ex16

January 8, 2024

[22]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
# sns.set_style("darkgrid", {"grid.color": ".6",
#                             "grid.linestyle": ":"})

from sklearn.preprocessing import StandardScaler , MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
import seaborn as sns
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier

# from xgboost import XGBClassifier
# from sklearn.metrics import r2_score
# from sklearn.metrics import mean_squared_error
# from sklearn.model_selection import GridSearchCV
```

[2]:

```
df = pd.read_csv('/Users/thutranghoa/Code/Data_analysis/Data/Breast Cancer␣
 ↪Wisconsin (Diagnostic) Data Set.csv')
df
```

[2]:

```
           id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0      842302         M        17.99         10.38          122.80     1001.0
1      842517         M        20.57         17.77          132.90     1326.0
2    84300903         M        19.69         21.25          130.00     1203.0
3    84348301         M        11.42         20.38           77.58      386.1
4    84358402         M        20.29         14.34          135.10     1297.0
..        …       …          …            …               …          …
564    926424         M        21.56         22.39          142.00     1479.0
```

```
565    926682         M         20.13         28.25          131.20     1261.0
566    926954         M         16.60         28.08          108.30      858.1
567    927241         M         20.60         29.33          140.10     1265.0
568     92751         B          7.76         24.54           47.92      181.0

     smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0            0.11840           0.27760         0.30010              0.14710   
1            0.08474           0.07864         0.08690              0.07017   
2            0.10960           0.15990         0.19740              0.12790   
3            0.14250           0.28390         0.24140              0.10520   
4            0.10030           0.13280         0.19800              0.10430   
..                 …               …             …                  …   
564          0.11100           0.11590         0.24390              0.13890   
565          0.09780           0.10340         0.14400              0.09791   
566          0.08455           0.10230         0.09251              0.05302   
567          0.11780           0.27700         0.35140              0.15200   
568          0.05263           0.04362         0.00000              0.00000   

     …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0    …          17.33           184.60      2019.0           0.16220   
1    …          23.41           158.80      1956.0           0.12380   
2    …          25.53           152.50      1709.0           0.14440   
3    …          26.50            98.87       567.7           0.20980   
4    …          16.67           152.20      1575.0           0.13740   
..   …            …               …          …               …   
564  …          26.40           166.10      2027.0           0.14100   
565  …          38.25           155.00      1731.0           0.11660   
566  …          34.12           126.70      1124.0           0.11390   
567  …          39.42           184.60      1821.0           0.16500   
568  …          30.37            59.16       268.6           0.08996   

     compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0              0.66560           0.7119                0.2654          0.4601   
1              0.18660           0.2416                0.1860          0.2750   
2              0.42450           0.4504                0.2430          0.3613   
3              0.86630           0.6869                0.2575          0.6638   
4              0.20500           0.4000                0.1625          0.2364   
..                 …              …                   …              …   
564            0.21130           0.4107                0.2216          0.2060   
565            0.19220           0.3215                0.1628          0.2572   
566            0.30940           0.3403                0.1418          0.2218   
567            0.86810           0.9387                0.2650          0.4087   
568            0.06444           0.0000                0.0000          0.2871   

     fractal_dimension_worst  Unnamed: 32  
0                    0.11890          NaN  
1                    0.08902          NaN  
```

```
2                    0.08758          NaN
3                    0.17300          NaN
4                    0.07678          NaN
..                       …          …
564                  0.07115          NaN
565                  0.06637          NaN
566                  0.07820          NaN
567                  0.12400          NaN
568                  0.07039          NaN

[569 rows x 33 columns]
```

[12]:

```
df = df.drop(['Unnamed: 32'], axis=1)
```

[18]:

```
df['diagnosis'] = df['diagnosis'].map({'M': 1, 'B': 0})
```

[15]:

```
df.shape
```

[15]:

```
(569, 32)
```

[19]:

```
df.describe()
```

[19]:

```
                 id   diagnosis  radius_mean  texture_mean  perimeter_mean  \
count  5.690000e+02  569.000000   569.000000    569.000000      569.000000
mean   3.037183e+07    0.372583    14.127292     19.289649       91.969033
std    1.250206e+08    0.483918     3.524049      4.301036       24.298981
min    8.670000e+03    0.000000     6.981000      9.710000       43.790000
25%    8.692180e+05    0.000000    11.700000     16.170000       75.170000
50%    9.060240e+05    0.000000    13.370000     18.840000       86.240000
75%    8.813129e+06    1.000000    15.780000     21.800000      104.100000
max    9.113205e+08    1.000000    28.110000     39.280000      188.500000

         area_mean  smoothness_mean  compactness_mean  concavity_mean  \
count   569.000000       569.000000        569.000000      569.000000
mean    654.889104         0.096360          0.104341        0.088799
std     351.914129         0.014064          0.052813        0.079720
min     143.500000         0.052630          0.019380        0.000000
25%     420.300000         0.086370          0.064920        0.029560
50%     551.100000         0.095870          0.092630        0.061540
75%     782.700000         0.105300          0.130400        0.130700
max    2501.000000         0.163400          0.345400        0.426800

       concave points_mean  …  radius_worst  texture_worst  perimeter_worst  \
count           569.000000  …    569.000000     569.000000       569.000000
mean              0.048919  …     16.269190      25.677223       107.261213
std               0.038803  …      4.833242       6.146258        33.602542
min               0.000000  …      7.930000      12.020000        50.410000
```

```
25%            0.020310  …    13.010000     21.080000      84.110000
50%            0.033500  …    14.970000     25.410000      97.660000
75%            0.074000  …    18.790000     29.720000     125.400000
max            0.201200  …    36.040000     49.540000     251.200000

        area_worst  smoothness_worst  compactness_worst  concavity_worst  \
count   569.000000        569.000000         569.000000       569.000000
mean    880.583128          0.132369           0.254265         0.272188
std     569.356993          0.022832           0.157336         0.208624
min     185.200000          0.071170           0.027290         0.000000
25%     515.300000          0.116600           0.147200         0.114500
50%     686.500000          0.131300           0.211900         0.226700
75%    1084.000000          0.146000           0.339100         0.382900
max    4254.000000          0.222600           1.058000         1.252000

       concave points_worst  symmetry_worst  fractal_dimension_worst
count            569.000000      569.000000               569.000000
mean               0.114606        0.290076                 0.083946
std                0.065732        0.061867                 0.018061
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
50%                0.099930        0.282200                 0.080040
75%                0.161400        0.317900                 0.092080
max                0.291000        0.663800                 0.207500

[8 rows x 32 columns]
```

[20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    int64
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(2)
memory usage: 142.4 KB
```

[43]:

```
df.columns
```

[43]:

```
Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst'],
      dtype='object')
```

0.1 What are they ?

This dataset includes features about diagnosis of breast cancer. For details :

- ID : Patient identifier

- Diagnosis : indicates whether the tumor is Benign (B) or malignant (M) –> Output

** Data about physical dimensions of tumor (each is calculated 3 values : Mean, Worst and SE) -
Radius : the size of the tumor
- Texture : a measures of the tumor's surface smoothness
- Perimeter : linked to the size and growth rate of the tumor
- Area : Larger tumor areas are seen in advanced stages of breast cancer

** Data about tumor texture and composition (each is calculated 3 values : Mean, Worst and SE)
- Smoothness : variations in the tumor surface
- Compactness : correlate with denser, potentially cancerous
- Concavity : sign of malignancy
- Concavity points : increased number of concave points -> malignant tumor

** Others - Symmetry : asymmetrical tumors are more likely to be cancerous.
- Fractal dimension : higher values indicate more complex, malignant

0.2 Why are they chosen ?

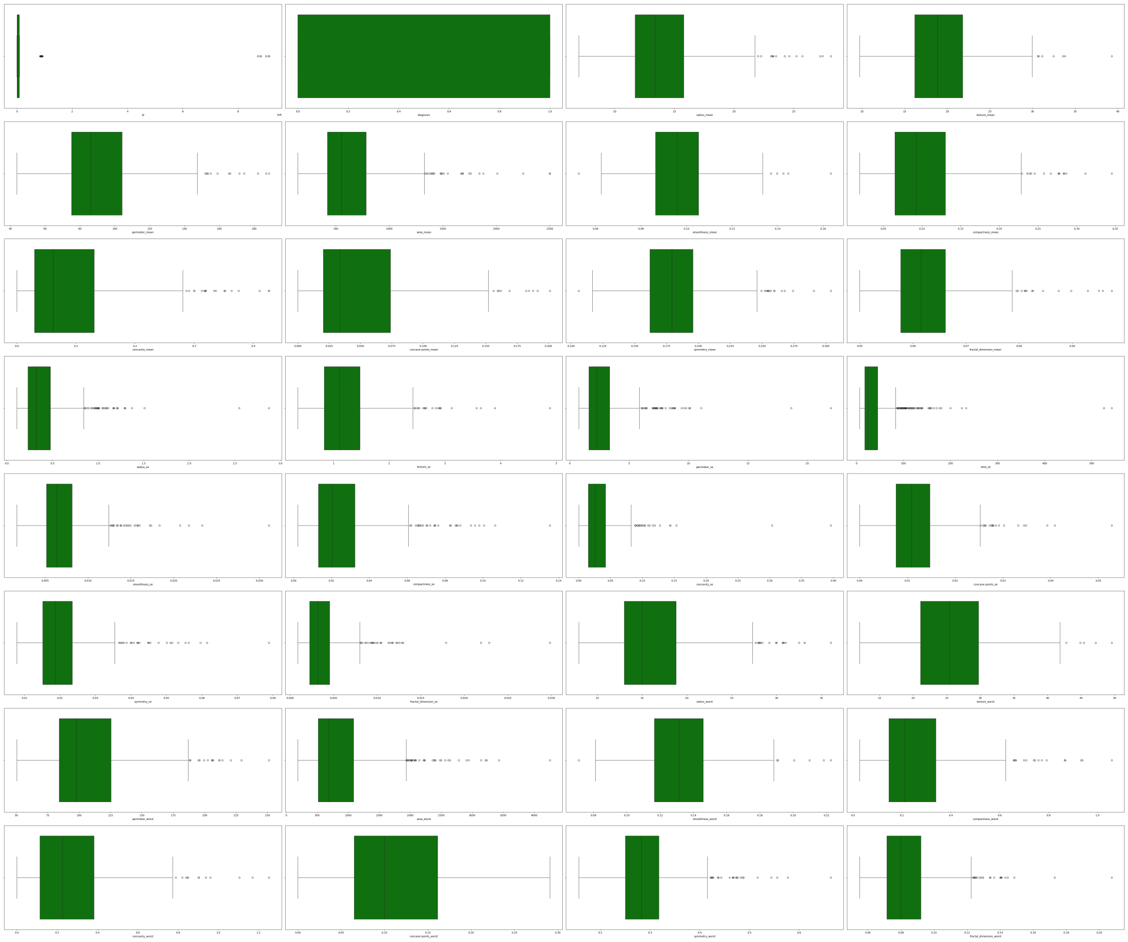
- Because these features provide a detailed profile of the tumor, for accurate diagnosis and treatment planning

- Features like radius, perimeter and area are related to physiscal size of tumor, important for staging the cancer

- Texture, smoothness and compactness offer insights into tumor;s cell structure, allow determining the type of cancer (B or M)

In conclusion, having and understanding features are essential for effective breast cancer management.

[21]:
```
' Box plot '
fig = plt.figure(figsize=(60, 50))
temp = df.columns.tolist()
for i, item in enumerate(temp):
    plt.subplot(8, 4, i+1)
    sns.boxplot(data=df, x=item, color='green')
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=2.0)
plt.show()
```



[23]:
```
scaler = MinMaxScaler()
columns = df.columns
df = pd.DataFrame(scaler.fit_transform(df))
df.columns = columns
df.head()
```

[23]:
```
         id  diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0  0.000915        1.0     0.521037      0.022658        0.545989   0.363733
1  0.000915        1.0     0.643144      0.272574        0.615783   0.501591
2  0.092495        1.0     0.601496      0.390260        0.595743   0.449417
3  0.092547        1.0     0.210090      0.360839        0.233501   0.102906
4  0.092559        1.0     0.629893      0.156578        0.630986   0.489290

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0         0.593753          0.792037        0.703140             0.731113
1         0.289880          0.181768        0.203608             0.348757
2         0.514309          0.431017        0.462512             0.635686
3         0.811321          0.811361        0.565604             0.522863
```

```
4         0.430351          0.347893        0.463918             0.518390

   …  radius_worst  texture_worst  perimeter_worst  area_worst  \
0  …      0.620776       0.141525         0.668310    0.450698
1  …      0.606901       0.303571         0.539818    0.435214
2  …      0.556386       0.360075         0.508442    0.374508
3  …      0.248310       0.385928         0.241347    0.094008
4  …      0.519744       0.123934         0.506948    0.341575

   smoothness_worst  compactness_worst  concavity_worst  concave points_worst  \
0          0.601136           0.619292         0.568610              0.912027
1          0.347553           0.154563         0.192971              0.639175
2          0.483590           0.385375         0.359744              0.835052
3          0.915472           0.814012         0.548642              0.884880
4          0.437364           0.172415         0.319489              0.558419

   symmetry_worst  fractal_dimension_worst
0        0.598462                 0.418864
1        0.233590                 0.222878
2        0.403706                 0.213433
3        1.000000                 0.773711
4        0.157500                 0.142595

[5 rows x 32 columns]
```

[26]:

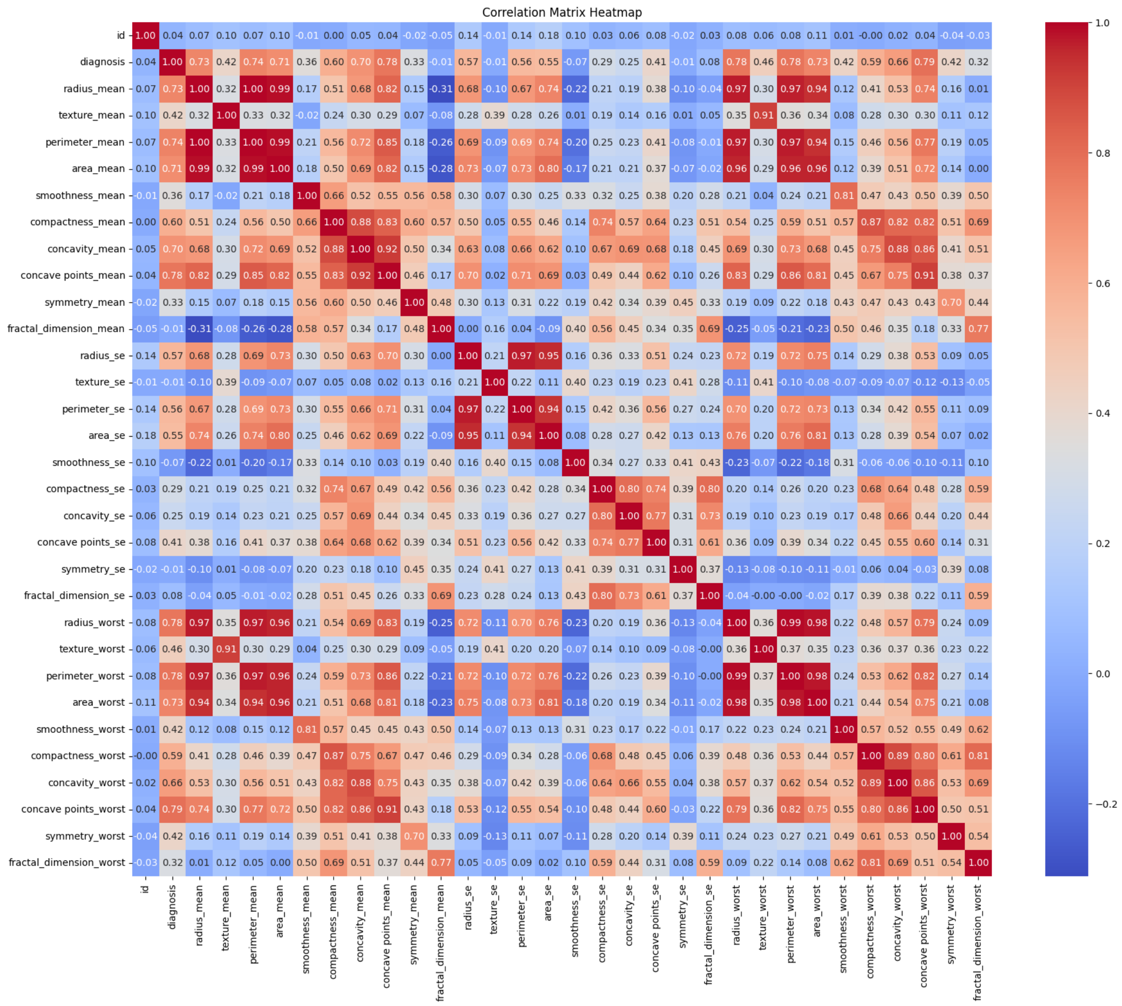
```
' Heat map'
corr_matrix = df.corr()

# Set up the matplotlib figure
plt.figure(figsize=(20, 16))

# Draw the heatmap
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm')

# Add title
plt.title('Correlation Matrix Heatmap')

# Show the plot
plt.show()
```



[27]:

```
X = df.drop('diagnosis', axis=1)
y = df['diagnosis']
```

[28]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
  ↪random_state=42, stratify = y)
```

[29]:

```
'Model '

rf=RandomForestClassifier()
dt=DecisionTreeClassifier()
lr=LogisticRegression()
```

[30]:

```
'RF '
print ('Random Forest model : ')
rf.fit(X_train,y_train)
y_pred_rf=rf.predict(X_test)
```

```
print ('Train : ', accuracy_score(y_train,rf.predict(X_train)))
print ('Test : ', accuracy_score(y_test,y_pred_rf))
```

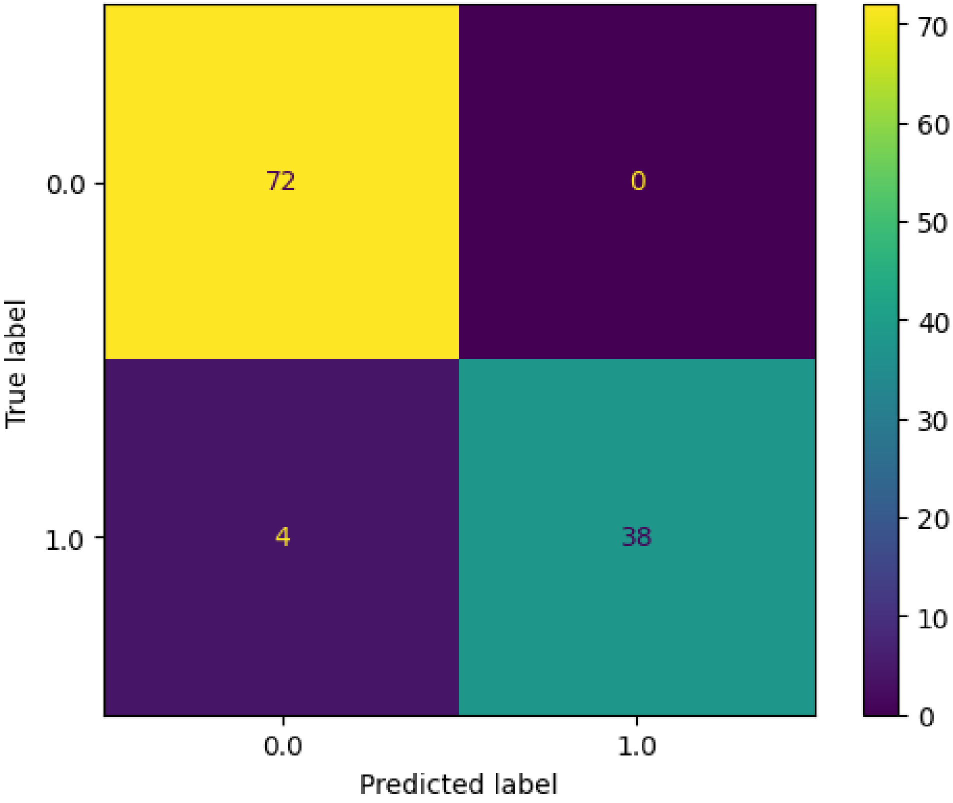
```
Random Forest model :
Train :  1.0
Test :  0.9649122807017544
```

[31]:

```
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix,␣
 ↪classification_report

disp = ConfusionMatrixDisplay.from_predictions(y_test, y_pred_rf)

plt.show()
```



[32]:

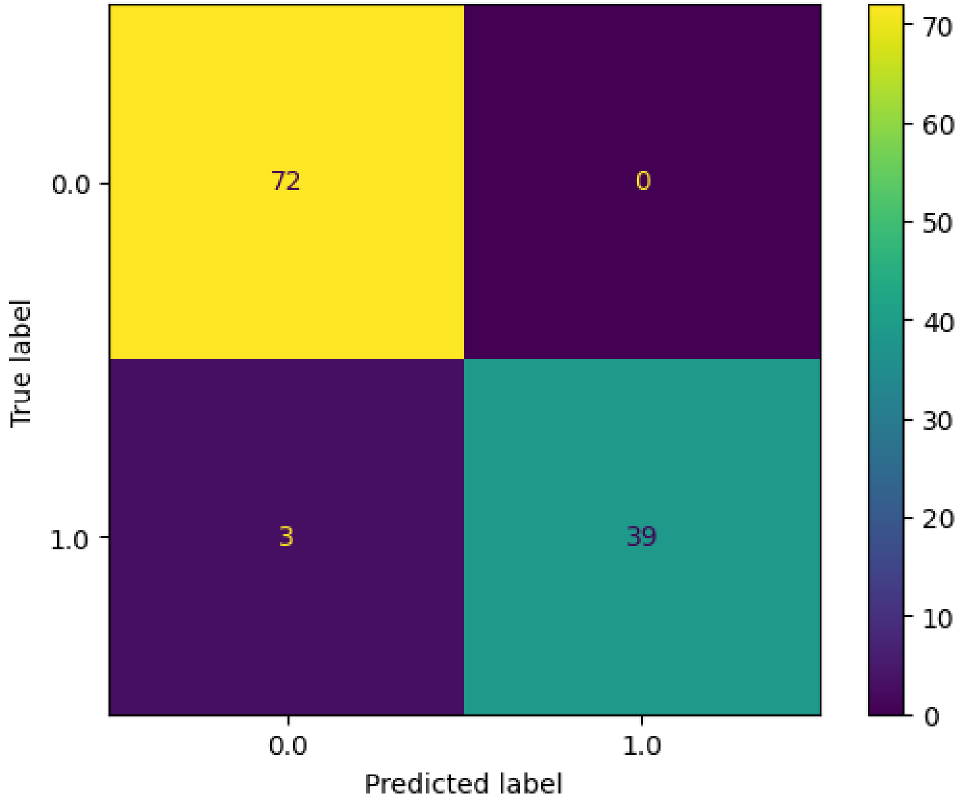
```
'Logistic '
print ('Logistic regression model : ')
lr.fit(X_train,y_train)
y_pred_lr=lr.predict(X_test)
print ('Train : ', accuracy_score(y_train,lr.predict(X_train)))
print ('Test : ', accuracy_score(y_test,y_pred_lr))
```

```
Logistic regression model :
```

```
Train :  0.9692307692307692
Test :  0.9736842105263158
```

[33]:
```
disp = ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lr)

plt.show()
```

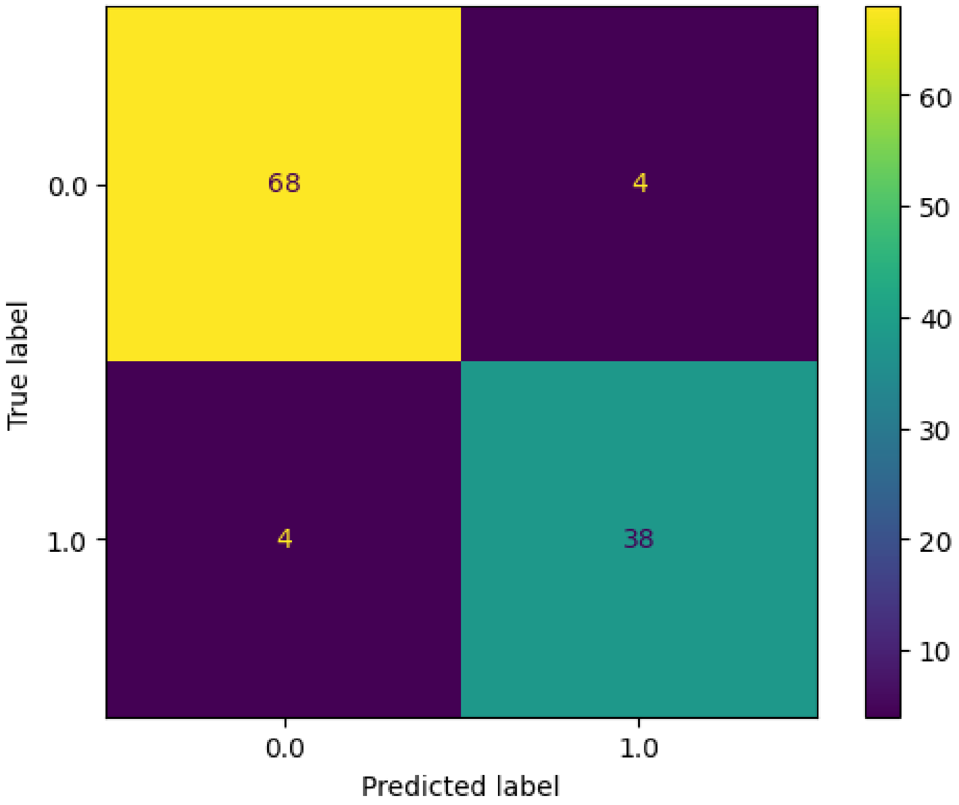


[34]:
```
'DT '
print ('Decision Tree model : ')
dt.fit(X_train,y_train)
y_pred_dt=dt.predict(X_test)
print ('Train : ', accuracy_score(y_train,dt.predict(X_train)))
print ('Test : ', accuracy_score(y_test,y_pred_dt))
```

```
Decision Tree model :
Train :  1.0
Test :  0.9298245614035088
```

[35]:
```
disp = ConfusionMatrixDisplay.from_predictions(y_test, y_pred_dt)

plt.show()
```



[36]:
```
para={'n_estimators':[20,60,100,120],
      'max_features' : [0.2,0.6,1.0],
      'max_depth':[2,8,None],
      'max_samples':[0.5,0.75,1.0]
     }

# param_grid = {
#     'n_estimators': [200, 500],
#     'max_features': ['auto', 'sqrt', 'log2'],
#     'max_depth' : [4,5,6,7,8],
#     'criterion' :['gini', 'entropy']
# }

rf = RandomForestClassifier()
CV_rfc = GridSearchCV(estimator=rf, param_grid=para, cv= 5)
CV_rfc.fit(X_train, y_train)

# rf_grid.fit(X_train,y_train)
```

[36]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [2, 8, None],
                                   'max_features': [0.2, 0.6, 1.0],
                                   'max_samples': [0.5, 0.75, 1.0],
                                   'n_estimators': [20, 60, 100, 120]})
```

[37]:
```
print (CV_rfc.best_score_)
'be improved not much'
```

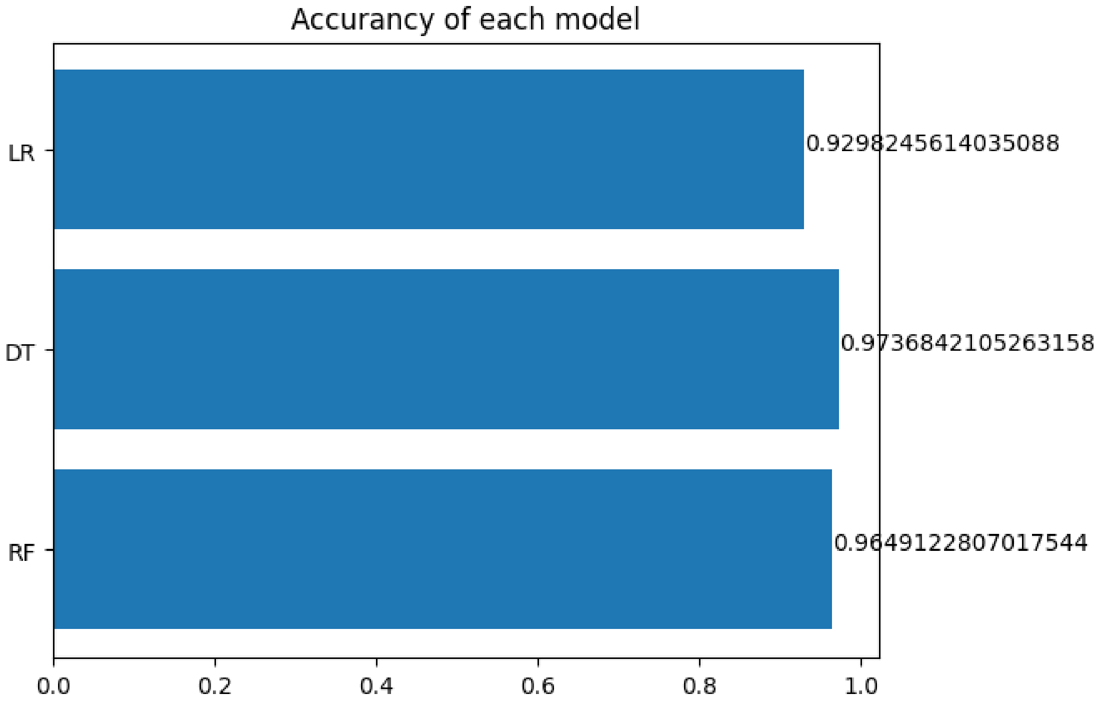
```
0.9670329670329672
```

[42]:
```
X = ['RF', 'DT', 'LR']
y = [accuracy_score(y_test,y_pred_rf),␣
 ↪accuracy_score(y_test,y_pred_lr),accuracy_score(y_test,y_pred_dt)]

plt.barh (X, y)

for index, value in enumerate(y):
    plt.text(value, index,
             str(value))
plt.title('Accurancy of each model')
```

[42]:
```
Text(0.5, 1.0, 'Accurancy of each model')
```


Accurancy of each model
LR
DT
RF