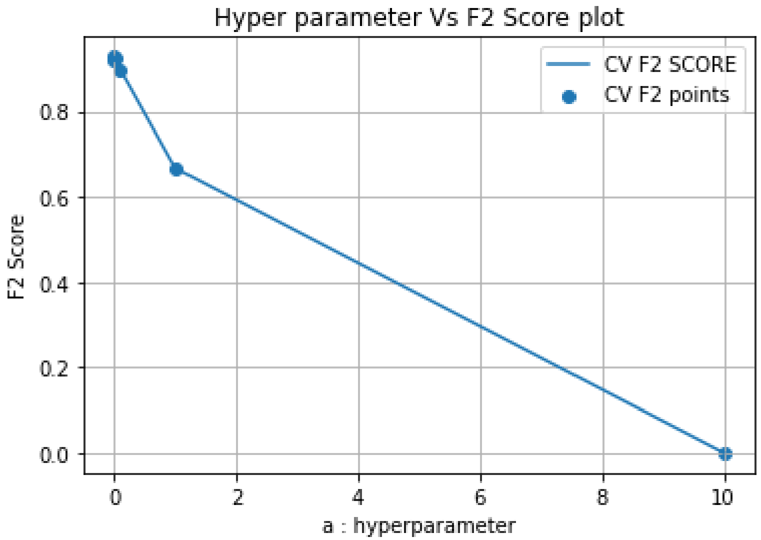
In [ ]:
```
np.save('a_list_SVM_SGD.npy',a_list_SVM_SGD)
#a_list_SVM_SGD=np.load("a_list_SVM_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_SVM_SGD_adasyn_data.npy',cv_f2_score_SVM_SGD_adasyn_data )
#cv_f2_score_SVM_SGD_adasyn_data=np.load("cv_f2_score_SVM_SGD_adasyn_data.npy")
```

In [ ]:
```
plt.plot(a_list_SVM_SGD,cv_f2_score_SVM_SGD_adasyn_data, label='CV F2 SCORE')

plt.scatter(a_list_SVM_SGD,cv_f2_score_SVM_SGD_adasyn_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



SVM on smotetomek data

In [ ]:
```
%%time
grid=run_Support_Vector_Machine_SGD(new_x_smotetomek_df, y_smotetomek)
grid
```

```
CPU times: user 1min 5s, sys: 138 ms, total: 1min 6s
Wall time: 3min 5s
```

Out[43]:
```
GridSearchCV(cv=5,
             estimator=SGDClassifier(class_weight='balanced', n_jobs=-1,
                                     penalty='l1'),
             n_jobs=-1, param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[44]:
```
SGDClassifier(class_weight='balanced', n_jobs=-1, penalty='l1')
```

In [ ]:
```
grid.best_params_
```

Out[45]:
```
{'alpha': 0.0001}
```

In [ ]:
```
grid.best_score_
```

Out[46]:
```
0.9638172755259242
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[47]:

	params	mean_test_score
0	{'alpha': 0.0001}	0.963817
1	{'alpha': 0.001}	0.963761
2	{'alpha': 0.01}	0.950818
3	{'alpha': 0.1}	0.928515
4	{'alpha': 1}	0.755389

In [ ]:
```
a_list_SVM_SGD=list(results["param_alpha"])
cv_f2_score_SVM_SGD_smotetomek_data=list(results["mean_test_score"])
```

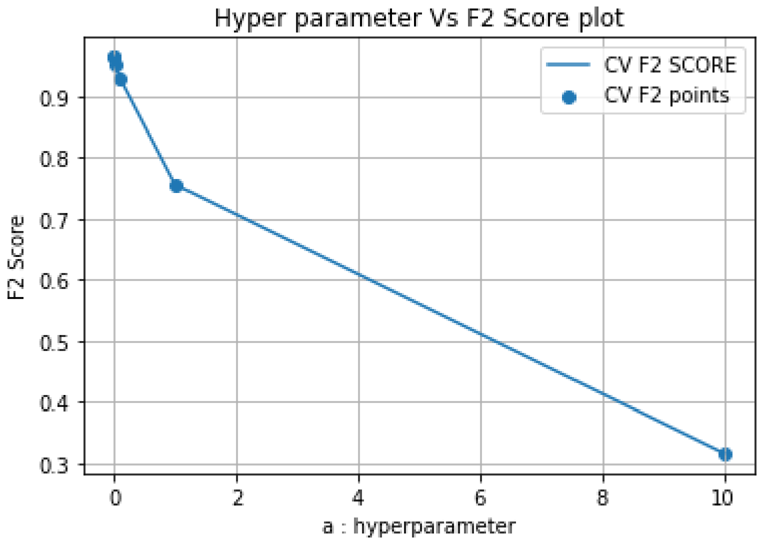
In [ ]:
```
np.save('a_list_SVM_SGD.npy',a_list_SVM_SGD)
#a_list_SVM_SGD=np.load("a_list_SVM_SGD.npy")
```

In [ ]:
```
np.save('cv_f2_score_SVM_SGD_smotetomek_data.npy',cv_f2_score_SVM_SGD_smotetomek_data )
#cv_f2_score_SVM_SGD_smotetomek_data=np.load("cv_f2_score_SVM_SGD_smotetomek_data.npy")
```

In [ ]:
```
plt.plot(a_list_SVM_SGD,cv_f2_score_SVM_SGD_smotetomek_data, label='CV F2 SCORE')

plt.scatter(a_list_SVM_SGD,cv_f2_score_SVM_SGD_smotetomek_data, label='CV F2 points')

plt.legend()
plt.xlabel("a : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_SVM_SGD_median_data)[::-1][0]
```
Out[52]:
```
0.6320824038784691
```

In [ ]:
```
np.sort(cv_f2_score_SVM_SGD_adasyn_data)[::-1][0]
```
Out[53]:
```
0.9284350232943241
```

In [ ]:
```
np.sort(cv_f2_score_SVM_SGD_smotetomek_data)[::-1][0]
```
Out[56]:
```
0.9638172755259242
```

In [34]:
```
a_list_SVM_SGD[np.argsort(cv_f2_score_SVM_SGD_smotetomek_data)[::-1][0]]
```
Out[34]:
```
0.0001
```

Running SVM_SGD on median data with appropriate hyperparameters

In [35]:
```
clf = SGDClassifier(loss='hinge',penalty='l1',alpha=0.0001,n_jobs=-1,class_weight="balanced")

#Fit with train data
clf.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = clf.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```
```
f2_score :  0.6844802342606151
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11421  379
1.0           13  187
```

Running SVM_SGD on adasyn data with appropriate hyperparameters

In [35]:
```
clf = SGDClassifier(loss='hinge',penalty='l1',alpha=0.001,n_jobs=-1,class_weight="balanced")

#Fit with train data
clf.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = clf.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.6844802342606151
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11421  379
1.0           13  187
```

The best value of cv score is 0.963817 with the a value of 0.0001 with smotetomek data. So I will take this value of a in my algorthim.

In [ ]:
```
clf = SGDClassifier(loss='hinge',penalty='l1',alpha=0.0001,n_jobs=-1,class_weight="balanced")

#Fit with train data
clf.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with test data.
y_predicted = clf.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.6499636891793755
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11402  398
1.0           21  179
```

Decision Trees

In [36]:
```
def run_Decision_Tree(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)

    depth_range=[4,6,8,9,10,12,14,17]
    min_samples_range=[2,10,20,30,40,50]

    parameters = {'max_depth': depth_range,'min_samples_split':min_samples_range}

    DT=DecisionTreeClassifier(criterion='gini',class_weight="balanced")

    grid = GridSearchCV(DT, parameters, cv=5,n_jobs=-1, scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

DT on median data

In [ ]:
```
%%time
grid=run_Decision_Tree(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

```
CPU times: user 5.56 s, sys: 225 ms, total: 5.78 s
Wall time: 2min 29s
```

Out[17]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(class_weight='balanced'),
             n_jobs=-1,
             param_grid={'max_depth': [4, 6, 8, 9, 10, 12, 14, 17],
                         'min_samples_split': [2, 10, 20, 30, 40, 50]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[18]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=12)
```

In [ ]:
```
grid.best_params_
```

Out[19]:
```
{'max_depth': 12, 'min_samples_split': 2}
```

In [ ]:
```
grid.best_score_
```

Out[20]:
```
0.8561706699053374
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[21]:

	params	mean_test_score
0	{'max_depth': 4, 'min_samples_split': 2}	0.788147
1	{'max_depth': 4, 'min_samples_split': 10}	0.789392
2	{'max_depth': 4, 'min_samples_split': 20}	0.789392
3	{'max_depth': 4, 'min_samples_split': 30}	0.788147
4	{'max_depth': 4, 'min_samples_split': 40}	0.789392

In [ ]:
```
depth_list_DT=list(results["param_max_depth"])
samples_list_DT=list(results["param_min_samples_split"])
cv_f2_score_DT_median_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_DT.npy',depth_list_DT)
np.save('samples_list_DT.npy',samples_list_DT)

#depth_list_DT=np.load("depth_list_DT.npy")
#samples_list_DT=np.load("samples_list_DT.npy")
```

In [ ]:
```
np.save('cv_f2_score_DT_median_data.npy',cv_f2_score_DT_median_data )
#cv_f2_score_DT_median_data=np.load("cv_f2_score_DT_median_data.npy")
```

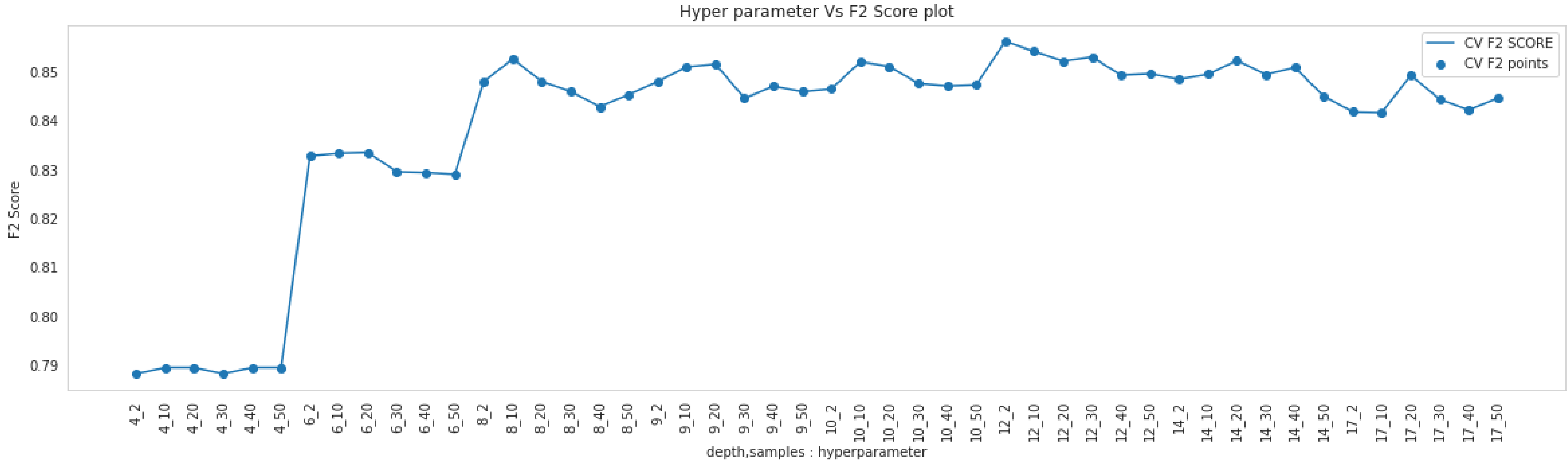
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_median_data, label

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_median_data, la

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,samples : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



DT on adasyn data

In [ ]:
```
%%time
grid=run_Decision_Tree(new_x_adasyn_df, y_adasyn)
grid
```

```
CPU times: user 18.7 s, sys: 380 ms, total: 19 s
Wall time: 9min 7s
```

Out[20]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(class_weight='balanced'),
             n_jobs=-1,
             param_grid={'max_depth': [4, 6, 8, 9, 10, 12, 14, 17],
                         'min_samples_split': [2, 10, 20, 30, 40, 50]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[21]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=12)
```

In [ ]:
```
grid.best_params_
```

Out[22]:
```
{'max_depth': 12, 'min_samples_split': 2}
```

In [ ]:
```
grid.best_score_
```

Out[23]:
```
0.9774154170065691
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[24]:

	params	mean_test_score
0	{'max_depth': 4, 'min_samples_split': 2}	0.973678
1	{'max_depth': 4, 'min_samples_split': 10}	0.973678
2	{'max_depth': 4, 'min_samples_split': 20}	0.973706
3	{'max_depth': 4, 'min_samples_split': 30}	0.973678
4	{'max_depth': 4, 'min_samples_split': 40}	0.973706

In [ ]:
```
depth_list_DT=list(results["param_max_depth"])
samples_list_DT=list(results["param_min_samples_split"])
cv_f2_score_DT_adasyn_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_DT.npy',depth_list_DT)
np.save('samples_list_DT.npy',samples_list_DT)

#depth_list_DT=np.load("depth_list_DT.npy")
#samples_list_DT=np.load("samples_list_DT.npy")
```

In [ ]:
```
np.save('cv_f2_score_DT_adasyn_data.npy',cv_f2_score_DT_adasyn_data )
#cv_f2_score_DT_adasyn_data=np.load("cv_f2_score_DT_adasyn_data.npy")
```

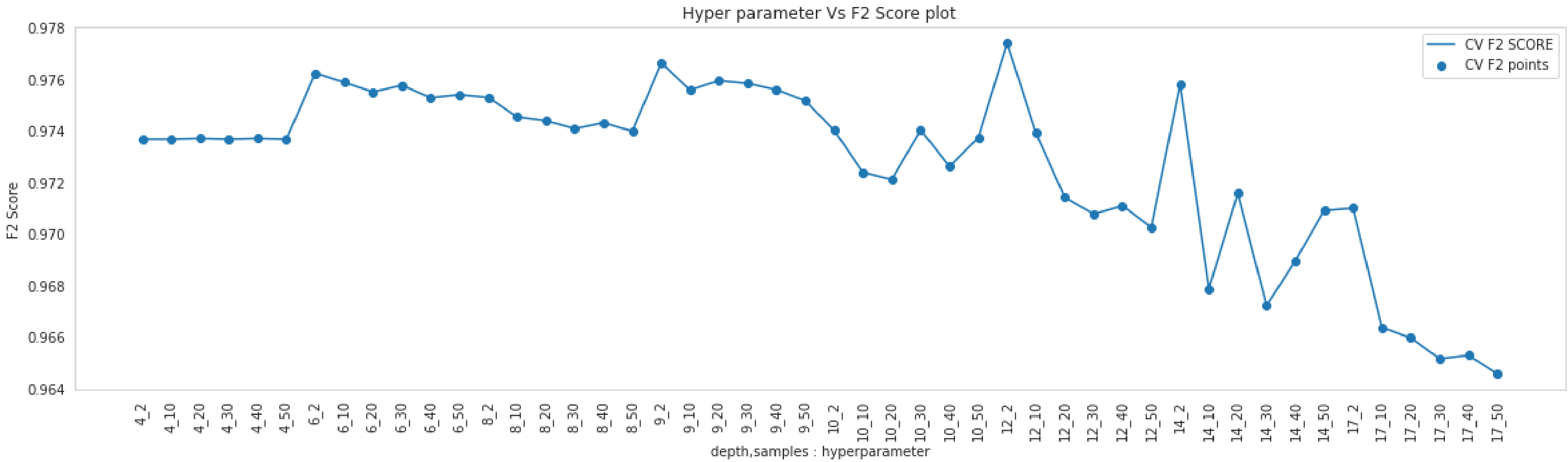
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_adasyn_data, label

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_adasyn_data, la

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,samples : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



DT on smotetomek data

In [ ]:
```
%%time
grid=run_Decision_Tree(new_x_smotetomek_df, y_smotetomek)
grid
```

```
CPU times: user 25.4 s, sys: 313 ms, total: 25.7 s
Wall time: 9min 8s
```

Out[35]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(class_weight='balanced'),
             n_jobs=-1,
             param_grid={'max_depth': [4, 6, 8, 9, 10, 12, 14, 17],
                         'min_samples_split': [2, 10, 20, 30, 40, 50]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[36]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=17)
```

In [ ]:
```
grid.best_params_
```

Out[37]:
```
{'max_depth': 17, 'min_samples_split': 2}
```

In [ ]:
```
grid.best_score_
```

Out[38]:
```
0.9960594883249249
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[39]:

	params	mean_test_score
0	{'max_depth': 4, 'min_samples_split': 2}	0.990432
1	{'max_depth': 4, 'min_samples_split': 10}	0.990455
2	{'max_depth': 4, 'min_samples_split': 20}	0.990432
3	{'max_depth': 4, 'min_samples_split': 30}	0.990432
4	{'max_depth': 4, 'min_samples_split': 40}	0.990455

In [ ]:
```
depth_list_DT=list(results["param_max_depth"])
samples_list_DT=list(results["param_min_samples_split"])
cv_f2_score_DT_smotetomek_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_DT.npy',depth_list_DT)
np.save('samples_list_DT.npy',samples_list_DT)
#depth_list_DT=np.load("depth_list_DT.npy")
#samples_list_DT=np.load("samples_list_DT.npy")
```

In [ ]:
```
np.save('cv_f2_score_DT_smotetomek_data.npy',cv_f2_score_DT_smotetomek_data )
#cv_f2_score_DT_smotetomek_data=np.load("cv_f2_score_DT_smotetomek_data.npy")
```

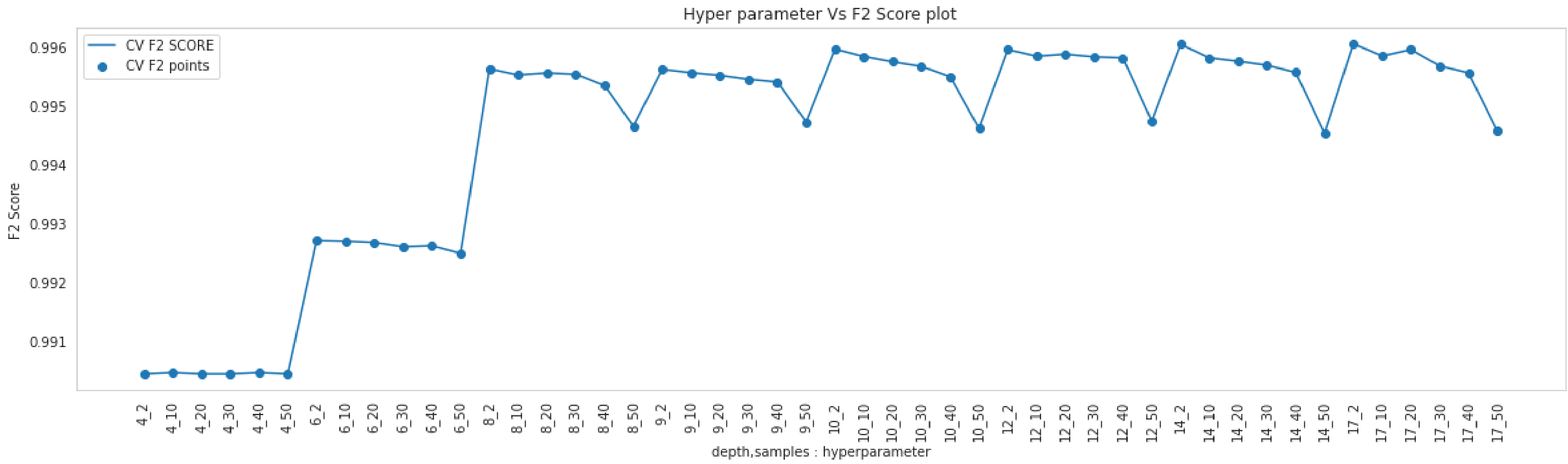
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_smotetomek_data, l

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)],cv_f2_score_DT_smotetomek_data

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,samples : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_DT_median_data)[::-1][0]
```

Out[56]:
```
0.8561706699053374
```

In [ ]:
```
np.sort(cv_f2_score_DT_adasyn_data)[::-1][0]
```

Out[57]:
```
0.9774154170065691
```

In [ ]:
```
np.sort(cv_f2_score_DT_smotetomek_data)[::-1][0]
```

Out[58]:
```
0.9960594883249249
```

In [ ]:
```
np.array([str(i)+"_"+str(j) for i,j in zip(depth_list_DT,samples_list_DT)])[np.argsort(cv_f2_score_DT_smotet
```

Out[59]:
```
'17_2'
```

Running DT on median data with appropriate hyperparameters

In [40]:
```
DT=DecisionTreeClassifier(criterion='gini',class_weight="balanced",max_depth=12,min_samples_split=2)

#Fit with train data
DT.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = DT.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.8472222222222222
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11703   97
1.0           17  183
```

Running DT on adasyn data with appropriate hyperparameters

In [41]:
```
DT=DecisionTreeClassifier(criterion='gini',class_weight="balanced",max_depth=12,min_samples_split=2)

#Fit with train data
DT.fit(new_x_adasyn_df, y_adasyn)

#Run the prediction with test data.
y_predicted = DT.predict(new_standard_test_adasyn_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.8575445173383318
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11716   84
1.0           17  183
```

The best value of cv score is 0.99605 with the parameters 17_2 with smotetomek data. So I will take this value of Depth,minimum_samples in my algorthim.

In [ ]:
```
DT=DecisionTreeClassifier(criterion='gini',class_weight="balanced",max_depth=17,min_samples_split=2)

#Fit with train data
DT.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with test data.
y_predicted = DT.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.855899419729207
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11743   57
1.0           23  177
```

Random Forest

In [ ]:
```
def run_Random_Forest(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0 , beta=2)


    depth_range=[16,18,20,22,24,26,28]
    n_estimators_list=[10, 50, 100, 150, 200, 300,500]

    parameters = {'max_depth': depth_range,'n_estimators':n_estimators_list}

    RF = RandomForestClassifier(criterion="gini",min_samples_split=2, min_samples_leaf=5,n_jobs=-1,class_wei

    grid = GridSearchCV(RF, parameters, cv=5,n_jobs=-1, scoring=f_2_score)

    grid.fit(x_train, y_train)

    return grid
```

RF on median data

In [ ]:
```
%%time
grid=run_Random_Forest(new_standard_train_median_all_features_df, y_train_median_all_features)
grid
```

```
CPU times: user 49.5 s, sys: 371 ms, total: 49.9 s
Wall time: 37min 57s
```

Out[67]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(class_weight='balanced',
                                              min_samples_leaf=5, n_jobs=-1),
             n_jobs=-1,
             param_grid={'max_depth': [16, 18, 20, 22, 24, 26, 28],
                         'n_estimators': [10, 50, 100, 150, 200, 300, 500]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[68]:
```
RandomForestClassifier(class_weight='balanced', max_depth=18,
                       min_samples_leaf=5, n_jobs=-1)
```

In [ ]:
```
grid.best_params_
```

Out[69]:
```
{'max_depth': 18, 'n_estimators': 100}
```

In [ ]:
```
grid.best_score_
```

Out[70]:
```
0.9022734842612415
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[72]:

	params	mean_test_score
0	{'max_depth': 16, 'n_estimators': 10}	0.864661
1	{'max_depth': 16, 'n_estimators': 50}	0.893405
2	{'max_depth': 16, 'n_estimators': 100}	0.897037
3	{'max_depth': 16, 'n_estimators': 150}	0.896595
4	{'max_depth': 16, 'n_estimators': 200}	0.898770

In [ ]:
```
depth_list_RF=list(results["param_max_depth"])
estimator_list_RF=list(results["param_n_estimators"])
cv_f2_score_RF_median_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_RF.npy',depth_list_RF)
np.save('estimator_list_RF.npy',estimator_list_RF)
#depth_list_RF=np.load("depth_list_RF.npy")
#estimator_list_RF=np.load("estimator_list_RF.npy")
```

In [ ]:
```
np.save('cv_f2_score_RF_median_data.npy',cv_f2_score_RF_median_data )
#cv_f2_score_RF_median_data=np.load("cv_f2_score_RF_median_data.npy")
```

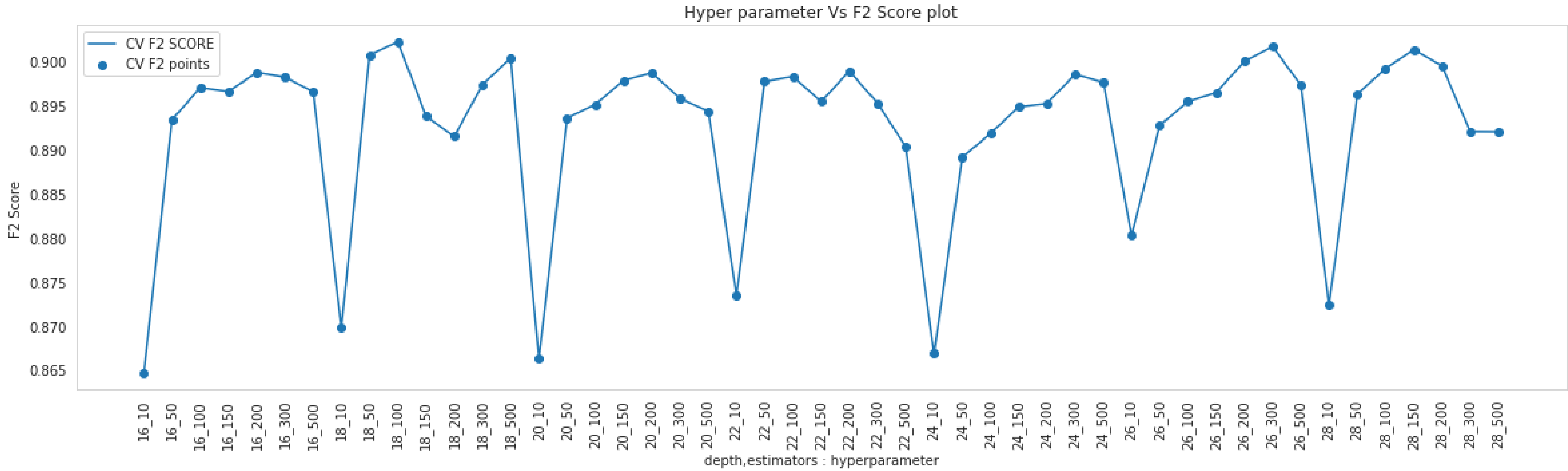
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_median_data, lab

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_median_data,

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,estimators : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



RF on adasyn data

In [ ]:
```
%%time
grid=run_Random_Forest(new_x_adasyn_df, y_adasyn)
grid
```

```
CPU times: user 1min, sys: 229 ms, total: 1min
Wall time: 1h 43min 12s
```

Out[17]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(class_weight='balanced',
                                              min_samples_leaf=5, n_jobs=-1),
             n_jobs=-1,
             param_grid={'max_depth': [16, 18, 20, 22, 24, 26, 28],
                         'n_estimators': [10, 50, 100, 150, 200, 300, 500]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[18]:
```
RandomForestClassifier(class_weight='balanced', max_depth=18,
                       min_samples_leaf=5, n_estimators=50, n_jobs=-1)
```

In [ ]:
```
grid.best_params_
```

Out[19]:
```
{'max_depth': 18, 'n_estimators': 50}
```

In [ ]:
```
grid.best_score_
```

Out[20]:
```
0.9947603737188798
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[21]:

	params	mean_test_score
0	{'max_depth': 16, 'n_estimators': 10}	0.991341
1	{'max_depth': 16, 'n_estimators': 50}	0.993759
2	{'max_depth': 16, 'n_estimators': 100}	0.994422
3	{'max_depth': 16, 'n_estimators': 150}	0.993736
4	{'max_depth': 16, 'n_estimators': 200}	0.994292

In [ ]:
```
depth_list_RF=list(results["param_max_depth"])
estimator_list_RF=list(results["param_n_estimators"])
cv_f2_score_RF_adasyn_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_RF.npy',depth_list_RF)
np.save('estimator_list_RF.npy',estimator_list_RF)
#depth_list_RF=np.load("depth_list_RF.npy")
#estimator_list_RF=np.load("estimator_list_RF.npy")
```

In [ ]:
```
np.save('cv_f2_score_RF_adasyn_data.npy',cv_f2_score_RF_adasyn_data )
#cv_f2_score_RF_adasyn_data=np.load("cv_f2_score_RF_adasyn_data.npy")
```

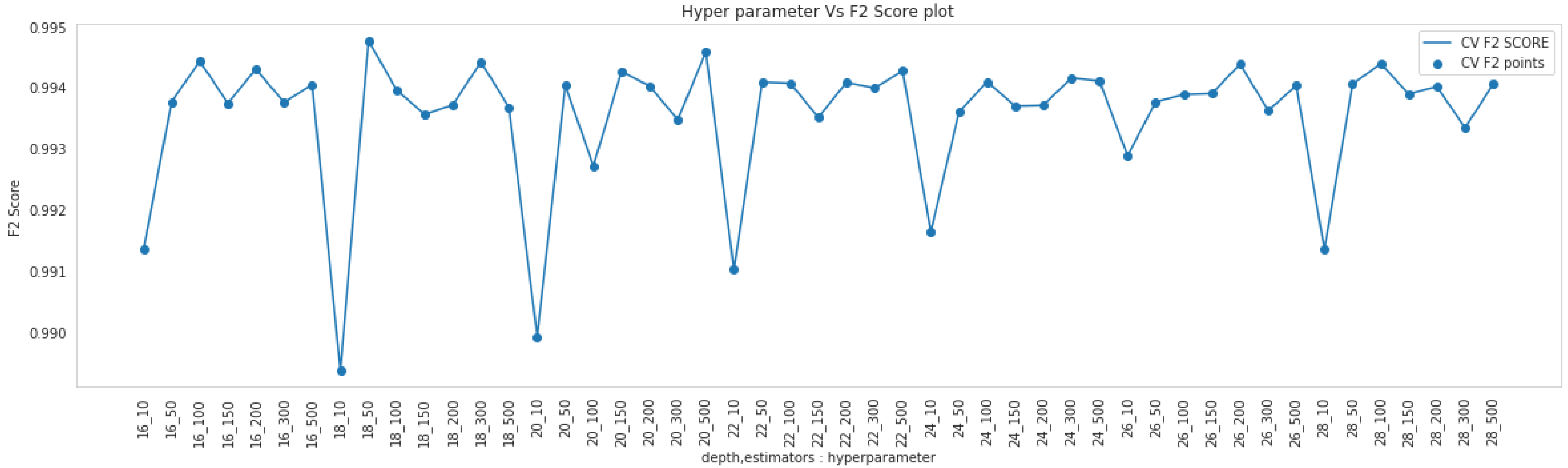
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_adasyn_data, lab

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_adasyn_data,

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,estimators : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



RF on smotetomek data

In [ ]:
```
%%time
grid=run_Random_Forest(new_x_smotetomek_df, y_smotetomek)
grid
```

```
CPU times: user 2min 31s, sys: 197 ms, total: 2min 31s
Wall time: 1h 51min 15s
```

Out[28]:
```
GridSearchCV(cv=5,
             estimator=RandomForestClassifier(class_weight='balanced',
                                              min_samples_leaf=5, n_jobs=-1),
             n_jobs=-1,
             param_grid={'max_depth': [16, 18, 20, 22, 24, 26, 28],
                         'n_estimators': [10, 50, 100, 150, 200, 300, 500]},
             scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [ ]:
```
grid.best_estimator_
```

Out[29]:
```
RandomForestClassifier(class_weight='balanced', max_depth=24,
                       min_samples_leaf=5, n_jobs=-1)
```

In [ ]:
```
grid.best_params_
```

Out[30]:
```
{'max_depth': 24, 'n_estimators': 100}
```

In [ ]:
```
grid.best_score_
```

Out[31]:
```
0.9990234723307889
```

In [ ]:
```
results = pd.DataFrame.from_dict(grid.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[32]:

	params	mean_test_score
0	{'max_depth': 16, 'n_estimators': 10}	0.998313
1	{'max_depth': 16, 'n_estimators': 50}	0.998646
2	{'max_depth': 16, 'n_estimators': 100}	0.998668
3	{'max_depth': 16, 'n_estimators': 150}	0.998764
4	{'max_depth': 16, 'n_estimators': 200}	0.998741

In [ ]:
```
depth_list_RF=list(results["param_max_depth"])
estimator_list_RF=list(results["param_n_estimators"])
cv_f2_score_RF_smotetomek_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_RF.npy',depth_list_RF)
np.save('estimator_list_RF.npy',estimator_list_RF)
#depth_list_RF=np.load("depth_list_RF.npy")
#estimator_list_RF=np.load("estimator_list_RF.npy")
```

In [ ]:
```
np.save('cv_f2_score_RF_smotetomek_data.npy',cv_f2_score_RF_smotetomek_data )
#cv_f2_score_RF_smotetomek_data=np.load("cv_f2_score_RF_smotetomek_data.npy")
```

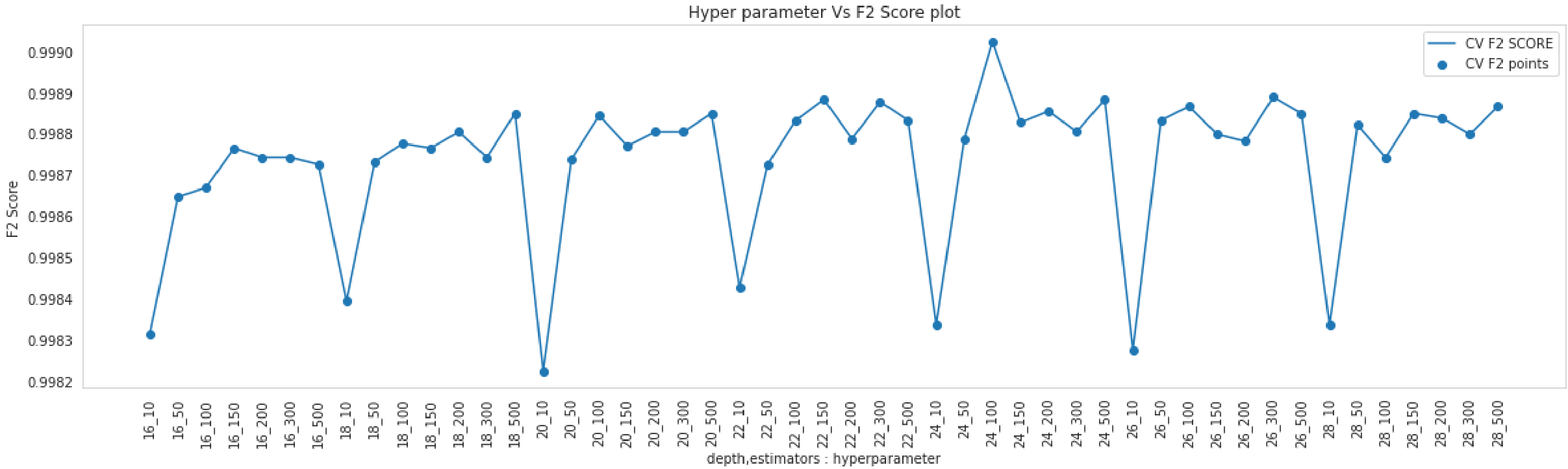
In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_smotetomek_data,

plt.scatter([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)],cv_f2_score_RF_smotetomek_da

plt.xticks(rotation=90)

plt.legend()
plt.xlabel("depth,estimators : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [ ]:
```
np.sort(cv_f2_score_RF_median_data)[::-1][0]
```

Out[41]:
```
0.9022734842612415
```

In [ ]:
```
np.sort(cv_f2_score_RF_adasyn_data)[::-1][0]
```

Out[42]:
```
0.9947603737188798
```

In [ ]:
```
np.sort(cv_f2_score_RF_smotetomek_data)[::-1][0]
```

Out[43]:
```
0.9990234723307889
```

In [ ]:
```
np.array([str(i)+"_"+str(j) for i,j in zip(depth_list_RF,estimator_list_RF)])[np.argsort(cv_f2_score_RF_smot
```

Out[45]:
```
'24_100'
```

Running RF on median data with appropriate hyperparameters

In [42]:
```
RF = RandomForestClassifier(criterion="gini",min_samples_split=2, min_samples_leaf=5,
                            n_jobs=-1,class_weight="balanced",max_depth=18,n_estimators=100)

#Fit with train data
RF.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

#Run the prediction with test data.
y_predicted = RF.predict(new_standard_test_median_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_median_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.9163346613545816
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11780   20
1.0           16  184
```

Running RF on adasyn data with appropriate hyperparameters

In [43]:
```
RF = RandomForestClassifier(criterion="gini",min_samples_split=2, min_samples_leaf=5,
                            n_jobs=-1,class_weight="balanced",max_depth=18,n_estimators=50)

#Fit with train data
RF.fit(new_x_adasyn_df,y_adasyn)

#Run the prediction with test data.
y_predicted = RF.predict(new_standard_test_adasyn_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.9121621621621623
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11753   47
1.0           11  189
```

The best value of cv score is 0.999023 with the a value of '24_100' with smotetomek data. So I will take this value of depth and estimators in my algorthim.

In [ ]:
```
RF = RandomForestClassifier(criterion="gini",min_samples_split=2, min_samples_leaf=5,
                            n_jobs=-1,class_weight="balanced",max_depth=24,n_estimators=100)

#Fit with train data
RF.fit(new_x_smotetomek_df, y_smotetomek)

#Run the prediction with test data.
y_predicted = RF.predict(new_standard_test_smotetomek_all_features_df)

#Get the F2 Score with test data.
f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, beta=2)
print("f2_score : ",f2_score)
print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.9289883268482491
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11763   37
1.0            9  191
```

GBDT

In [16]:
```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
```

In [31]:
```
def run_GBDT_XGB(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0, beta=2)

    depth_range=[4, 6, 8, 10,12,14]
    n_estimators_list=[50,100, 200, 300, 500, 1000]
    learning_rate=[.0001,.001,.01,.05,.10,.20,.30]

    parameters = {'max_depth': depth_range,'n_estimators':n_estimators_list,
                  'learning_rate':learning_rate}

    GBDT = XGBClassifier(nthread=-1,tree_method='gpu_hist',n_jobs=-1)

    rand = RandomizedSearchCV(GBDT, parameters, cv=5,n_jobs=3, scoring=f_2_score)

    rand.fit(x_train, y_train)

    return rand
```

GBDT on median data

In [ ]:
```
%%time
rand=run_GBDT_XGB(new_standard_train_median_all_features_df, y_train_median_all_features)
```

In [ ]:
```
rand.best_estimator_
```

Out[17]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=0,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.3, max_delta_step=0, max_depth=4,
              min_child_weight=1, missing=nan,
              monotone_constraints='(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,...,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)',
              n_estimators=300, n_jobs=-1, nthread=-1, num_parallel_tree=1,
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='gpu_hist', validate_parameters=1,
              verbosity=None)
```

In [ ]:
```
rand.best_params_
```

Out[18]:
```
{'n_estimators': 300, 'max_depth': 4, 'learning_rate': 0.3}
```

In [ ]:
```
rand.best_score_
```

Out[19]:
```
0.9395437457866332
```

In [ ]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[20]:

	params	mean_test_score
0	{'n_estimators': 200, 'max_depth': 6, 'learnin...	0.937123
1	{'n_estimators': 100, 'max_depth': 12, 'learni...	0.908650
2	{'n_estimators': 500, 'max_depth': 6, 'learnin...	0.935351
3	{'n_estimators': 100, 'max_depth': 12, 'learni...	0.826143
4	{'n_estimators': 300, 'max_depth': 12, 'learni...	0.928424

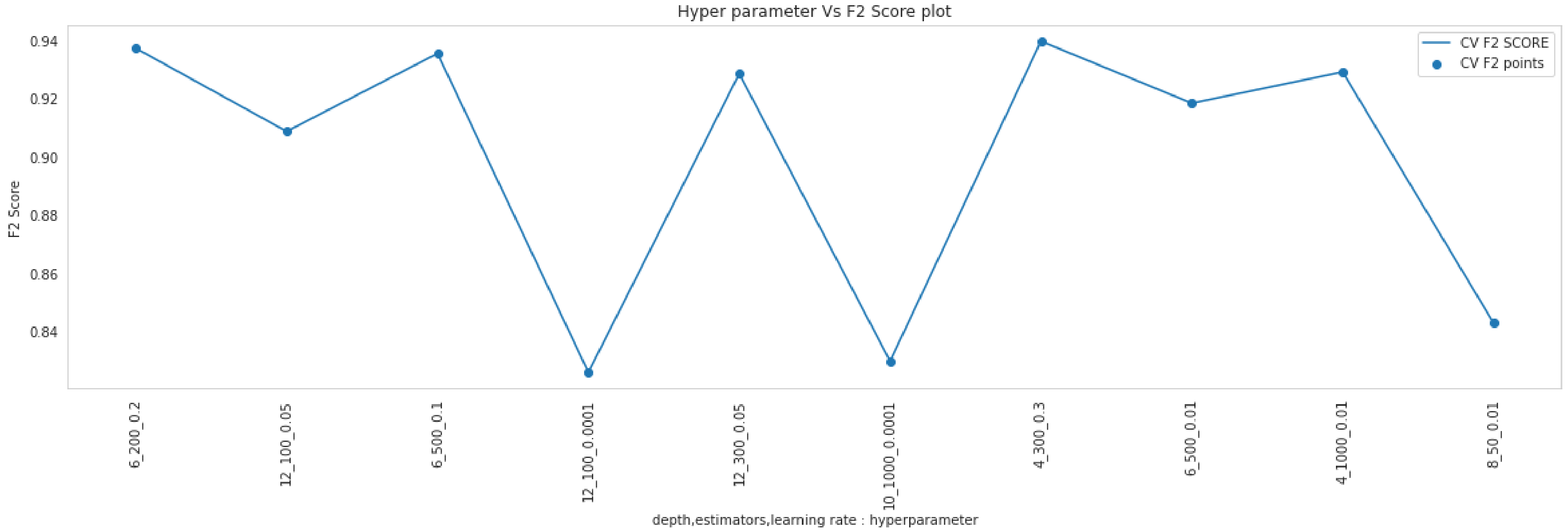
In [ ]:
```
depth_list_GBDT_XGB=list(results["param_max_depth"])
estimator_list_GBDT_XGB=list(results["param_n_estimators"])
learning_rate_list_GBDT_XGB=list(results["param_learning_rate"])
cv_f2_score_GBDT_XGB_median_data=list(results["mean_test_score"])
```

In [ ]:
```
np.save('depth_list_GBDT_XGB.npy',depth_list_GBDT_XGB)
np.save('estimator_list_GBDT_XGB.npy',estimator_list_GBDT_XGB)
np.save('learning_rate_list_GBDT_XGB.npy',learning_rate_list_GBDT_XGB)
#depth_list_GBDT_XGB=np.load('depth_list_GBDT_XGB.npy')
#estimator_list_GBDT_XGB=np.load('estimator_list_GBDT_XGB.npy')
#learning_rate_list_GBDT_XGB=np.load('learning_rate_list_GBDT_XGB.npy')
```

In [ ]:
```
np.save('cv_f2_score_GBDT_XGB_median_data.npy',cv_f2_score_GBDT_XGB_median_data )
#cv_f2_score_GBDT_XGB_median_data=np.load('cv_f2_score_GBDT_XGB_median_data.npy')
```

In [ ]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB,estimator_list_GBDT_XGB,learning
plt.scatter([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB,estimator_list_GBDT_XGB,learn
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



GBDT on adasyn data

In [32]:
```
%%time
rand=run_GBDT_XGB(new_x_adasyn_df, y_adasyn)
rand
```

```
CPU times: user 1min 1s, sys: 321 ms, total: 1min 2s
Wall time: 21min 48s
```

Out[32]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n_estimators=100,...
                                           random_state=None, reg_alpha=None,
                                           reg_lambda=None,
                                           scale_pos_weight=None,
                                           subsample=None,
                                           tree_method='gpu_hist',
                                           validate_parameters=None,
                                           verbosity=None),
                   n_jobs=3,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.05, 0.1, 0.2, 0.3],
                                        'max_depth': [4, 6, 8, 10, 12, 14],
                                        'n_estimators': [50, 100, 200, 300, 500,
                                                         1000]},
                   scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [33]:
```
rand.best_estimator_
```

Out[33]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=0,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.05, max_delta_step=0, max_depth=12,
              min_child_weight=1, missing=nan,
              monotone_constraints='(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,...,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)',
              n_estimators=500, n_jobs=-1, nthread=-1, num_parallel_tree=1,
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='gpu_hist', validate_parameters=1,
              verbosity=None)
```

In [34]:
```
rand.best_params_
```

Out[34]:
```
{'n_estimators': 500, 'max_depth': 12, 'learning_rate': 0.05}
```

In [35]:
```
rand.best_score_
```

Out[35]:
```
0.9962555722147115
```

In [36]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[36]:

	params	mean_test_score
0	{'n_estimators': 50, 'max_depth': 10, 'learnin...	0.987538
1	{'n_estimators': 200, 'max_depth': 8, 'learnin...	0.996063
2	{'n_estimators': 50, 'max_depth': 10, 'learnin...	0.980611
3	{'n_estimators': 50, 'max_depth': 4, 'learning...	0.971709
4	{'n_estimators': 500, 'max_depth': 8, 'learnin...	0.979073

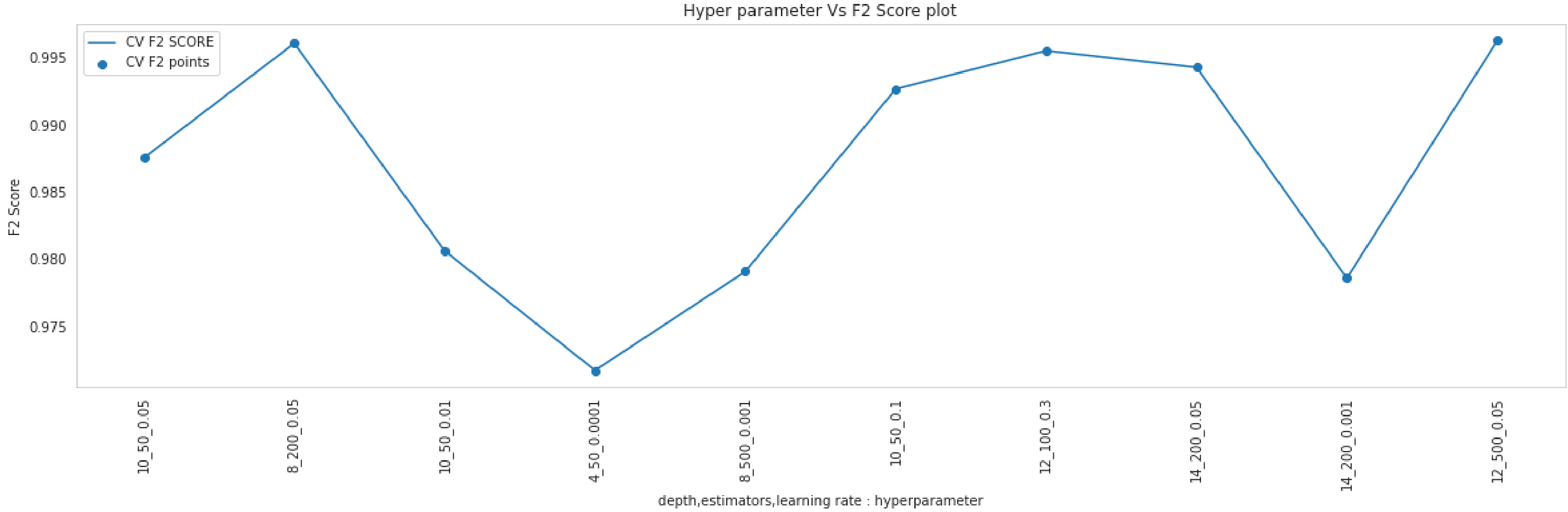
In [41]:
```
depth_list_GBDT_XGB_adasyn=list(results["param_max_depth"])
estimator_list_GBDT_XGB_adasyn=list(results["param_n_estimators"])
learning_rate_list_GBDT_XGB_adasyn=list(results["param_learning_rate"])
cv_f2_score_GBDT_XGB_adasyn_data=list(results["mean_test_score"])
```

In [45]:
```
np.save('depth_list_GBDT_XGB_adasyn.npy',depth_list_GBDT_XGB_adasyn)
np.save('estimator_list_GBDT_XGB_adasyn.npy',estimator_list_GBDT_XGB_adasyn)
np.save('learning_rate_list_GBDT_XGB_adasyn.npy',learning_rate_list_GBDT_XGB_adasyn)
#depth_list_GBDT_XGB_adasyn=np.load('depth_list_GBDT_XGB_adasyn.npy')
#estimator_list_GBDT_XGB_adasyn=np.load('estimator_list_GBDT_XGB_adasyn.npy')
#learning_rate_list_GBDT_XGB_adasyn=np.load('learning_rate_list_GBDT_XGB_adasyn.npy')
```

In [46]:
```
np.save('cv_f2_score_GBDT_XGB_adasyn_data.npy',cv_f2_score_GBDT_XGB_adasyn_data )
#cv_f2_score_GBDT_XGB_adasyn_data=np.load('cv_f2_score_GBDT_XGB_adasyn_data.npy')
```

In [47]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_adasyn,estimator_list_GBDT_XGB_a
plt.scatter([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_adasyn,estimator_list_GBDT_XG
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



GBDT on smotetomek data

In [48]:
```
%%time
rand=run_GBDT_XGB(new_x_smotetomek_df, y_smotetomek)
rand
```

```
CPU times: user 34 s, sys: 431 ms, total: 34.5 s
Wall time: 20min 20s
```

Out[48]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n_estimators=100,...
                                           random_state=None, reg_alpha=None,
                                           reg_lambda=None,
                                           scale_pos_weight=None,
                                           subsample=None,
                                           tree_method='gpu_hist',
                                           validate_parameters=None,
                                           verbosity=None),
                   n_jobs=3,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.05, 0.1, 0.2, 0.3],
                                        'max_depth': [4, 6, 8, 10, 12, 14],
                                        'n_estimators': [50, 100, 200, 300, 500,
                                                         1000]},
                   scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [49]:
```
rand.best_estimator_
```

Out[49]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=0,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=8,
              min_child_weight=1, missing=nan,
              monotone_constraints='(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)',
              n_estimators=500, n_jobs=-1, nthread=-1, num_parallel_tree=1,
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=1, tree_method='gpu_hist', validate_parameters=1,
              verbosity=None)
```

In [50]:
```
rand.best_params_
```

Out[50]:
```
{'n_estimators': 500, 'max_depth': 8, 'learning_rate': 0.1}
```

In [51]:
```
rand.best_score_
```

Out[51]:
```
0.9994408534502123
```

In [52]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[52]:

	params	mean_test_score
0	{'n_estimators': 200, 'max_depth': 12, 'learni...	0.995564
1	{'n_estimators': 50, 'max_depth': 8, 'learning...	0.999068
2	{'n_estimators': 500, 'max_depth': 14, 'learni...	0.995123
3	{'n_estimators': 200, 'max_depth': 6, 'learnin...	0.999108
4	{'n_estimators': 500, 'max_depth': 8, 'learnin...	0.999441

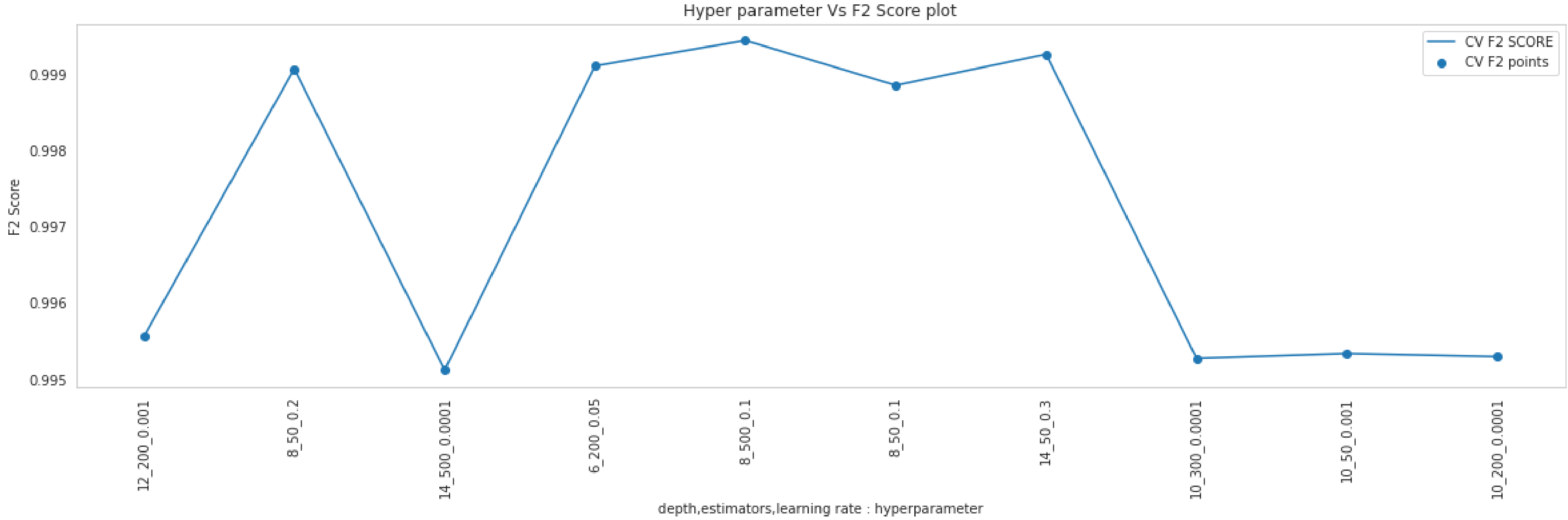
In [57]:
```
depth_list_GBDT_XGB_smotetomek=list(results["param_max_depth"])
estimator_list_GBDT_XGB_smotetomek=list(results["param_n_estimators"])
learning_rate_list_GBDT_XGB_smotetomek=list(results["param_learning_rate"])
cv_f2_score_GBDT_XGB_smotetomek_data=list(results["mean_test_score"])
```

In [58]:
```
np.save('depth_list_GBDT_XGB_smotetomek.npy',depth_list_GBDT_XGB_smotetomek)
np.save('estimator_list_GBDT_XGB_smotetomek.npy',estimator_list_GBDT_XGB_smotetomek)
np.save('learning_rate_list_GBDT_XGB_smotetomek.npy',learning_rate_list_GBDT_XGB_smotetomek)
#depth_list_GBDT_XGB_smotetomek=np.load('depth_list_GBDT_XGB_smotetomek.npy')
#estimator_list_GBDT_XGB_smotetomek=np.load('estimator_list_GBDT_XGB_smotetomek.npy')
#learning_rate_list_GBDT_XGB_smotetomek=np.load('learning_rate_list_GBDT_XGB_smotetomek.npy')
```

In [59]:
```
np.save('cv_f2_score_GBDT_XGB_smotetomek_data.npy',cv_f2_score_GBDT_XGB_smotetomek_data )
#cv_f2_score_GBDT_XGB_smotetomek_data=np.load('cv_f2_score_GBDT_XGB_smotetomek_data.npy')
```

In [60]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_smotetomek,estimator_list_GBDT_X
plt.scatter([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_smotetomek,estimator_list_GBD
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [29]:
```
np.sort(cv_f2_score_GBDT_XGB_median_data)[::-1][0]
```

Out[29]: 0.9395437457866332

In [30]:
```
np.array([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB,estimator_list_GBDT_XGB,learning
```

Out[30]: '4_300_0.3'

In [70]:
```
np.sort(cv_f2_score_GBDT_XGB_adasyn_data)[::-1][0]
```

Out[70]: 0.9962555722147115

In [31]:
```
np.array([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_adasyn,estimator_list_GBDT_XGB_a
```

Out[31]: '12_500_0.05'

In [75]:
```
np.sort(cv_f2_score_GBDT_XGB_smotetomek_data)[::-1][0]
```

Out[75]: 0.9994408534502123

In [74]:
```
np.array([str(i)+"_"+str(j)+"_"+str(k) for i,j,k in zip(depth_list_GBDT_XGB_smotetomek,estimator_list_GBDT_X
```

Out[74]: '8_500_0.1'

Running GBDT_XGB on median data with appropriate hyperparameters

In [44]:
```
GBDT = XGBClassifier(nthread=-1, tree_method='gpu_hist',n_jobs=-1,n_estimators= 300,max_depth=4,learning_rat

GBDT.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

y_predicted=GBDT.predict(new_standard_test_median_all_features_df)

f2_score=fbeta_score(y_test_median_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.9718026183282982
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11800    0
1.0            7  193
```

Running GBDT_XGB on adasyn data with appropriate hyperparameters

In [45]:
```
GBDT = XGBClassifier(nthread=-1, tree_method='gpu_hist',n_jobs=-1,n_estimators= 500,max_depth=12,learning_ra

GBDT.fit(new_x_adasyn_df, y_adasyn)

y_predicted=GBDT.predict(new_standard_test_adasyn_all_features_df)

f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.9632571996027806
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11787   13
1.0            6  194
```

The best value of cv score is 0.99944 with the parameters 8_500_0.1 with smotetomek data. So I will take this value of Depth,minimum_samples and learning rate in my algorthim.

In [17]:
```
GBDT = XGBClassifier(nthread=-1, tree_method='gpu_hist',n_jobs=-1,n_estimators= 500,max_depth=8,learning_rat

GBDT.fit(new_x_smotetomek_df, y_smotetomek)

y_predicted=GBDT.predict(new_standard_test_smotetomek_all_features_df)

f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.9720837487537389
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11792    8
1.0            5  195
```

Adaboost

In [46]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import RandomizedSearchCV
```

In [50]:
```
def run_AdaBoost(x_train, y_train):

    f_2_score = make_scorer(fbeta_score, pos_label=1.0, beta=2)

    n_estimators_list=[50,100, 200, 300, 500, 1000]
    learning_rate=[.0001,.001,.01,.05,.10,.20,.30,.50,.70,.90]

    parameters = {'n_estimators':n_estimators_list,
                  'learning_rate':learning_rate}

    clf = AdaBoostClassifier()

    rand = RandomizedSearchCV(clf, parameters, cv=5,n_jobs=-1, scoring=f_2_score)

    rand.fit(x_train, y_train)

    return rand
```

AdaBoost on median data

In [51]:
```
%%time
rand=run_AdaBoost(new_standard_train_median_all_features_df, y_train_median_all_features)
rand
```

```
CPU times: user 15min 10s, sys: 969 ms, total: 15min 11s
Wall time: 51min 2s
```

Out[51]:
```
RandomizedSearchCV(cv=5, estimator=AdaBoostClassifier(), n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.05, 0.1, 0.2, 0.3,
                                                          0.5, 0.7, 0.9],
                                        'n_estimators': [50, 100, 200, 300, 500,
                                                         1000]},
                   scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [57]:
```
rand.best_estimator_
```

Out[57]:
```
AdaBoostClassifier(learning_rate=0.3, n_estimators=1000)
```

In [58]:
```
rand.best_params_
```

Out[58]:
```
{'n_estimators': 1000, 'learning_rate': 0.3}
```

In [59]:
```
rand.best_score_
```

Out[59]:
```
0.9268327781099532
```

In [60]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[60]:

	params	mean_test_score
0	{'n_estimators': 200, 'learning_rate': 0.3}	0.887615
1	{'n_estimators': 50, 'learning_rate': 0.0001}	0.691494
2	{'n_estimators': 300, 'learning_rate': 0.7}	0.921753
3	{'n_estimators': 500, 'learning_rate': 0.7}	0.925532
4	{'n_estimators': 100, 'learning_rate': 0.5}	0.877913

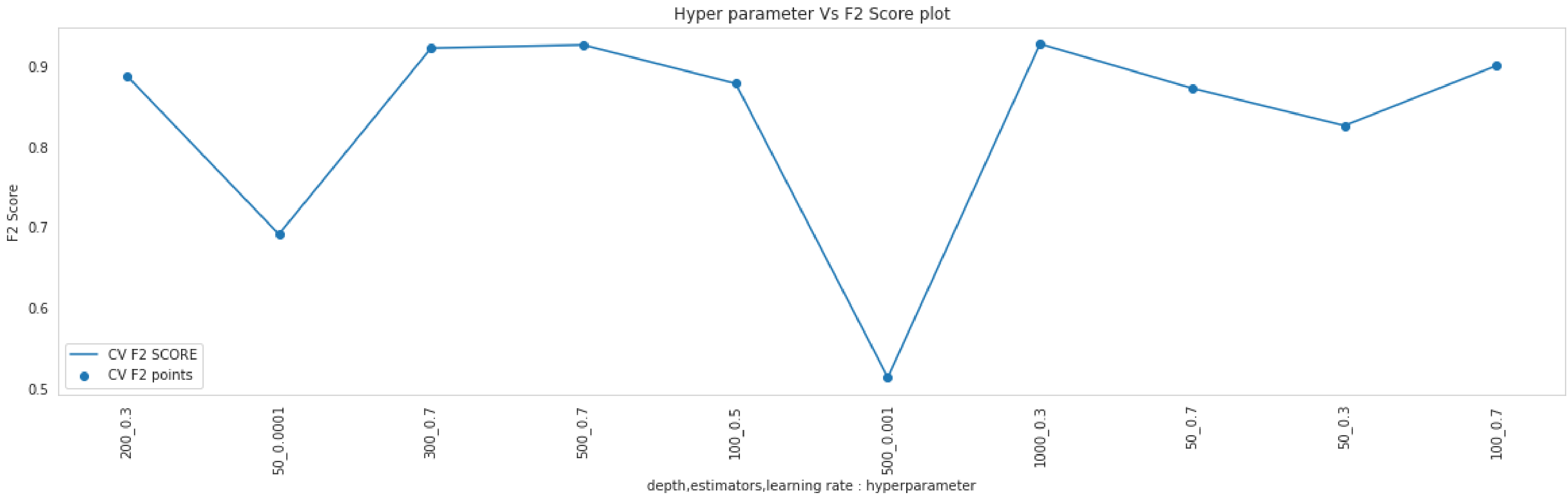
In [66]:
```
estimator_list_Adaboost=list(results["param_n_estimators"])
learning_rate_list_Adaboost=list(results["param_learning_rate"])
cv_f2_score_Adaboost_median_data=list(results["mean_test_score"])
```

In [67]:
```
np.save('estimator_list_Adaboost.npy',estimator_list_Adaboost)
np.save('learning_rate_list_Adaboost.npy',learning_rate_list_Adaboost)
#estimator_list_Adaboost=np.load('estimator_list_Adaboost.npy')
#learning_rate_list_Adaboost=np.load('learning_rate_list_Adaboost.npy')
```

In [68]:
```
np.save('cv_f2_score_Adaboost_median_data.npy',cv_f2_score_Adaboost_median_data )
#cv_f2_score_Adaboost_median_data=np.load('cv_f2_score_Adaboost_median_data.npy')
```

In [71]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost,learning_rate_list_Adaboost)],cv_f2_score
plt.scatter([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost,learning_rate_list_Adaboost)],cv_f2_sc
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



AdaBoost on adasyn data

In [72]:
```
%%time
rand=run_AdaBoost(new_x_adasyn_df, y_adasyn)
rand
```

```
CPU times: user 6min 6s, sys: 1.2 s, total: 6min 7s
Wall time: 1h 13min 29s
```

Out[72]:
```
RandomizedSearchCV(cv=5, estimator=AdaBoostClassifier(), n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.05, 0.1, 0.2, 0.3,
                                                          0.5, 0.7, 0.9],
                                        'n_estimators': [50, 100, 200, 300, 500,
                                                         1000]},
                   scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [73]:
```
rand.best_estimator_
```

Out[73]:
```
AdaBoostClassifier(learning_rate=0.5, n_estimators=200)
```

In [74]:
```
rand.best_params_
```

Out[74]:
```
{'n_estimators': 200, 'learning_rate': 0.5}
```

In [75]:
```
rand.best_score_
```

Out[75]:
```
0.9940109523031383
```

In [76]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[76]:

	params	mean_test_score
0	{'n_estimators': 300, 'learning_rate': 0.2}	0.991492
1	{'n_estimators': 100, 'learning_rate': 0.01}	0.929967
2	{'n_estimators': 300, 'learning_rate': 0.001}	0.892946
3	{'n_estimators': 200, 'learning_rate': 0.1}	0.983556
4	{'n_estimators': 200, 'learning_rate': 0.001}	0.887886

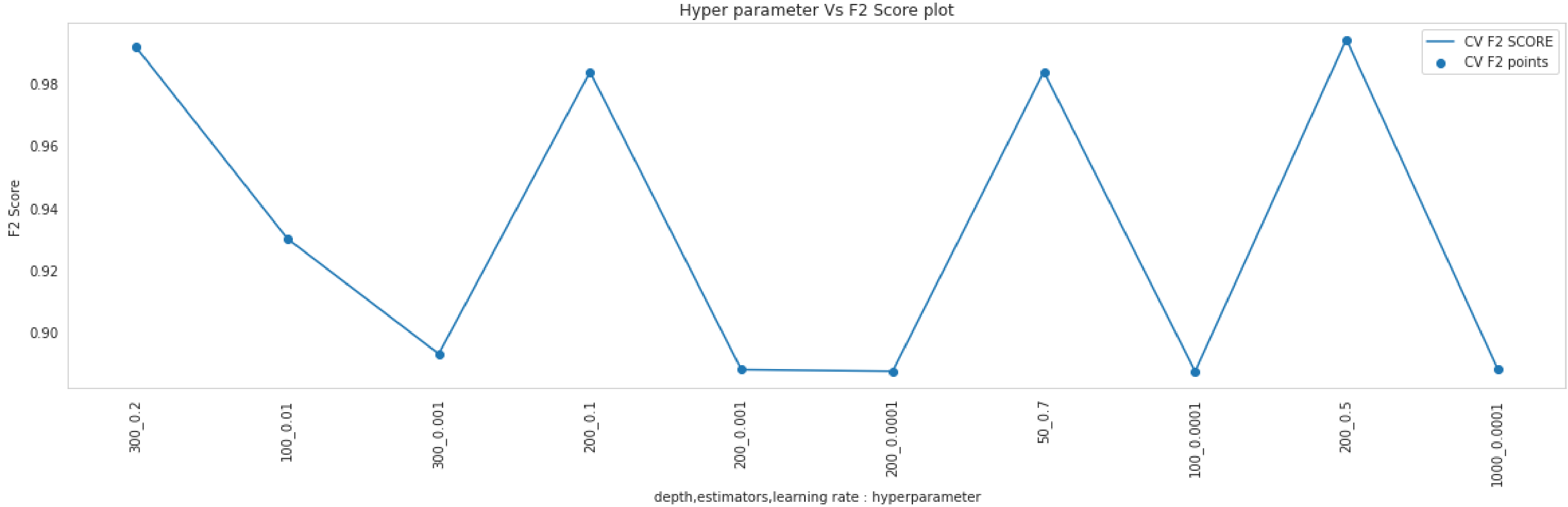
In [82]:
```
estimator_list_Adaboost_adasyn_data=list(results["param_n_estimators"])
learning_rate_list_Adaboost_adasyn_data=list(results["param_learning_rate"])
cv_f2_score_Adaboost_adasyn_data=list(results["mean_test_score"])
```

In [83]:
```
np.save('estimator_list_Adaboost_adasyn_data.npy',estimator_list_Adaboost_adasyn_data)
np.save('learning_rate_list_Adaboost_adasyn_data.npy',learning_rate_list_Adaboost_adasyn_data)
#estimator_list_Adaboost_adasyn_data=np.load('estimator_list_Adaboost_adasyn_data.npy')
#learning_rate_list_Adaboost_adasyn_data=np.load('learning_rate_list_Adaboost_adasyn_data.npy')
```

In [84]:
```
np.save('cv_f2_score_Adaboost_adasyn_data.npy',cv_f2_score_Adaboost_adasyn_data )
#cv_f2_score_Adaboost_adasyn_data=np.load('cv_f2_score_Adaboost_adasyn_data.npy')
```

In [85]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_adasyn_data,learning_rate_list_Adaboost_a
plt.scatter([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_adasyn_data,learning_rate_list_Adaboos
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



AdaBoost on smotetomek data

In [86]:
```
%%time
rand=run_AdaBoost(new_x_smotetomek_df, y_smotetomek)
rand
```

```
CPU times: user 16min 41s, sys: 1.17 s, total: 16min 42s
Wall time: 1h 22min 42s
```

Out[86]:
```
RandomizedSearchCV(cv=5, estimator=AdaBoostClassifier(), n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.05, 0.1, 0.2, 0.3,
                                                          0.5, 0.7, 0.9],
                                        'n_estimators': [50, 100, 200, 300, 500,
                                                         1000]},
                   scoring=make_scorer(fbeta_score, pos_label=1.0, beta=2))
```

In [87]:
```
rand.best_estimator_
```

Out[87]:
```
AdaBoostClassifier(learning_rate=0.7, n_estimators=1000)
```

In [88]:
```
rand.best_params_
```

Out[88]:
```
{'n_estimators': 1000, 'learning_rate': 0.7}
```

In [89]:
```
rand.best_score_
```

Out[89]:
```
0.9993505458615074
```

In [90]:
```
results = pd.DataFrame.from_dict(rand.cv_results_)
results[0:5][["params","mean_test_score"]]
```

Out[90]:

	params	mean_test_score
0	{'n_estimators': 1000, 'learning_rate': 0.7}	0.999351
1	{'n_estimators': 200, 'learning_rate': 0.1}	0.986327
2	{'n_estimators': 300, 'learning_rate': 0.9}	0.999085
3	{'n_estimators': 50, 'learning_rate': 0.1}	0.973251
4	{'n_estimators': 50, 'learning_rate': 0.01}	0.946198

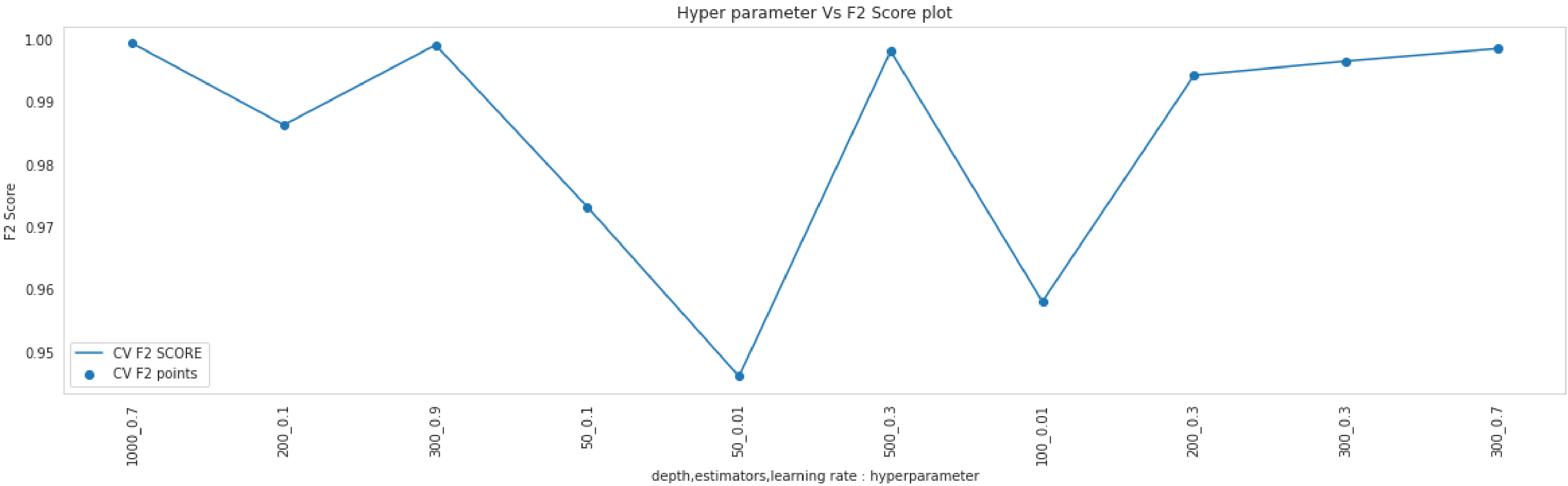
In [91]:
```
estimator_list_Adaboost_smotetomek_data=list(results["param_n_estimators"])
learning_rate_list_Adaboost_smotetomek_data=list(results["param_learning_rate"])
cv_f2_score_Adaboost_smotetomek_data=list(results["mean_test_score"])
```

In [92]:
```
np.save('estimator_list_Adaboost_smotetomek_data.npy',estimator_list_Adaboost_smotetomek_data)
np.save('learning_rate_list_Adaboost_smotetomek_data.npy',learning_rate_list_Adaboost_smotetomek_data)
#estimator_list_Adaboost_smotetomek_data=np.load('estimator_list_Adaboost_smotetomek_data.npy')
#learning_rate_list_Adaboost_smotetomek_data=np.load('learning_rate_list_Adaboost_smotetomek_data.npy')
```

In [93]:
```
np.save('cv_f2_score_Adaboost_smotetomek_data.npy',cv_f2_score_Adaboost_smotetomek_data )
#cv_f2_score_Adaboost_smotetomek_data=np.load('cv_f2_score_Adaboost_smotetomek_data.npy')
```

In [94]:
```
plt.figure(figsize=(20,5))
sns.set_style('whitegrid')

plt.plot([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_smotetomek_data,learning_rate_list_Adaboo
plt.scatter([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_smotetomek_data,learning_rate_list_Ada
plt.xticks(rotation=90)
plt.legend()
plt.xlabel("depth,estimators,learning rate : hyperparameter")
plt.ylabel("F2 Score")
plt.title("Hyper parameter Vs F2 Score plot")
plt.grid()
plt.show()
```



In [98]:
```
np.sort(cv_f2_score_Adaboost_median_data)[::-1][0]
```
Out[98]: 0.9268327781099532

In [100]:
```
np.array([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost,learning_rate_list_Adaboost)])[np.argsort
```
Out[100]: '1000_0.3'

In [101]:
```
np.sort(cv_f2_score_Adaboost_adasyn_data)[::-1][0]
```
Out[101]: 0.9940109523031383

In [104]:
```
np.array([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_adasyn_data,learning_rate_list_Adaboost_a
```
Out[104]: '200_0.5'

In [105]:
```
np.sort(cv_f2_score_Adaboost_smotetomek_data)[::-1][0]
```
Out[105]: 0.9993505458615074

In [106]:
```
np.array([str(i)+"_"+str(j) for i,j in zip(estimator_list_Adaboost_smotetomek_data,learning_rate_list_Adaboo
```
Out[106]: '1000_0.7'

Running GBDT_Adaboost on median data with appropriate hyperparameters

In [47]:
```
AdaBoost = AdaBoostClassifier(n_estimators=1000,learning_rate=0.3)

AdaBoost.fit(new_standard_train_median_all_features_df, y_train_median_all_features)

y_predicted=AdaBoost.predict(new_standard_test_median_all_features_df)

f2_score=fbeta_score(y_test_median_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_median_all_features, y_predicted))
```

```
f2_score :  0.9444444444444445
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11797    3
1.0           13  187
```

Running GBDT_Adaboost on adasyn data with appropriate hyperparameters

In [48]:
```
AdaBoost = AdaBoostClassifier(n_estimators=200,learning_rate=0.5)

AdaBoost.fit(new_x_adasyn_df, y_adasyn)

y_predicted=AdaBoost.predict(new_standard_test_adasyn_all_features_df)

f2_score=fbeta_score(y_test_adasyn_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_adasyn_all_features, y_predicted))
```

```
f2_score :  0.9125117591721542
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11731   69
1.0            6  194
```

The best value of cv score is 0.99935 with the parameters 1000_0.7 with smotetomek data. So I will take this value of number of trees and learning rate in my algorthim.

In [107]:
```
AdaBoost = AdaBoostClassifier(n_estimators=1000,learning_rate=0.7)

AdaBoost.fit(new_x_smotetomek_df, y_smotetomek)

y_predicted=AdaBoost.predict(new_standard_test_smotetomek_all_features_df)

f2_score=fbeta_score(y_test_smotetomek_all_features, y_predicted, pos_label=1.0, beta=2)

print("f2_score : ",f2_score)

print("confusion_matrix : \n",confusion_matrix(y_test_smotetomek_all_features, y_predicted))
```

```
f2_score :  0.9643916913946587
confusion_matrix :
 Predicted    0.0  1.0
True
0.0        11784   16
1.0            5  195
```

Conclusion : I am able to minimize the False Negatives and I get the best score with Gradient Boosted Decision Trees with median imputed data.