In [46]:
```python
# Importing the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
sns.set()
```

In [47]:
```python
# Read the data that we git from the UCI Repositary and printing a few v
alues to see the data
df = pd.read_csv('Training_Dataset.csv')
df.head()
```

Out[47]:

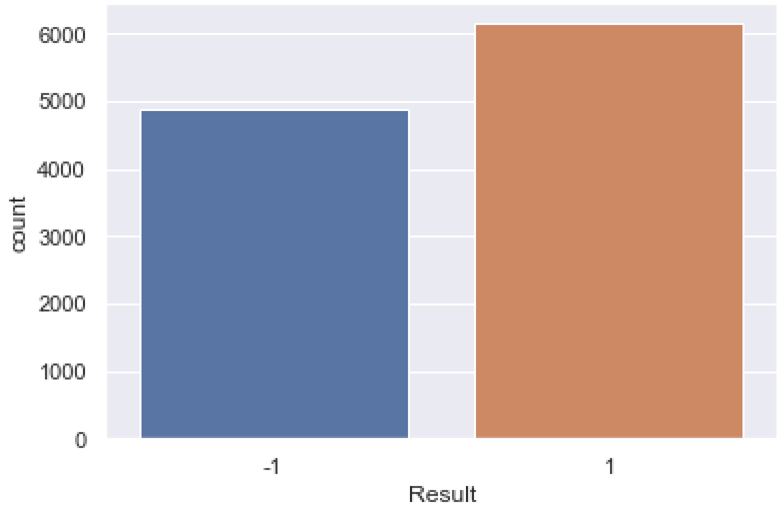
	id	having_IP_Address	URL_Length	Shortining_Service	having_At_Symbol	double_slash_redire
0	1	-1	1	1	1	
1	2	1	1	1	1	
2	3	1	0	1	1	
3	4	1	0	1	1	
4	5	1	0	-1	1	

5 rows × 32 columns

In [48]:
```python
# Counting the discting results and their counts
neg_output=len(df[df.Result==-1])
pos_output=len(df[df.Result==1])
print("Count of -1 in dataset:", neg_output)
print("Count of 1 in dataset:", pos_output)
sns.countplot(df['Result'])
```

```
Count of -1 in dataset: 4898
Count of 1 in dataset: 6157
```

Out[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff62da3bed0>
```




```
In [49]: # to see the distribution and the stats of the variables in the dataset
         df.describe()
```

Out[49]:

	id	having_IP_Address	URL_Length	Shortining_Service	having_At_Symbol	dou
count	11055.000000	11055.000000	11055.000000	11055.000000	11055.000000	
mean	5528.000000	0.313795	-0.633198	0.738761	0.700588	
std	3191.447947	0.949534	0.766095	0.673998	0.713598	
min	1.000000	-1.000000	-1.000000	-1.000000	-1.000000	
25%	2764.500000	-1.000000	-1.000000	1.000000	1.000000	
50%	5528.000000	1.000000	-1.000000	1.000000	1.000000	
75%	8291.500000	1.000000	-1.000000	1.000000	1.000000	
max	11055.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 32 columns

In [50]:
```
# to check if there are any null values
df.isnull().sum()
```

Out[50]:
```
id                             0
having_IP_Address              0
URL_Length                     0
Shortining_Service             0
having_At_Symbol               0
double_slash_redirecting       0
Prefix_Suffix                  0
having_Sub_Domain              0
SSLfinal_State                 0
Domain_registeration_length    0
Favicon                        0
port                           0
HTTPS_token                    0
Request_URL                    0
URL_of_Anchor                  0
Links_in_tags                  0
SFH                            0
Submitting_to_email            0
Abnormal_URL                   0
Redirect                       0
on_mouseover                   0
RightClick                     0
popUpWidnow                    0
Iframe                         0
age_of_domain                  0
DNSRecord                      0
web_traffic                    0
Page_Rank                      0
Google_Index                   0
Links_pointing_to_page         0
Statistical_report             0
Result                         0
dtype: int64
```

In [51]:
```
#to see the counts of unique values for all the variables
df.hist(bins=20,figsize=(20,20))
plt.show()
```

In [52]:

```
# corelation matrix with values
corr =df.corr()
corr.style.background_gradient(cmap='YlGnBu').set_precision(2)
```

Out[52]:

	id	having_IP_Address	URL_Length	Shortining_Service	having_

id	1	-0.39	0.0061	-0.0063
having_IP_Address	-0.39	1	-0.052	0.4
URL_Length	0.0061	-0.052	1	-0.098
Shortining_Service	-0.0063	0.4	-0.098	1
having_At_Symbol	-0.17	0.16	-0.075	0.1
double_slash_redirecting	-0.0034	0.4	-0.081	0.84
Prefix_Suffix	-0.0073	-0.0053	0.055	-0.08
having_Sub_Domain	0.23	-0.081	0.004	-0.042
SSLfinal_State	-0.0067	0.071	0.049	-0.061
Domain_registeration_length	-0.0012	-0.023	-0.22	0.061
Favicon	0.0073	0.087	-0.042	0.0061
port	0.0017	0.061	0.00032	0.0022
HTTPS_token	0.0029	0.36	-0.089	0.76
Request_URL	-0.00086	0.03	0.25	-0.037
URL_of_Anchor	-0.0051	0.1	-0.023	0.00056
Links_in_tags	-0.029	0.0062	0.053	-0.13
SFH	0.085	-0.011	0.41	-0.023
Submitting_to_email	0.0058	0.078	-0.014	0.049
Abnormal_URL	0.0032	0.34	-0.11	0.74
Redirect	0.017	-0.32	0.047	-0.53
on_mouseover	0.0036	0.084	-0.045	0.062
RightClick	-0.0053	0.043	-0.014	0.038
popUpWidnow	0.0065	0.097	-0.049	0.037
Iframe	0.0025	0.055	-0.014	0.017
age_of_domain	0.12	-0.01	0.18	-0.053
DNSRecord	0.4	-0.051	-0.041	0.44
web_traffic	-0.015	0.0029	0.009	-0.047
Page_Rank	0.065	-0.092	0.18	0.015
Google_Index	-0.013	0.029	0.0029	0.16
Links_pointing_to_page	0.0024	-0.34	-0.023	-0.2
Statistical_report	0.16	-0.019	-0.067	0.085

Result	0.00098	0.094	0.057	-0.068	

In [53]:
```
# Trying to implement logistic regression from scratch
```

In [54]:
```
#Choosing only a few variables which are more related to the Result valu
e
x = df[['Prefix_Suffix','having_Sub_Domain','SSLfinal_State','web_traffi
c','Page_Rank','age_of_domain']]
y = df['Result']
```

In [55]:
```
# defining the sigmoid function whose output lies between 0 and 1 and ba
sed on which the output value is predicted
def sigmoid(input):
    output = 1 / (1 + np.exp(-input))
    return output
```

In [56]:
```
# to intialize the optimization function
def optimize(x, y,learning_rate,iterations,parameters):
    size = x.shape[0]
    weight = parameters["weight"]
    bias = parameters["bias"]
    for i in range(iterations):
        sigma = sigmoid(np.dot(x, weight) + bias)
        loss = -1/size * np.sum(y * np.log(sigma)) + (1 - y) * np.log(1-
sigma)
        dW = 1/size * np.dot(x.T, (sigma - y))
        db = 1/size * np.sum(sigma - y)
        weight -= learning_rate * dW
        bias -= learning_rate * db
    parameters["weight"] = weight
    parameters["bias"] = bias
    return parameters
```

In [57]:
```
# Initialize the parameters
init_parameters = {}
init_parameters["weight"] = np.zeros(x.shape[1])
init_parameters["bias"] = 0
```

In [58]:
```
# defining a training function
def train(x, y, learning_rate,iterations):
    parameters_out = optimize(x, y, learning_rate, iterations ,init_para
```

```
meters)
    return parameters_out
```

In [59]:
```
parameters_out = train(x, y, learning_rate = 0.02, iterations = 100)
parameters_out
```

Out[59]:
```
{'weight': array([0.7559238 , 0.34468434, 0.93349031, 0.31416192, 0.3725
6392,
        0.14226714]), 'bias': -0.55990882387332}
```

In [71]:
```
# predicting the values and adding it to the dataset to calculate the pa
rameters
output_values = np.dot(x,parameters_out['weight']) + parameters_out['bia
s']
predictions = sigmoid(output_values) >= 0.25
df['y_pred'] = predictions
```

In [72]:
```
# to convert the boolean variables to -1 and 1
df['y_pred'] = df['y_pred']*1
df['y_pred'].replace({0: -1}, inplace=True)
df.head()
```

Out[72]:

	id	having_IP_Address	URL_Length	Shortining_Service	having_At_Symbol	double_slash_redire
0	1	-1	1	1	1	
1	2	1	1	1	1	
2	3	1	0	1	1	
3	4	1	0	1	1	
4	5	1	0	-1	1	

5 rows × 33 columns

In [73]:
```
print("Accuracy for Logistic Regression (LREG without library): Test Dat
a",metrics.accuracy_score(df['Result'],df['y_pred'])*100)
```

```
Accuracy for Logistic Regression (LREG without library): Test Data 88.34
916327453641
```

In [18]:
```
lg_cm = confusion_matrix(df['Result'],df['y_pred'])
tp_lg ,fp_lg , fn_lg , tn_lg = lg_cm.ravel()
precision_lg = (tp_lg)/(tp_lg+fp_lg)
recall_lg = (tp_lg)/(tp_lg+fn_lg)
```

```
recall_lg = (tp_lg)/(tp_lg+fn_lg)
specificity_lg = (tn_lg)/(tn_lg+fp_lg)
f1_score_lg = (2*recall_lg*precision_lg)/(precision_lg+recall_lg)
print("Precision for test data is (LREG without library): " , precision_lg * 100)
print("Recall for test data is (LREG without library): " , recall_lg * 100)
print("Specificity for test data is (LREG without library): " , specificity_lg * 100)
print("F-Score for test data is (LREG without library): " , f1_score_lg*100)
```

```
Precision for test data is (LREG without library):  85.6267864434463
Recall for test data is (LREG without library):  87.77731268313102
Specificity for test data is (LREG without library):  88.78445117094154
F-Score for test data is (LREG without library):  86.68871434477056
```

In [19]:
```
# Using the sklearn library
```

In [74]:
```
# Read the data that we git from the UCI Repositary and printing a few values to see the data
df = pd.read_csv('Training_Dataset.csv')
df.head()
```

Out[74]:

	id	having_IP_Address	URL_Length	Shortining_Service	having_At_Symbol	double_slash_redire
0	1	-1	1	1	1	
1	2	1	1	1	1	
2	3	1	0	1	1	
3	4	1	0	1	1	
4	5	1	0	-1	1	

5 rows × 32 columns

In [78]:
```
# diving the features and target variables. Considering all the variables as features
x = df.drop(['Result', 'id'], axis = 1)
y = df['Result']
```

In [79]:
```
#Dividing the dataset into train and test datasets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=365)
x_train.shape
```

Out[79]: (8844, 30)

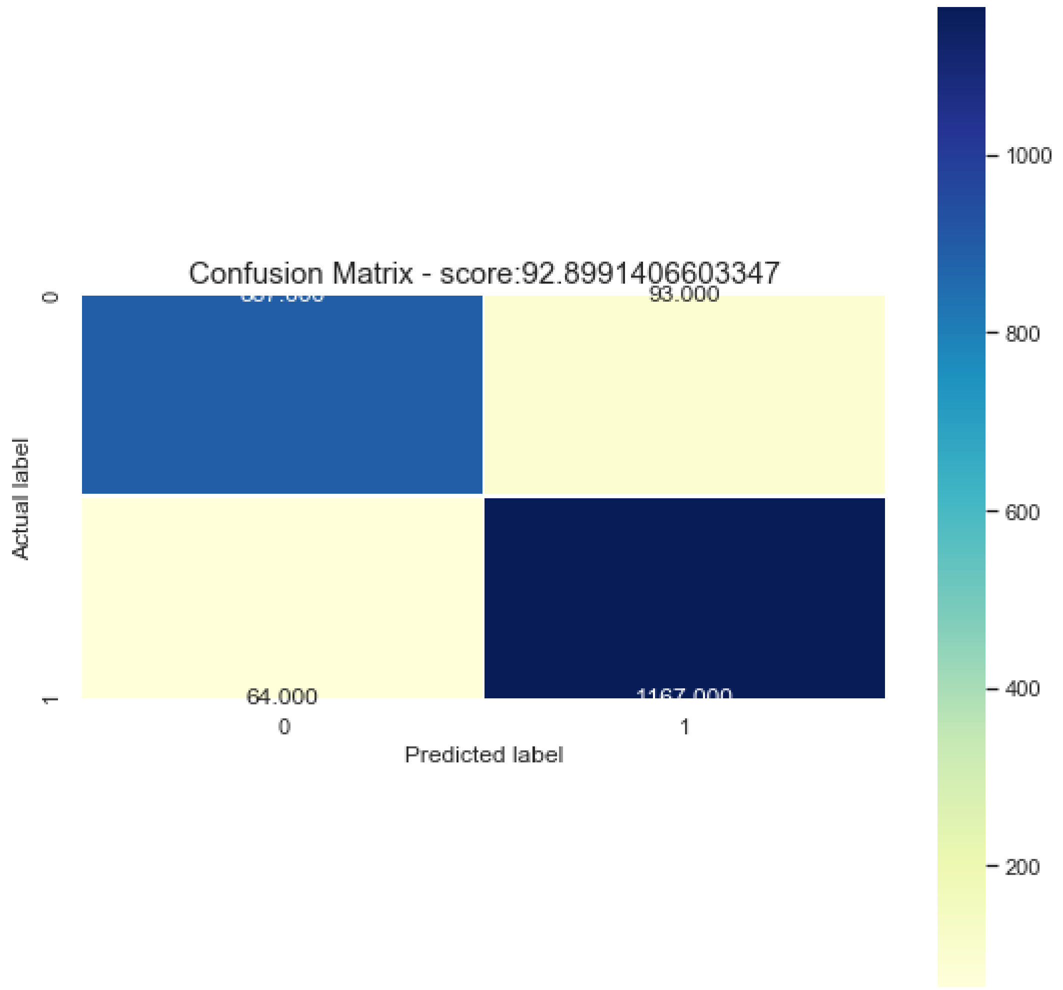
In [80]:
```
# Logistic Regression
lg = LogisticRegression(solver = 'lbfgs',max_iter =300)
lg = lg.fit(x_train,y_train)
y_train_pred = lg.predict(x_train)
y_test_pred = lg.predict(x_test)
print("Accuracy for Logistic Regression : Training data",metrics.accurac
y_score(y_train, y_train_pred)*100)
print("Accuracy for Logistic Regression: Test Data",metrics.accuracy_sco
re(y_test, y_test_pred)*100)
```

```
Accuracy for Logistic Regression : Training data 92.75214834916328
Accuracy for Logistic Regression: Test Data 92.8991406603347
```

In [81]:
```
lg_cm = confusion_matrix(y_test_pred , y_test)
tp_lg ,fp_lg , fn_lg , tn_lg = lg_cm.ravel()
precision_lg = (tp_lg)/(tp_lg+fp_lg)
recall_lg = (tp_lg)/(tp_lg+fn_lg)
specificity_lg = (tn_lg)/(tn_lg+fp_lg)
f1_score_lg = (2*recall_lg*precision_lg)/(precision_lg+recall_lg)
print("Precision for test data is: " , precision_lg * 100)
print("Recall for test data is: " , recall_lg * 100)
print("Specificity for test data is: " , specificity_lg * 100)
print("F-Score for test data is: " , f1_score_lg*100)
```

```
Precision for test data is:  93.27024185068349
Recall for test data is:  90.51020408163265
Specificity for test data is:  94.80097481722177
F-Score for test data is:  91.86949766960124
```

In [82]:
```
# Confusion matrix
cm = confusion_matrix(y_test, y_test_pred)
plt.figure(figsize=(9,9))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cma
p = 'YlGnBu');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Confusion Matrix - score:'+str(metrics.accuracy_scor
e(y_test,y_test_pred)*100)
plt.title(all_sample_title, size = 15);
plt.show()
print(metrics.classification_report(y_test,y_test_pred))
```



	precision	recall	f1-score	support
-1	0.93	0.91	0.92	980

```
           1       0.93      0.95      0.94      1231

    accuracy                           0.93      2211
   macro avg       0.93      0.93      0.93      2211
weighted avg       0.93      0.93      0.93      2211
```

In [83]:
```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators = 10)
rfc=rfc.fit(x_train,y_train.ravel())
y_train_pred = rfc.predict(x_train)
y_test_pred = rfc.predict(x_test)
print("Accuracy for Random Forest : Training data",metrics.accuracy_scor
e(y_train, y_train_pred)*100)
print("Accuracy for Random Forest: Test Data",metrics.accuracy_score(y_t
est, y_test_pred)*100)
```

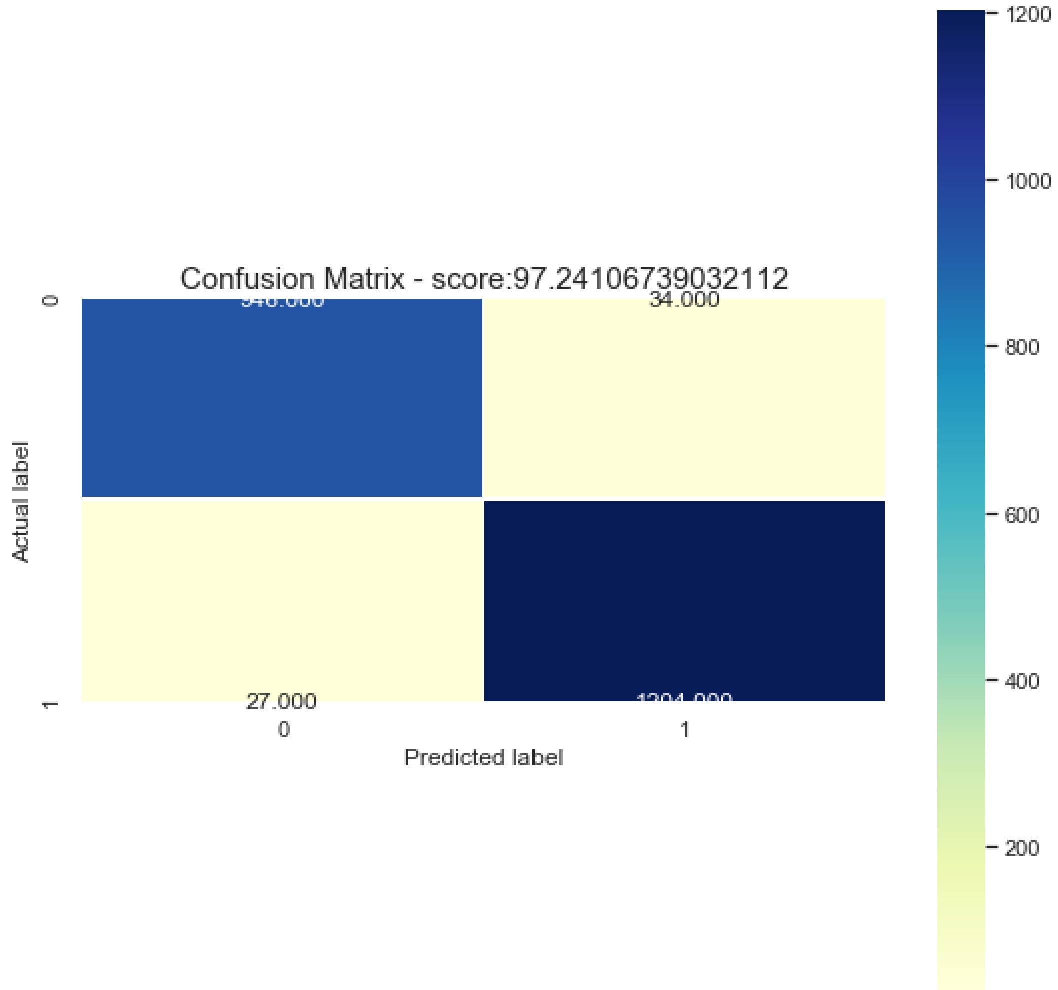
```
Accuracy for Random Forest : Training data 98.86928991406604
Accuracy for Random Forest: Test Data 97.24106739032112
```

In [84]:
```
rfc_cm = confusion_matrix(y_test_pred , y_test)
tp_rfc ,fp_rfc , fn_rfc , tn_rfc = rfc_cm.ravel()
precision_rfc = (tp_rfc)/(tp_rfc+fp_rfc)
recall_rfc = (tp_rfc)/(tp_rfc+fn_rfc)
specificity_rfc = (tn_rfc)/(tn_rfc+fp_rfc)
f1_score_rfc = (2*recall_rfc*precision_rfc)/(precision_rfc+recall_rfc)
print("Precision for test data is: " , precision_rfc * 100)
print("Recall for test data is: " , recall_rfc * 100)
print("Specificity for test data is: " , specificity_rfc * 100)
print("F-Score for test data is: " , f1_score_rfc*100)
```

```
Precision for test data is:  97.2250770811922
Recall for test data is:  96.53061224489797
Specificity for test data is:  97.80666125101544
F-Score for test data is:  96.87660010240656
```

In [85]:
```
# Confusion matrix
cm = confusion_matrix(y_test, y_test_pred)
plt.figure(figsize=(9,9))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cma
p = 'YlGnBu');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Confusion Matrix - score:'+str(metrics.accuracy_scor
e(y_test,y_test_pred)*100)
plt.title(all_sample_title, size = 15);
```

```
plt.show()
print(metrics.classification_report(y_test,y_test_pred))
```




```
             precision    recall  f1-score   support

         -1       0.97      0.97      0.97       980
```

```
           1       0.97      0.98      0.98      1231

    accuracy                           0.97      2211
   macro avg       0.97      0.97      0.97      2211
weighted avg       0.97      0.97      0.97      2211
```

In [86]:
```python
from sklearn.tree import DecisionTreeClassifier
dtree=DecisionTreeClassifier()
dtree=dtree.fit(x_train,y_train.ravel())
y_train_pred = dtree.predict(x_train)
y_test_pred = dtree.predict(x_test)
print("Accuracy for Decision Tree Classifier: Training data",metrics.acc
uracy_score(y_train, y_train_pred)*100)
print("Accuracy for Decision Tree Classifier: Test Data",metrics.accurac
y_score(y_test, y_test_pred)*100)
```

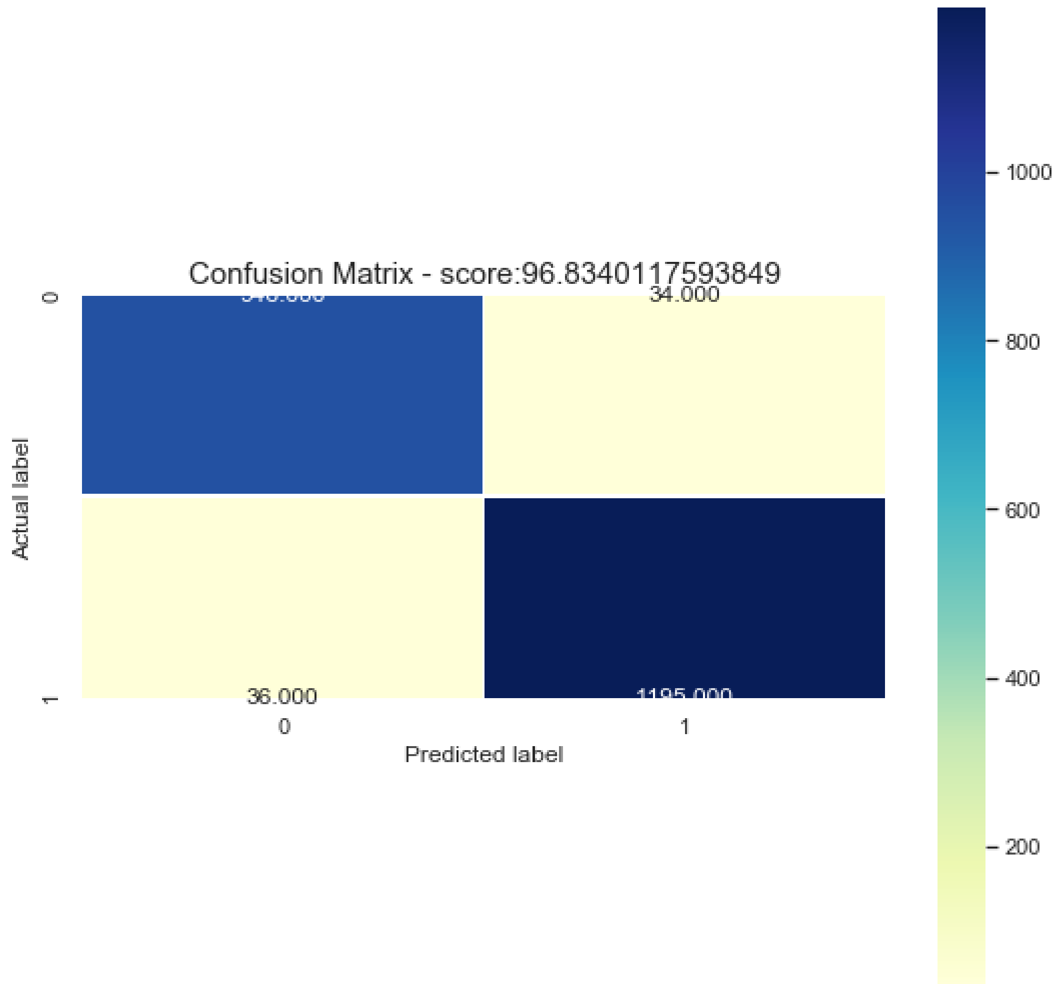
```
Accuracy for Decision Tree Classifier: Training data 98.98236092265942
Accuracy for Decision Tree Classifier: Test Data 96.8340117593849
```

In [87]:
```python
dtree_cm = confusion_matrix(y_test_pred , y_test)
tp_d ,fp_d , fn_d , tn_d = dtree_cm.ravel()
precision_d = (tp_d)/(tp_d+fp_d)
recall_d = (tp_d)/(tp_d+fn_d)
specificity_d = (tn_d)/(tn_d+fp_d)
f1_score_d = (2*recall_d*precision_d)/(precision_d+recall_d)
print("Precision for test data is: " , precision_d * 100)
print("Recall for test data is: " , recall_d * 100)
print("Specificity for test data is: " , specificity_d * 100)
print("F-Score for test data is: " , f1_score_d*100)
```

```
Precision for test data is:  96.33401221995926
Recall for test data is:  96.53061224489797
Specificity for test data is:  97.07554833468724
F-Score for test data is:  96.43221202854231
```

In [88]:
```python
# Confusion matrix
cm = confusion_matrix(y_test, y_test_pred)
plt.figure(figsize=(9,9))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cma
p = 'YlGnBu');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Confusion Matrix - score:'+str(metrics.accuracy_scor
e(y_test,y_test_pred)*100)
```

```
plt.title(all_sample_title, size = 15);
plt.show()
print(metrics.classification_report(y_test,y_test_pred))
```




```
              precision    recall  f1-score   support
```

```
          -1       0.96      0.97      0.96       980
           1       0.97      0.97      0.97      1231

    accuracy                           0.97      2211
   macro avg       0.97      0.97      0.97      2211
weighted avg       0.97      0.97      0.97      2211
```

In [89]:

```python
# Implement k-nearest-neighbors classifcation on dataset
from sklearn.neighbors import KNeighborsClassifier

neigh = KNeighborsClassifier(n_neighbors=5)
neigh.fit(x_train, y_train)
```

Out[89]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=
2,
                     weights='uniform')
```

In [90]:

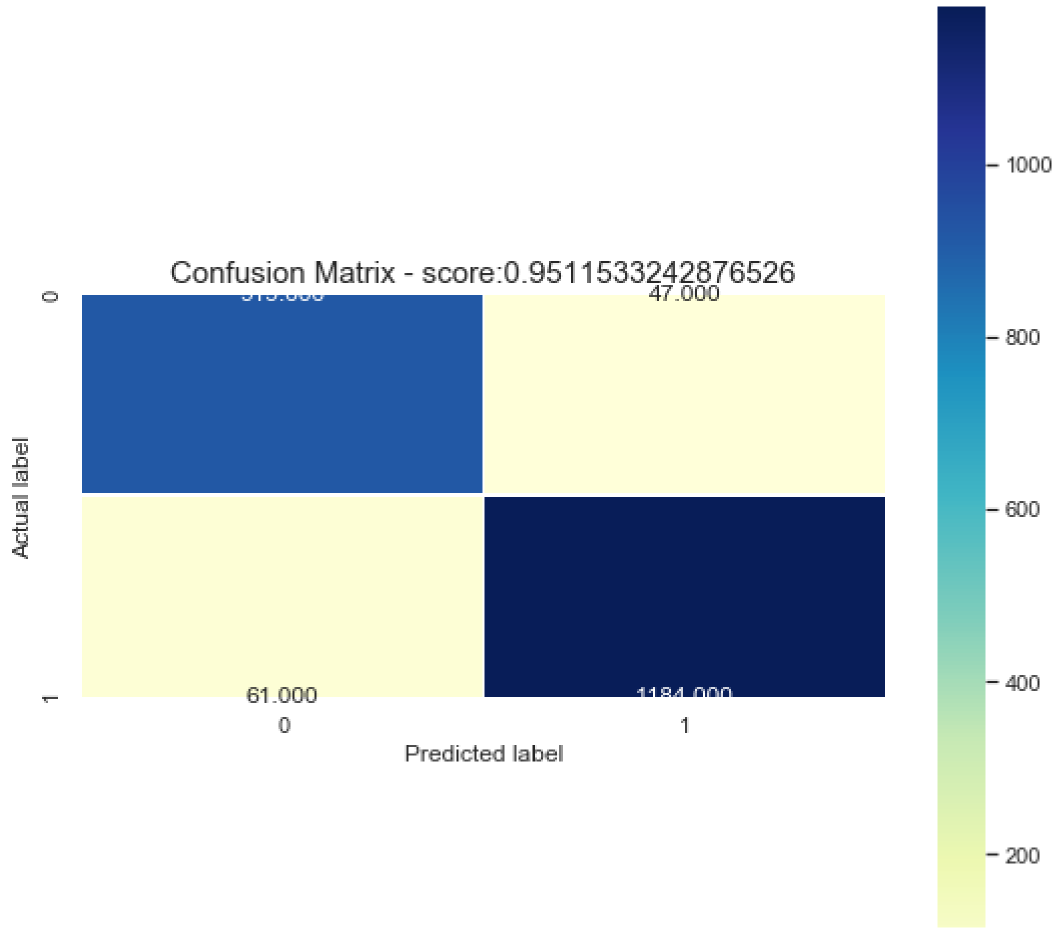
```python
# Accuracy scores for training and test sets
score_train = neigh.score(x_train, y_train)
score_test = neigh.score(x_test, y_test)
print("Training accuracy: ", score_train*100)
print("Testing accuracy: ", score_test*100)
```

```
Training accuracy:  96.56264133876074
Testing accuracy:  95.11533242876527
```

In [91]:

```python
# Confusion matrix for test data
y_test_pred = neigh.predict(x_test)

from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
neigh_cm = confusion_matrix(y_test_pred, y_test)
plt.figure(figsize=(9,9))
sns.heatmap(neigh_cm, annot=True, fmt=".3f", linewidths=.5, square = Tru
e, cmap = 'YlGnBu');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Confusion Matrix - score:'+str(metrics.accuracy_scor
e(y_test,y_test_pred))
plt.title(all_sample_title, size = 15);
plt.show()
print(metrics.classification_report(y_test,y_test_pred))
```


Confusion Matrix - score:0.9511533242876526
47.000
61.000
0
1
Actual label
0
1
Predicted label
1000
800
600
400
200

```
              precision    recall  f1-score   support

          -1       0.95      0.94      0.94       980
           1       0.95      0.96      0.96      1231

    accuracy                           0.95      2211
   macro avg       0.95      0.95      0.95      2211
weighted avg       0.95      0.95      0.95      2211
```

In [92]:

```python
tp_neigh ,fp_neigh , fn_neigh , tn_neigh = neigh_cm.ravel()
precision_neigh = (tp_neigh)/(tp_neigh+fp_neigh)
recall_neigh = (tp_neigh)/(tp_neigh+fn_neigh)
specificity_neigh = (tn_neigh)/(tn_neigh+fp_neigh)
f1_score_neigh = (2*recall_neigh*precision_neigh)/(precision_neigh+recal
l_neigh)
print("Precision for test data is: " , precision_neigh * 100)
print("Recall for test data is: " , recall_neigh * 100)
print("Specificity for test data is: " , specificity_neigh * 100)
print("F-Score for test data is: " , f1_score_neigh*100)
```

```
Precision for test data is:  95.13457556935818
Recall for test data is:  93.77551020408164
Specificity for test data is:  96.18196588139723
F-Score for test data is:  94.45015416238438
```

In [93]:

```python
# k-nearest-neighbors with default parameters (n=3)
neigh_def = KNeighborsClassifier(n_neighbors=3)
neigh_def.fit(x_train, y_train)

train_acc = neigh_def.score(x_train, y_train)
test_acc = neigh_def.score(x_test, y_test)
print("Training accuracy: ", train_acc*100)
print("Testing accuracy: ", test_acc*100)
```

```
Training accuracy:  97.60289461781998
Testing accuracy:  95.38670284938942
```

In [94]:

```python
# k-nearest-neighbors with n=10
neigh_alt = KNeighborsClassifier(n_neighbors=10)
neigh_alt.fit(x_train, y_train)

train_acc = neigh_alt.score(x_train, y_train)
```

```
test_acc = neigh_alt.score(x_test, y_test)
print("Training accuracy: ", train_acc*100)
print("Testing accuracy: ", test_acc*100)
```

```
Training accuracy:  95.01356852103122
Testing accuracy:  94.5273631840796
```

In [95]:

```
# k-nearest-neighbors with n=1
neigh_alt = KNeighborsClassifier(n_neighbors=1)
neigh_alt.fit(x_train, y_train)

train_acc = neigh_alt.score(x_train, y_train)
test_acc = neigh_alt.score(x_test, y_test)
print("Training accuracy: ", train_acc*100)
print("Testing accuracy: ", test_acc*100)
```

```
Training accuracy:  98.79014020805066
Testing accuracy:  95.88421528720036
```

In [ ]:

```

```