Part :1 (fiter method used to get the unique features)

In [3]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
```

In [4]:
```python
from sklearn.feature_selection import VarianceThreshold
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

In [5]:
```python
data = pd.read_csv('santander-train.csv',nrows=2000)
data.head()
```

Out[5]:

	ID	var3	var15	imp_ent_var16_ult1	imp_op_var39_comer_ult1	imp_op_var39_comer_ult3	imp_op_var40_comer_ult1	imp_op_var40_comer_ult3
0	1	2	23	0.0	0.0	0.0	0.0	0.0
1	3	2	34	0.0	0.0	0.0	0.0	0.0
2	4	2	23	0.0	0.0	0.0	0.0	0.0
3	8	2	37	0.0	195.0	195.0	0.0	0.0
4	10	2	39	0.0	0.0	0.0	0.0	0.0

5 rows × 371 columns

In [6]:
```python
x = data.drop( labels='TARGET',axis=1)
y = data['TARGET']

x.shape,y.shape
```

Out[6]: ((2000, 370), (2000,))

In [7]:
```python
x_train,x_test,y_train,y_test = train_test_split(x,y,train_size =.80,random_state=0,stratify=y)

x_train.shape,x_test.shape
```

Out[7]: ((1600, 370), (400, 370))

Remove constant,quaisi and duplicate

In [8]:
```python
#remove constant and quaisi constant
```

In [9]:
```python
constant_filter = VarianceThreshold(threshold=0.01)
constant_filter.fit(x_train)
x_train_filter = constant_filter.transform(x_train)
x_test_filter  = constant_filter.transform(x_test)

x_train_filter.shape,x_test_filter.shape
```

Out[9]: ((1600, 223), (400, 223))

In [10]:
```python
#Duplicate feature removal
```

In [11]:
```python
x_train_T = x_train_filter.T
x_test_T  = x_test_filter.T

x_train_T = pd.DataFrame(x_train_T)
x_test_T  = pd.DataFrame(x_test_T)

duplicate_features = x_train_T.duplicated()
keep_them = [not index for index in duplicate_features]

x_train_unique = x_train_T[keep_them].T
x_test_unique  = x_test_T[keep_them].T

x_train_unique.shape,x_test_unique.shape
```

Out[11]: ((1600, 200), (400, 200))

In [12]:
```python
%%time
def randomforest(x_train,x_test,y_train,y_test):
    clf = RandomForestClassifier(n_estimators=1000,n_jobs=-1,random_state=0)
    clf.fit(x_train,y_train)
    y_pred = clf.predict(x_test)
    print('Accuracy : ',accuracy_score(y_test,y_pred))
randomforest(x_train_unique,x_test_unique,y_train,y_test)
```

```
Accuracy :  0.955
Wall time: 11.2 s
```

In [13]:
```python
%%time
randomforest(x_train,x_test,y_train,y_test)
```

```
Accuracy :  0.955
Wall time: 12.5 s
```

However we got neccessary model with the acuracy of 95 %

Part :2(by using the corelation coeficient remove the corrrelated features)

Feature Selection with Filtering Method -Correlated Feature Removal

In that we are going to remove the feature those who are co-related by cartain coeficient or point.

If the correlation coeficient is more than 0.85 or less than -0.85 in that case features are highly correlated and this fetures might not give us the extra information to make the final prediction of classifition so we remove those features and by doing this ultimately improve our model and it will take less time train our model.

A dataset can be correlated features.Two or more than two features are correlated if they are close to each other in the linear space.

Correlation between the output observations and input features is very important and such features should be retained.

Our aim is to rreduce the correlative function and reduce diamensionality of the overall feature space.

Because our model gives us the better performace for the perticalar position at time performace of classifier high. But after the some time as soon as diamensinality of the feature space is increse that time modle start to decreasing its performace.

So,that is always recomanded or desirable that we should have select optimal number of features.

In the feature space there are lots of the features are avalible that can predicted themself we use one of them at one time.So,this kind of feature not giveing any information for prediction of the model so that is why its very necessary to remove this kind features.Those feature also called as co-linear feature.

Co-linearaity in the feature space and output is always desirable but the co-linearity amongs the features space space is not desirable.

Summary:-

Feature Space to target coeficient is desired.

Feature to feature is not desurable.

If two features are highly correlated then either features is redudant (either we have to remove feature 1 or feature 2)

Correlation is feature space increases the model complexity.

Removing Correlated features improve the model performance.

Different model shows the different performance over the correlated features.

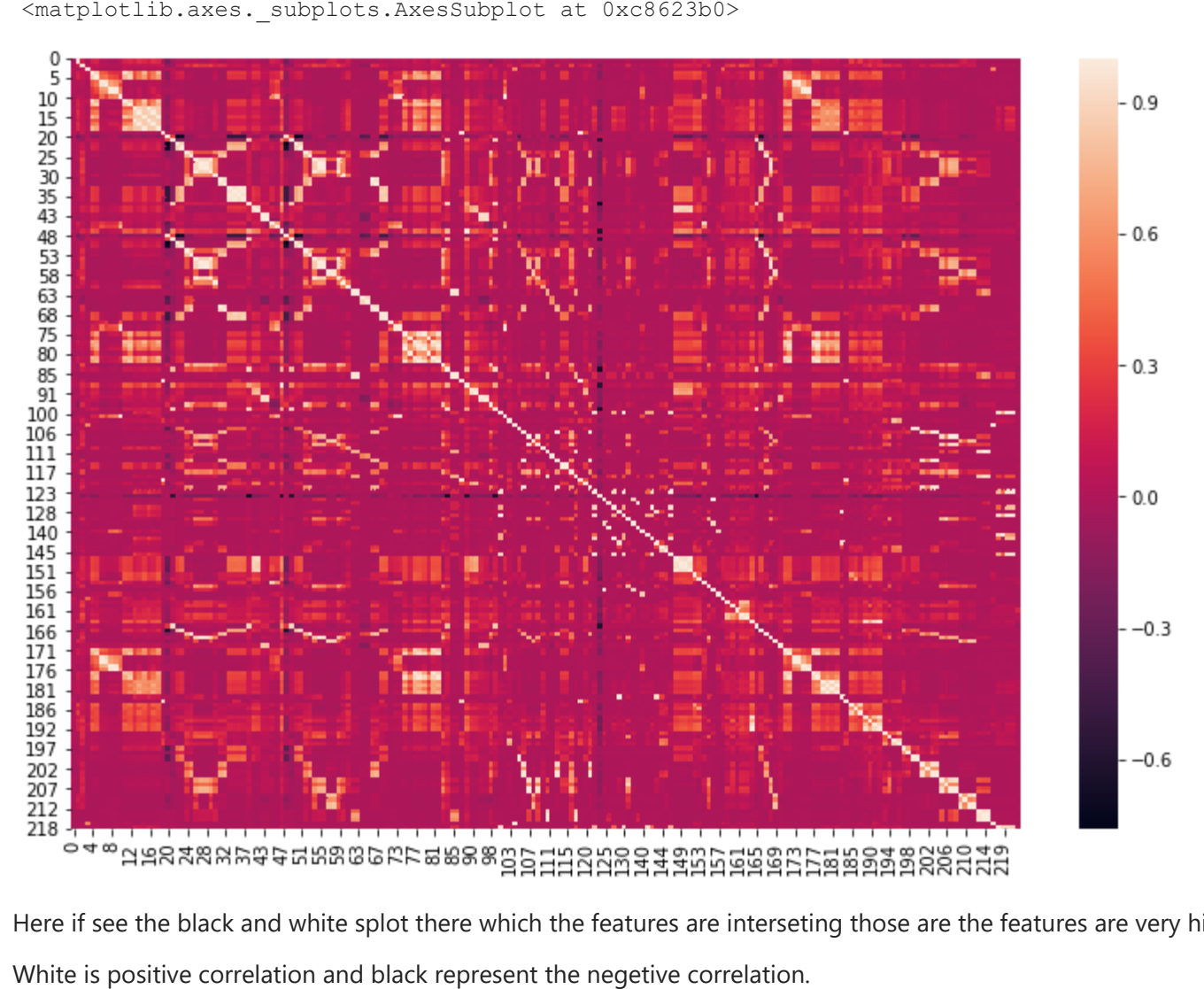
Before the work on the correlation feature we need to think about the previous part -1 there we have got the x_train_unique,x_test_unique. Afterwards we have to think about the correlation feature.First we will calculate peierson correlation coefficient for traing and testing datasets and then we will select only those features which have correlation less than 0.85.

In [14]:
```python
#first we are going to use the correlation matrix by using cormat
```

In [15]:
```python
cormat = x_train_unique.corr()
```

In [16]:
```python
plt.figure(figsize = (12,8) )
sns.heatmap(cormat)
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0xc8623b0>



Here if see the black and white splot there which the features are interseting those are the features are very highly correlated.

White is positive correlation and black represent the negetive correlation.

If we observed that the black is below -.85% and white is above the +85%.

In [17]:
```python
#we are using the python method to get the corrlation features
#here we are defining function that is correlation with attributes are data,threshold
#data = x_train_unique to reduce the chances of overfitting
#threshold is the limit upto which we count as no correlative faeture but above which is counted as correlative
#thresold means gives the limit after which we discard the features.
def correlation(data,threshold):

#there could be the possibility of the same features occurance on multiple time.
#here we are using set with the corr_col the set method is avoid to use the same feature multipletime.

    corr_col = set()
#then we use the cormat which is presenting the correlation between the features of the data which we will prod
    cormat = data.corr()
#so,after we use the for loop for the range(len(cormat.columns))
#That means it is iterating features from features range it will start from 0 to final number from 0 to final i
#range(0,219)
    for i in range(len(cormat.columns)):
#by using above its possible to get the sitiation range(1,1),range(2,2) to avoid that kind of situation
#if we use the range in that we containg the same features that time the correlation will become 1 because we a
#that kind of correlation we not to consider.
        for j in range(i):
#after we we mention condition wherever we i and j values in cormat like when the i is 1 that time j will be 0 an
#time j is will be the 1 and also it take care if we taken the 0 and 1 then it will not repeat the same iterat


#we mention the condition when the abs(absolute values) of the cormat.iloc(ilocation)[i,j] will be greater than

            if abs(cormat.iloc[i,j])>threshold:
#that time,what feature will above the threshold they will add in corr_col and it will add those features which
                colname = cormat.columns[i]
#above list is will contain the feature which are availbe in correlation format and it will gone add to the cor
                corr_col.add(colname)
    return corr_col
```

In [18]:
```python
def correlation(data,threshold):
    corr_col = set()
    cormat = data.corr()
    for i in range(len(cormat.columns)):
        for j in range(i):
            if abs(cormat.iloc[i,j]) > threshold:
                colname = cormat.columns[i]
                corr_col.add(colname)
    return corr_col
```

In [19]:
```python
correlated_features = correlation(x_train_unique,0.85)

correlated_features
```

Out[19]:
```
{5,
 7,
 9,
 11,
 12,
 14,
 16,
 17,
 18,
 23,
 27,
 28,
 29,
 32,
 34,
 35,
 37,
 39,
 41,
 44,
 48,
 49,
 50,
 51,
 52,
 53,
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 199,
 200,
 201,
 203,
 204,
 205,
 206,
 207,
 208,
 211,
 212,
 213,
 214,
 215,
 216,
 218,
 219,
 220,
 221}
```

In [20]:
```python
len(correlated_features)
```

Out[20]: 121

We have got the correlated feature then our next task to remove this features and then strat to train model.

In [21]:
```python
x_train_uncorr = x_train_unique.drop(labels=correlated_features,axis=1)
x_test_uncorr  = x_test_unique.drop(labels=correlated_features,axis=1)
```

In [22]:
```python
x_train_uncorr.shape,x_test_uncorr.shape
```

Out[22]: ((1600, 79), (400, 79))

In [26]:
```python
%%time
randomforest(x_train_uncorr,x_test_uncorr,y_train,y_test)
```

```
Accuracy :  0.9575
Wall time: 9.75 s
```

In [24]:
```python
%%time
randomforest(x_train,x_test,y_train,y_test)
```

```
Accuracy :  0.955
Wall time: 10.9 s
```

In [28]:
```python
(10.9-9.75)*100/9.75

#It shows that the 11 % time gain into our training time by removing the correlative features.
```

Out[28]: 11.794871794871797

From the above we can only say that the it does not making any on the accuracy but it impacting on the training time which is equired less than the original datasets.

Here we use the broot force techinique to reduce the diamensionality of the datasets by removing the correlated featutres.

Till now we can make any statement that visit our accuracy doesn't improve pretty much are very high but the training time has reduced the effect source around 11% of the training time has been reduced to increase if you are doing a very big data set in that place where you can remove uncorrelated features and unnecessarily features and you can reduce dimensions of your data and you can handle curse of dimension what we did we actually we did kind of the brute force that we had removed all the correlated features but you know this is not always recommended there could be a places where some group of features are correlated with each others only that mean we only need to remove a certain features and we can keep some features bye testing the features importance.for example it's a year in out of 121 features there would be kind of the 10 groups where they are correlated that we can avoid these all the correlated features in kind of the groups and then finally we can select a single feature in each of those groups after performing feature importance so here now we are going to do what feature importance and the grouping of these correlated features.

In [ ]:

Feature Grouping and Feature Important.

In [40]:
```python
cormat
```

Out[40]:

	0	1	2	3	4	5	6	7	8	9	...	212	213	2
0	1.000000	-0.027387	-0.006389	0.035624	0.031820	0.014071	0.022963	0.023790	0.031051	0.028532	...	0.007409	-0.017482	-0.015
1	-0.027387	1.000000	0.129309	-0.003721	0.162310	0.183237	0.026635	0.027339	-0.002888	-0.002831	...	0.093521	-0.002286	-0.002
2	-0.006389	0.129309	1.000000	0.039272	0.094338	0.098071	0.041147	0.033639	0.020170	0.018505	...	0.122776	-0.021590	-0.026
3	0.035624	-0.003721	0.039272	1.000000	0.084736	0.044504	-0.004283	-0.003979	-0.003148	-0.003086	...	-0.006308	-0.002492	-0.003
4	0.031820	0.162310	0.094338	0.084736	1.000000	0.871544	0.388872	0.368375	0.242827	0.216412	...	-0.014652	-0.005787	-0.007
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
218	-0.040836	-0.002733	0.009685	-0.002979	-0.006920	0.004181	-0.001592	-0.001479	-0.001170	-0.001147	...	-0.002345	-0.000926	-0.001
219	-0.030185	-0.002054	0.001744	-0.002239	-0.005200	0.006882	-0.001196	-0.001111	-0.000879	-0.000862	...	-0.001762	-0.000696	-0.000
220	-0.043733	-0.002894	0.015735	-0.003155	-0.007327	0.000722	-0.001686	-0.001566	-0.001239	-0.001215	...	-0.002483	-0.000981	-0.001
221	-0.043562	-0.002879	0.016210	-0.003139	-0.007290	0.000344	-0.001677	-0.001558	-0.001233	-0.001208	...	-0.002470	-0.000976	-0.001
222	-0.011098	-0.006643	-0.006950	-0.026085	-0.013012	-0.008666	-0.004132	-0.003413	-0.010453	-0.011169	...	0.001086	-0.001878	-0.003

200 rows × 200 columns

In [41]:
```python
#lets do the the verically stacking (make the 0th row into the form oth column)
```

In [42]:
```python
corrdata = cormat.abs().stack()
corrdata
```

Out[42]:
```
0    0      1.000000
     1      0.027387
     2      0.006389
     3      0.035624
     4      0.031820
              ...
222  218    0.000578
     219    0.000434
     220    0.000612
     221    0.000609
     222    1.000000
Length: 40000, dtype: float64
```

In [43]:
```python
#sort the values of the stack formate of the corrdata
corrdata = corrdata.sort_values(ascending=False)
corrdata
#it is the form of desending order format due to this reason lowest values come first and highest at last.
```

Out[43]:
```
142  127    1.000000e+00
127  142    1.000000e+00
139  126    1.000000e+00
126  139    1.000000e+00
125  156    1.000000e+00
                ...
45   24     1.269902e-16
24   51     3.905293e-17
51   24     3.905293e-17
23   52     3.862636e-17
52   23     3.862636e-17
Length: 40000, dtype: float64
```

If we see the above sorted corrdata in that we get to know that the 142 is correlated with 127 similarly 127 is correlated with the 142 and in similar fashion 139 is correlated with the 126

After the some time we will get the correlation with the same features space like 166 is correlated with the 166 an so on.We will not gone filter out this correlated otherwise will get the at least one correlation for each feature.we remove this kind ,I means we keep this like 166 will correlated other than the same feature i.e.166

Now,for that we are going to do grouping lets say if feature space is 142 so what are other features for which this feature 142 is correlated.

We can do that by selecting the features inbetween o.85 and 1.

In [44]:
```python
corrdata = corrdata[corrdata>0.85]
corrdata = corrdata[corrdata<1]

corrdata
```

Out[44]:
```
22   50     1.000000
50   22     1.000000
67   32     1.000000
32   67     1.000000
216  104    1.000000
              ...
108  58     0.852894
99   165    0.852609
165  99     0.852609
5    172    0.850782
172  5      0.850782
Length: 526, dtype: float64
```

It is representing the data in such manner that 22 is correlated with the 50 and 50 then correlated 22 it is showing that correlation is equal to 1 but but this is not exacly 1 due to the limitation of the digital thats is why it is showing 1 but it is somehow nearby 1.Since we had remove all features with are correlated equal to 1.Other than same features there is no features which is correlated.why ?

If the correlation is exctly 1 other than the same feature that means those features are duplicate and we already remove those duplicate features.

Now just go ahead and perform the grouping.

For that we need to covert into the pandas DataFrame.

reset_index() function to reset the index of the given DataFrame object. andas reset_index() is a method to reset index of a Data Frame. reset_index() method sets a list of integer ranging from 0 to length of data as index.

In [45]:
```python
#before going to that
corrdata = pd.DataFrame(corrdata).reset_index()
corrdata.columns = ['features1','features2','corr_value']
corrdata
```

Out[45]:

	features1	features2	corr_value
0	22	50	1.000000
1	50	22	1.000000
2	67	32	1.000000
3	32	67	1.000000
4	216	104	1.000000
...	...	...	...
521	108	58	0.852894
522	99	165	0.852609
523	165	99	0.852609
524	5	172	0.850782
525	172	5	0.850782

526 rows × 3 columns

we got the nice visualization and we will go for the grouping.

In [47]:
```python
#we had created empty list by the name groupped_feature_list
#Similarly, we had created the empty list by the name correlated_grouped_list
#first we are going to create the group of the feature and then we are going to create the list of those featu
#Then we will find the feature importance of each group then we wil select only one feature from each group the

grouped_feature_list =[]
correlated_grouped_list = []
for feature in corrdata.features1.unique():
#that means it is going to see if this  feature is not present into a grouped_feature_list then we shold consid
#otherwise,grouping already done and dont we need to do grouping.
#so,lets find out all correlated feature in group
    if feature not in grouped_feature_list:
#when the feature from the group is become equal to the corrdata.features1 feature then only it will be accept
        correlated_block = corrdata[corrdata.features1==feature]
#we going to do if the two features are same that means they are same correlated group then we are going to get

#If we have here the feature 22 so it going to get the all features in feature1 then it will look all the featu
#That those features are fall into the same group
#Since 22 is correlated with 50 the any feature correlated with 50 will be also highly correlatated with 22 .
#so, in this way we are going the get the same correlation ith 22 and similar kind of the features.
        grouped_feature_list= grouped_feature_list + list(correlated_block.features2.unique()) + [feature]
#by doing so, we have created the list of grouped features.
        correlated_grouped_list.append(correlated_block)
```

In [81]:
```python
grouped_feature_list =[]
correlated_grouped_list = []
for feature in corrdata.features1.unique():
    if feature not in grouped_feature_list:
        correlated_block = corrdata[corrdata.features1==feature]
        grouped_feature_list= grouped_feature_list + list(correlated_block.features2.unique()) + [feature]
        correlated_grouped_list.append(correlated_block)
```

In [49]:
```python
len(correlated_grouped_list)
#In 121 correlated faeture  we had found the 54 groups that there is 54 group exisied in out of those correlate
```

Out[49]: 54

In [ ]:
```python
#After in correlated group  that we are going to get a single feature based on the feature importance of toatl
```

In [50]:
```python
#toltal feature
x_train.shape
```

Out[50]: (1600, 370)

In [51]:
```python
#uncorr_feature
x_train_uncorr.shape
```

Out[51]: (1600, 79)

We had removed the all the constant,quaisi constant,duplicate and correlated_features then we having the remaing feature those are only 79.

In [52]:
```python
#if we want to see the group in that we can by the below way
for group in correlated_grouped_list:
    print(group)
```

```
     features1  features2  corr_value
0           22         50    1.000000
439         22         23    0.880913
443         22         51    0.880913
     features1  features2  corr_value
2           67         32    1.000000
266         67         31    0.932090
273         67         66    0.932090
513         67         25    0.854618
515         67         53    0.854618
   features1  features2  corr_value
4        216        104         1.0
     features1  features2  corr_value
6           55         27    1.000000
89          55         28    0.984542
94          55         56    0.984542
146         55        168    0.971592
340         55         26    0.906471
412         55         29    0.889905
464         55         59    0.872808
501         55         54    0.858043
    features1  features2  corr_value
12         80         76    0.999639
     features1  features2  corr_value
14         182        180    0.999309
411        182        181    0.891920
420        182        179    0.887881
     features1  features2  corr_value
18         220        221    0.998978
34         220        100    0.996027
37         220        130    0.996027
163        220        123    0.968460
214        220        147    0.945985
339        220        218    0.906773
     features1  features2  corr_value
20          14         17    0.998268
418         14         16    0.888829
430         14         13    0.884528
     features1  features2  corr_value
22          79         75    0.997895
290         79         78    0.924509
293         79         82    0.924409
371         79        178    0.899640
498         79        172    0.858715
     features1  features2  corr_value
24         192        164    0.997722
288        192        189    0.924586
366        192        191    0.902160
    features1  features2  corr_value
26        115        114    0.997564
     features1  features2  corr_value
32         107        207    0.996469
79         107        208    0.987490
226        107        109    0.943435
329        107        205    0.911424
     features1  features2  corr_value
38          49         21    0.995872
296         49        165    0.924121
468         49         99    0.872330
484         49         39    0.862160
     features1  features2  corr_value
40         176          9    0.995491
124        176          8    0.977777
209        176        175    0.948624
     features1  features2  corr_value
42          87         19    0.994812
391         87        184    0.894371
     features1  features2  corr_value
45         119         19    0.994812
393        119        184    0.894371
     features1  features2  corr_value
46         214        111    0.994539
51         214        215    0.993871
200        214        213    0.950188
294        214        118    0.924339
     features1  features2  corr_value
54         113        106    0.993512
96         113        203    0.983377
137        113        122    0.975637
139        113        204    0.974640
316        113        201    0.915972
     features1  features2  corr_value
58         102         10    0.993242
179        102         74    0.962638
194        102         73    0.955192
    features1  features2  corr_value
68         18         15    0.990243
     features1  features2  corr_value
72         199        105    0.988634
154        199        200    0.970682
     features1  features2  corr_value
74          85         86    0.988555
129         85         62    0.976990
171         85         63    0.965301
     features1  features2  corr_value
82         211        212    0.986452
279        211        209    0.929306
     features1  features2  corr_value
84         174          6    0.986042
118        174        173    0.979471
192        174          7    0.955663
     features1  features2  corr_value
100        150        149    0.982667
228        150        151    0.942860
287        150        148    0.924779
453        150         40    0.878397
     features1  features2  corr_value
106         33         35    0.981668
180         33         37    0.961639
230         33         34    0.942617
     features1  features2  corr_value
108         47         89      0.9811
     features1  features2  corr_value
134         77         81    0.976041
158         77        177    0.969167
334         77         78    0.909309
373         77         82    0.899416
401         77        178    0.892827
483         77        171    0.865390
     features1  features2  corr_value
142         44         43    0.974164
222         44         96    0.943971
318         44         93    0.913456
     features1  features2  corr_value
150         68         70    0.971481
459         68         34    0.876622
     features1  features2  corr_value
182         58         57    0.960556
463         58        169    0.873121
520         58        108    0.852894
     features1  features2  corr_value
184        167         25    0.960544
186        167         53    0.960544
     features1  features2  corr_value
190         20         48    0.956784
     features1  features2  corr_value
219         41         40    0.945008
381         41        148    0.897611
449         41        151    0.880398
     features1  features2  corr_value
224        163        162    0.943497
     features1  features2  corr_value
248         90         91    0.938967
     features1  features2  corr_value
250        183        143    0.937678
     features1  features2  corr_value
253        128        143    0.937678
     features1  features2  corr_value
261        142        147    0.933636
362        142        123    0.902732
     features1  features2  corr_value
262        127        147    0.933636
364        127        123    0.902732
     features1  features2  corr_value
284         11          4    0.926345
490         11         12    0.861091
     features1  features2  corr_value
307        166         51     0.92231
309        166         23     0.92231
     features1  features2  corr_value
332         84         99    0.909353
385         84         39    0.894656
     features1  features2  corr_value
348        141        218    0.904901
     features1  features2  corr_value
351        219        218    0.904901
     features1  features2  corr_value
374        138        156    0.898029
376        138        125    0.898029
     features1  features2  corr_value
378        195        196    0.897852
     features1  features2  corr_value
398         64         65    0.893865
     features1  features2  corr_value
416        154         45    0.889285
     features1  features2  corr_value
434        206        137    0.882534
     features1  features2  corr_value
445          5         12    0.880788
470          5          4    0.871544
524          5        172    0.850782
     features1  features2  corr_value
478        140        157    0.867632
     features1  features2  corr_value
486        187        185    0.861732
     features1  features2  corr_value
496        145        144    0.859122
```

But here,We are now going to put 54 more features so that from each group.

Feature importance based on tress based classifiers.

So, We are going to do a feature important based on the tree based classifier.

In [61]:
```python
#first we had created the empty list for important features.
important_features = []

#then we go group by group and from the correlated_grouped_list
#In each group we are calculating here most important feature which is located at 0 i.e feat = importance.iloc
#Because we had sorted in the desecending order i.e.    importance.sort_values(by = 'importance', ascending = F
#Once we got the most important feature from each group then we make here list of the most important features i
#now we got feature list that we can print by calling important_features.

#then we go group by group
for group in correlated_grouped_list:


#In each group  having the unique feature if we observed that unique features from group and feature1 couluns s
#we added them given the name that variable as features i.e. common for all with combine unique features from e

    features = list(group.features1.unique()) + list(group.features2.unique())

#Afterwards use the Randomforestclassifier


    rf = RandomForestClassifier(n_estimators=1000,random_state=0)

#fit the model on the data x_train_unique[features],y_train
#here,x_train_unique[features] is noting but x_train_unique is the  data with inclusion of the unique feature a

    rf.fit(x_train_unique[features],y_train)

#to get imporatnce feature we have to concatenate two kind of series.
#First is filled with the combine unique features of eah group.
#Second Series of the dataframe which is filled with the whhichever feature the randomforest classifier gives u

#rf.feature_importances_ gives us the imporatnt features
#features only giving  unique features of avalible in group.


    importance = pd.concat([pd.Series(features),pd.Series(rf.feature_importances_)],axis =1)

#create the two columns for the importance
#first = feature(it only providing the unique features avalible )
#second = importance(it providing the imporatnt feature in each group)

    importance.columns = ['features','importance']

#sort the value of the importance in ascending format so higher values come first with the starting of imporata

    importance.sort_values(by = 'importance', ascending = False,inplace = True )

#start to get the lower values from the position zeroth ith location of the imporatnce column.

    feat = importance.iloc[0]
#then lastly it added the imporance which having two columns feature and importance data in sorted manner .
    important_features.append(feat)
```

In [62]:
```python
important_features
```

Out[62]:
```
[features      23.000000
 importance     0.290988
 Name: 2, dtype: float64, features      25.000000
 importance     0.322323
 Name: 4, dtype: float64, features      104.000000
 importance     0.522979
 Name: 1, dtype: float64, features      168.000000
 importance     0.384278
 Name: 4, dtype: float64, features      80.000000
 importance     0.506065
 Name: 0, dtype: float64, features      180.000000
 importance     0.437209
 Name: 1, dtype: float64, features      147.000000
 importance     0.160047
 Name: 5, dtype: float64, features      14.000000
 importance     0.360843
 Name: 0, dtype: float64, features      82.000000
 importance     0.186798
 Name: 3, dtype: float64, features      192.000000
 importance     0.359525
 Name: 0, dtype: float64, features      114.000000
 importance     0.523164
 Name: 1, dtype: float64, features      109.000000
 importance     0.270426
 Name: 3, dtype: float64, features      165.000000
 importance     0.476715
 Name: 2, dtype: float64, features      9.00000
 importance    0.30866
 Name: 1, dtype: float64, features      19.000000
 importance     0.443676
 Name: 1, dtype: float64, features      19.000000
 importance     0.443676
 Name: 1, dtype: float64, features      118.000000
 importance     0.621775
 Name: 4, dtype: float64, features      122.000000
 importance     0.995193
 Name: 3, dtype: float64, features      10.000000
 importance     0.345847
 Name: 1, dtype: float64, features      15.000000
 importance     0.505214
 Name: 1, dtype: float64, features      200.000000
 importance     0.356489
 Name: 2, dtype: float64, features      85.000000
 importance     0.484196
 Name: 0, dtype: float64, features      212.000
 importance     0.356
 Name: 1, dtype: float64, features      6.000000
 importance    0.266495
 Name: 1, dtype: float64, features      40.000000
 importance     0.333204
 Name: 4, dtype: float64, features      37.000000
 importance     0.351427
 Name: 2, dtype: float64, features      47.000000
 importance     0.541774
 Name: 0, dtype: float64, features      178.000000
 importance     0.196509
 Name: 5, dtype: float64, features      96.000000
 importance     0.476923
 Name: 2, dtype: float64, features      70.000000
 importance     0.484083
 Name: 1, dtype: float64, features      108.000
 importance     0.354
 Name: 3, dtype: float64, features      25.000
 importance     0.356
 Name: 1, dtype: float64, features      48.000000
 importance     0.683515
 Name: 1, dtype: float64, features      40.000000
 importance     0.288148
 Name: 1, dtype: float64, features      162.00000
 importance     0.81676
 Name: 1, dtype: float64, features      91.000000
 importance     0.591767
 Name: 1, dtype: float64, features      143.000000
 importance     0.510613
 Name: 1, dtype: float64, features      143.000000
 importance     0.510613
 Name: 1, dtype: float64, features      147.000000
 importance     0.445206
 Name: 1, dtype: float64, features      147.000000
 importance     0.389844
 Name: 1, dtype: float64, features      11.000000
 importance     0.357875
 Name: 0, dtype: float64, features      166.000000
 importance     0.785356
 Name: 0, dtype: float64, features      84.000000
 importance     0.374779
 Name: 0, dtype: float64, features      218.000000
 importance     0.761991
 Name: 1, dtype: float64, features      218.000000
 importance     0.761991
 Name: 1, dtype: float64, features      125.000000
 importance     0.484199
 Name: 2, dtype: float64, features      196.00000
 importance     0.57198
 Name: 1, dtype: float64, features      64.0000
 importance     0.5867
 Name: 0, dtype: float64, features      154.000000
 importance     0.805808
 Name: 0, dtype: float64, features      137.000000
 importance     0.607398
 Name: 1, dtype: float64, features      4.000000
 importance    0.332152
 Name: 2, dtype: float64, features      140.000000
 importance     0.608851
 Name: 0, dtype: float64, features      185.000000
 importance     0.788932
 Name: 1, dtype: float64, features      145.000000
 importance     0.629176
 Name: 0, dtype: float64]
```

In [64]:
```
#now make the DataFrame of important_features
important_features = pd.DataFrame(important_features)
important_features.reset_index(inplace = True,drop = True)
important_features
```

Out[64]:

	features	importance
0	23.0	0.290988
1	25.0	0.322323
2	104.0	0.522979
3	168.0	0.384278
4	80.0	0.506065
5	180.0	0.437209
6	147.0	0.160047
7	14.0	0.360843
8	82.0	0.186798
9	192.0	0.359525
10	114.0	0.523164
11	109.0	0.270426
12	165.0	0.476715
13	9.0	0.308660
14	19.0	0.443676
15	19.0	0.443676
16	118.0	0.621775
17	122.0	0.995193
18	10.0	0.345847
19	15.0	0.505214
20	200.0	0.356489
21	85.0	0.484196
22	212.0	0.356000
23	6.0	0.266495
24	40.0	0.333204
25	37.0	0.351427
26	47.0	0.541774
27	178.0	0.196509
28	96.0	0.476923
29	70.0	0.484083
30	108.0	0.354000
31	25.0	0.356000
32	48.0	0.683515
33	40.0	0.288148
34	162.0	0.816760
35	91.0	0.591767
36	143.0	0.510613
37	143.0	0.510613
38	147.0	0.445206
39	147.0	0.389844
40	11.0	0.357875
41	166.0	0.785356
42	84.0	0.374779
43	218.0	0.761991
44	218.0	0.761991
45	125.0	0.484199
46	196.0	0.571980
47	64.0	0.586700
48	154.0	0.805808
49	137.0	0.607398
50	4.0	0.332152
51	140.0	0.608851
52	185.0	0.788932
53	145.0	0.629176

We had already to know that we had 54 group then we can see here also 0 to 53 that means 54.

In [69]:
```
#feature are to be consider means important features : features selected from the important_feature

features_to_consider = set(important_features['features'])

#feature which are to be discared it means the correlated_features and feature that was accpted due to high imp

features_discarded   = set(correlated_features)  - set(features_to_consider)

#make list of features which are discarded.

features_discarded = list(features_discarded)
```

Now we have to take a new datasets because we had discared correlated features and keeping the atleat the one features from one group.

We had taken the new datasets in that we pass the x_train_unique,x_test_unique data with drop of the feature which are discareded.

In [71]:
```
x_train_grouped_uncorr = x_train_unique.drop(labels= features_discarded,axis =1)

x_train_grouped_uncorr.shape
```

Out[71]:
```
(1600, 110)
```

In [75]:
```
x_test_grouped_uncorr = x_test_unique.drop(labels= features_discarded,axis=1)

x_test_grouped_uncorr.shape
```

Out[75]:
```
(400, 110)
```

We had taken the imporant features from each group then we use these features to get the accuracy.

In [74]:
```
%%time
randomforest(x_train_grouped_uncorr,x_test_grouped_uncorr,y_train,y_test)
```

```
Accuracy :  0.955
Wall time: 9.79 s
```

Lets check the same accuracy and computing time with the original dataset for the comparision.

In [76]:
```
%%time
randomforest(x_train,x_test,y_train,y_test)
```

```
Accuracy :  0.955
Wall time: 10.7 s
```

In [78]:
```
%%time
randomforest(x_train_uncorr,x_test_uncorr,y_train,y_test)
```

```
Accuracy :  0.9575
Wall time: 9.68 s
```

Time GAIN is 9% Decrease.

In [79]:
```
(10.7-9.79)*100/9.79
```

Out[79]:
```
9.295199182839635
```

In [ ]:

In [ ]:

In [ ]: