Improving going-concern assumption through machine learning

In [1]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import seaborn as sns

%matplotlib inline
from matplotlib import pyplot as plt
from matplotlib.colors import ListedColormap

from sklearn.preprocessing import MinMaxScaler, LabelBinarizer
from sklearn.linear_model import RidgeClassifier, RidgeClassifierCV
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, recall_score, preci
from sklearn.neighbors import KNeighborsClassifier

from scipy.stats import norm, spearmanr
import plotly.graph_objects as go
import warnings
warnings.filterwarnings('ignore')
```

Working sample

Sample consists of 100 entities operating in the construction sector in Bulgaria. 50% of them are declared bankrupt in 2021. 50% of them are with good financial performance. All the necessary data are derived from the Bulgarian Commercial Register.

In [2]:
```
gc_data = pd.read_excel("data/sample.xlsx")
```

In [3]:
```
gc_data.head()
```

Out[3]:

	COMPANY	ID_COM_REG	TLTA	RETA	QACL	NITA	CLASS
0	VODOPROVODI I KANALI EOOD	202638174	3.131944	-1.378472	0.018847	0.21700	NGC
1	JuLISIS 09 EOOD	200543293	0.857576	0.124242	0.085714	0.00318	NGC
2	AVE-STROJ EOOD	105544996	0.752412	0.199357	0.248366	0.03499	NGC
3	ALERLO EOOD	204845976	0.000000	0.000000	0.000000	0.00000	NGC
4	OKSET EOOD	200760731	0.000000	0.000000	0.000000	-1.00000	NGC

Feature selection and preprocessing

Being features with high entropy, COMPANY and ID_COM_REG are ignored for the analysis.

In [4]:
```
features = gc_data[["TLTA", "RETA", "QACL","NITA"]]
target = gc_data["CLASS"]
```

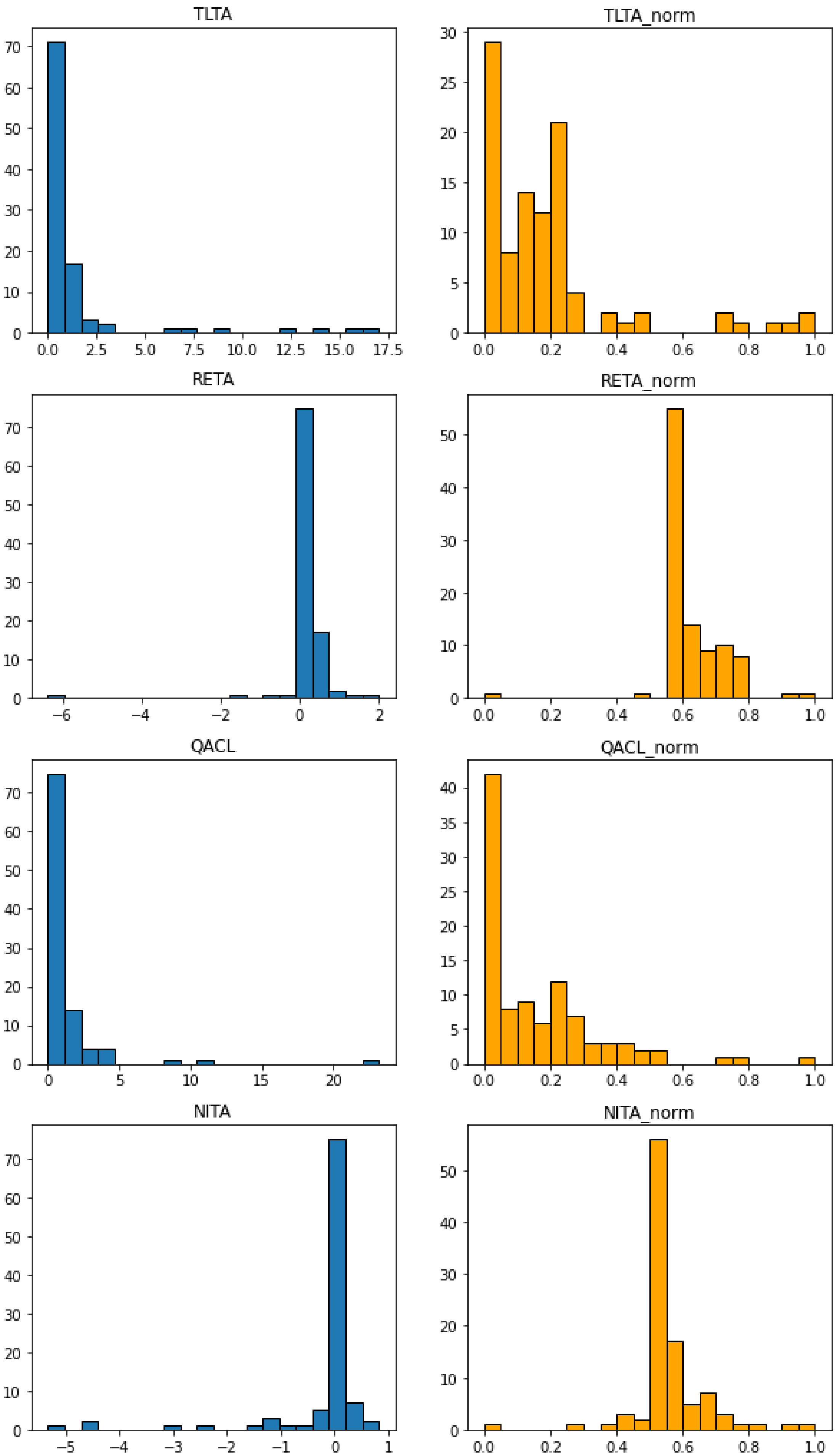
Features are fit to normal distribution by applying log transformation. NaN and inf/-inf values are replaced with 0.

In [5]:
```
def fit_normal_distr(features, target):

    # Applying log transformation to fit to normal distribution
    norm_features = np.log1p(features)

    # Reaplacing values where log has returnd "inf" or "nan" with 0
    norm_features.replace([np.inf, -np.inf], 0, inplace=True)
    norm_features.fillna(value=0, axis=1, inplace=True)

    # Performs normalization
    normalizer = MinMaxScaler(copy=False)
    normalizer.fit_transform(norm_features)

    # One-Hot-Encoding target variable
    encoder = LabelBinarizer()
    target = encoder.fit_transform(target)


    return norm_features, target
```

In [6]:
```
norm_features, target = fit_normal_distr(features, target)
```

Plotting features before and after preprocessing.

In [7]:
```
# Plots features before and after preprocessing

fig, axs = plt.subplots(nrows=4, ncols=2, figsize=(10,18))
fig.canvas.set_window_title('Window Title')

axs[0, 0].hist(features["TLTA"], edgecolor='black', bins=20)
axs[0, 0].set_title("TLTA")
axs[0, 1].hist(norm_features["TLTA"], edgecolor='black', bins=20, color="orange")
axs[0, 1].set_title("TLTA_norm")

axs[1, 0].hist(features["RETA"], edgecolor='black', bins=20)
axs[1, 0].set_title("RETA")
axs[1, 1].hist(norm_features["RETA"], edgecolor='black', bins=20, color="orange")
axs[1, 1].set_title("RETA_norm")

axs[2, 0].hist(features["QACL"], edgecolor='black', bins=20)
axs[2, 0].set_title("QACL")
axs[2, 1].hist(norm_features["QACL"], edgecolor='black', bins=20, color="orange")
axs[2, 1].set_title("QACL_norm")

axs[3, 0].hist(features["NITA"], edgecolor='black', bins=20)
axs[3, 0].set_title("NITA")
axs[3, 1].hist(norm_features["NITA"], edgecolor='black', bins=20, color="orange")
axs[3, 1].set_title("NITA_norm")

plt.savefig("norm")
plt.show()
```



In [8]:
```
# Creating a new dataframe in order to calculate correlation between features and target
corr_df = norm_features[["TLTA", "RETA", "QACL","NITA"]].copy()
corr_df["CLASS"] = target.copy()
```

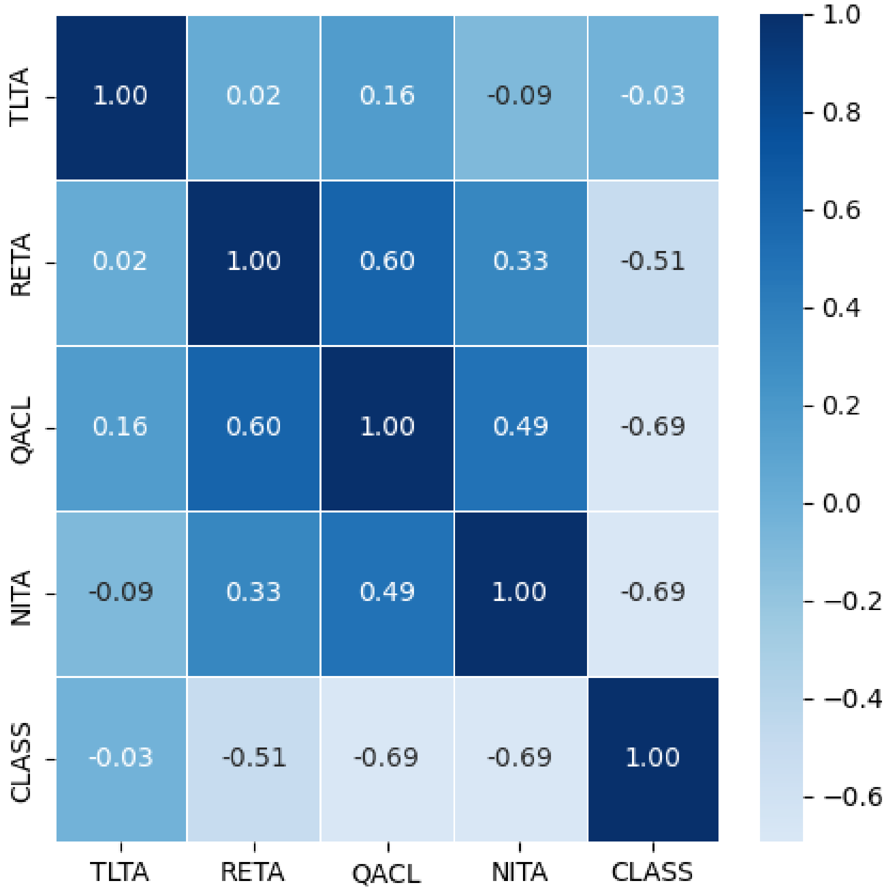
In [9]:
```
corr_df
```

Out[9]:

	TLTA	RETA	QACL	NITA	CLASS
0	0.490853	0.574217	0.005859	0.689508	1
1	0.214254	0.619604	0.025806	0.539741	1
2	0.194090	0.644671	0.069612	0.563938	1
3	0.000000	0.574217	0.000000	0.537280	1
4	0.000000	0.574217	0.000000	0.537280	1
...	...	...	...	...	...
95	0.083436	0.000000	0.265883	0.928138	0
96	0.384048	0.574217	0.062487	0.537280	0
97	0.152877	0.574217	0.140559	0.708955	0
98	0.113143	0.717217	0.103398	0.532142	0
99	0.133035	0.643967	0.203069	0.800212	0

100 rows × 5 columns

In [10]:
```
plt.figure(figsize=(5,5), dpi=100)
sns.heatmap(corr_df.corr(method="spearman"), annot=True, linewidth=0.5, fmt=".2f", cmap="
plt.tight_layout()
plt.savefig("corrmatrix")
plt.show()
```



KNN Model

The first algorithm to be implemented is k-Nearest Neighbor (kNN). It would be hypertuned (number of neighbors from 1 to 24) through GridSearchCV.

In [17]:
```
# Setting a parameter grid which contains different values of number of neighbors (from 1

parameter_grid = {"n_neighbors": np.arange(1, 25)}
```

In [18]:
```
parameter_grid
```

Out[18]:
```
{'n_neighbors': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 1
7,
        18, 19, 20, 21, 22, 23, 24])}
```

In [19]:
```
knn_classifier = KNeighborsClassifier()
```

In [20]:
```
# Applying 10-fold cross-validation

knn_gscv = GridSearchCV(knn_classifier, param_grid=parameter_grid, cv=10, return_train_sc
```

In [21]:
```
knn_gscv.fit(norm_features, target)
```

Out[21]:
```
GridSearchCV(cv=10, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 1
1, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24])},
             return_train_score=True)
```

In [22]:
```
knn_gscv.best_estimator_
```

Out[22]:
```
KNeighborsClassifier(n_neighbors=6)
```

In [23]:
```
knn_gscv.best_score_
```

Out[23]:
```
0.8800000000000001
```

In [24]:
```
knn = knn_gscv.best_estimator_
```

In [25]:
```
knn_predictions = knn.predict(norm_features)
```

In [26]:
```
actuals = target
```

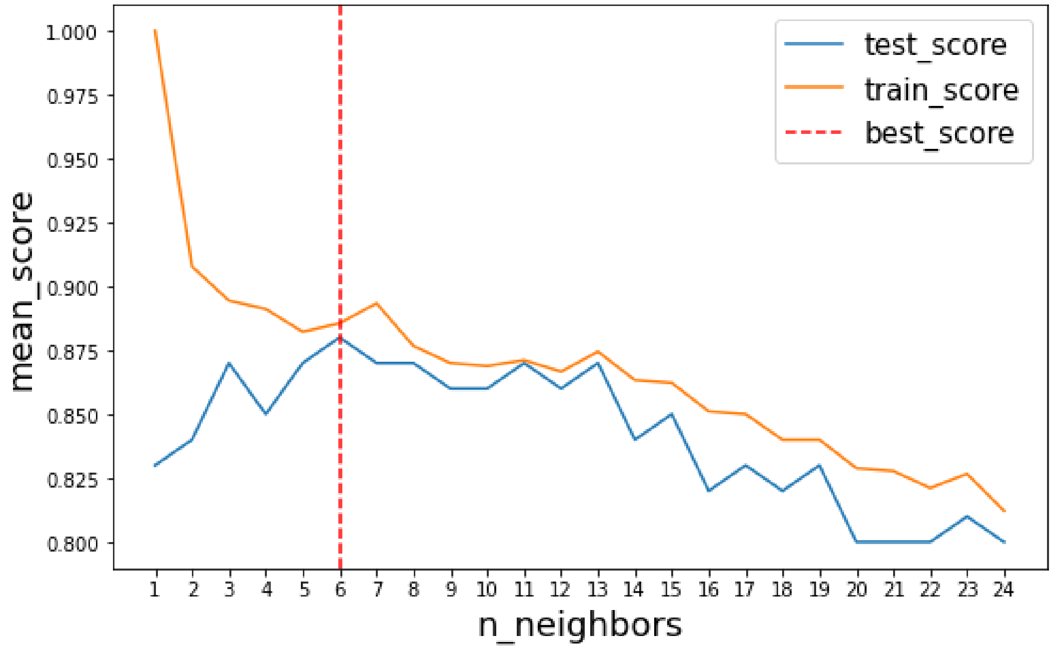
In [27]:
```
# Function which plots test vs train accuracy

def plot_train_test_score(test_score, train_score, x, best_parameter, xlabel, ylabel, xti
    plt.figure(figsize=(8,5))
    plt.plot(x, test_score, label="test_score")
    plt.plot(x, train_score, label="train_score")
    plt.axvline(x=best_parameter, color="r", ls="--", label="best_score")
    plt.xlabel(xlabel, fontsize=18)
    plt.xticks(xticks)
    plt.ylabel(ylabel, fontsize=18)
    plt.legend(prop={'size': 15})
    plt.tight_layout()
    plt.savefig("train_test_plot_knn.png")
    plt.show()
```

In [28]:
```
def plot_confusion_matrix(actuals, predictions,fig_name="fig_name", save=False):
    conf_matrix = confusion_matrix(actuals, predictions)
    cm_display = ConfusionMatrixDisplay(confusion_matrix = conf_matrix, display_labels =
    fig, ax = plt.subplots(figsize=(7,6))
    plt.tight_layout()
    cm_display.plot(ax=ax, colorbar=False)
    font = {'family': 'sans-serif',
```

```
    'weight': 'bold',
    'size': 15}
    plt.rc('font', **font)
    if save:
        plt.savefig(fig_name, dpi=300)
    plt.show()
```

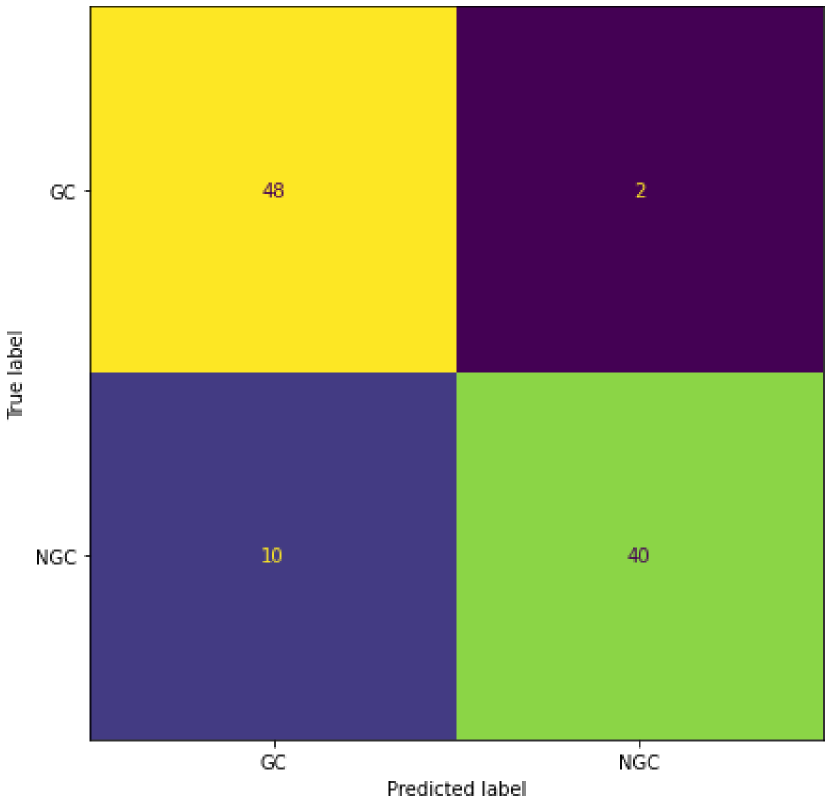
In [29]:
```
def precision_recall(actuals, predictions):
    precision = precision_score(predictions, actuals)
    recall = recall_score(predictions, actuals)
    print(f"kNN precision: {precision:.2f}")
    print(f"kNN recall: {recall:.2f}")
```

In [30]:
```
plot_train_test_score(test_score=knn_gscv.cv_results_["mean_test_score"],
                      train_score=knn_gscv.cv_results_["mean_train_score"],
                      x=parameter_grid["n_neighbors"],
                      best_parameter=knn_gscv.best_params_["n_neighbors"],
                      xlabel="n_neighbors",
                      ylabel="mean_score",
                      xticks=parameter_grid["n_neighbors"])
```



The number of neighbors which yields highest classification (0.88) is 6.

In [31]:
```
plot_confusion_matrix(actuals, knn_predictions, "knn_conf_matrix", save=True)
```



In [32]:
```
precision_recall(target, knn_predictions)
```

```
kNN precision: 0.80
kNN recall: 0.95
```

Linear Regression

In [33]:
```
alphas_grid = [0.001, 0.01, 0.1, 1, 10]
```

In [34]:
```
ridgereg = RidgeClassifierCV(alphas=alphas_grid, cv=5)
ridgereg.fit(norm_features, actuals)
```

Out[34]:
```
RidgeClassifierCV(alphas=array([1.e-03, 1.e-02, 1.e-01, 1.e+00, 1.e+01]), cv=5)
```

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

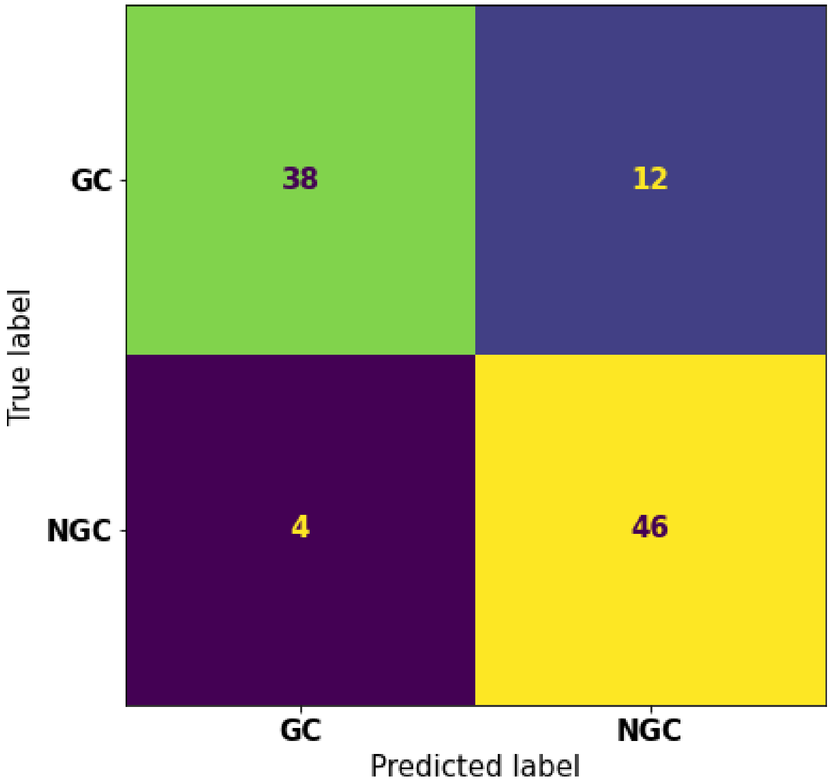
Out[35]:
```
0.85
```

In [36]:
```
ridgereg.alpha_
```

Out[36]:
```
0.001
```

In [37]:
```
ridge_predictions = ridgereg.predict(norm_features)
actuals = target
```

In [38]:
```
plot_confusion_matrix(actuals, ridge_predictions, fig_name="ridge_conf_matrix", save=True
```



In [39]:
```
precision_recall(target, ridge_predictions)
```

```
kNN precision: 0.92
kNN recall: 0.79
```

Decision Tree

In [44]:
```
params =  {
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': [1, 2, 3 , 4],
    'max_depth': [1, 2, 3, 4]}
```

In [45]:
```
dt = DecisionTreeClassifier(random_state=42)
```

In [46]:
```
dt_gscv = GridSearchCV(dt, params, cv=10, return_train_score=True)
```

In [47]:
```
dt_gscv.fit(norm_features, target)
```

Out[47]:
```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'max_depth': [1, 2, 3, 4],
                         'max_features': [1, 2, 3, 4],
                         'min_samples_leaf': [1, 2, 3, 4]},
             return_train_score=True)
```

In [48]:
```
dt_gscv.best_estimator_
```

Out[48]:
```
DecisionTreeClassifier(max_depth=3, max_features=2, min_samples_leaf=2,
                       random_state=42)
```

In [49]:
```
dt_gscv.best_score_
```

Out[49]:
```
0.89
```

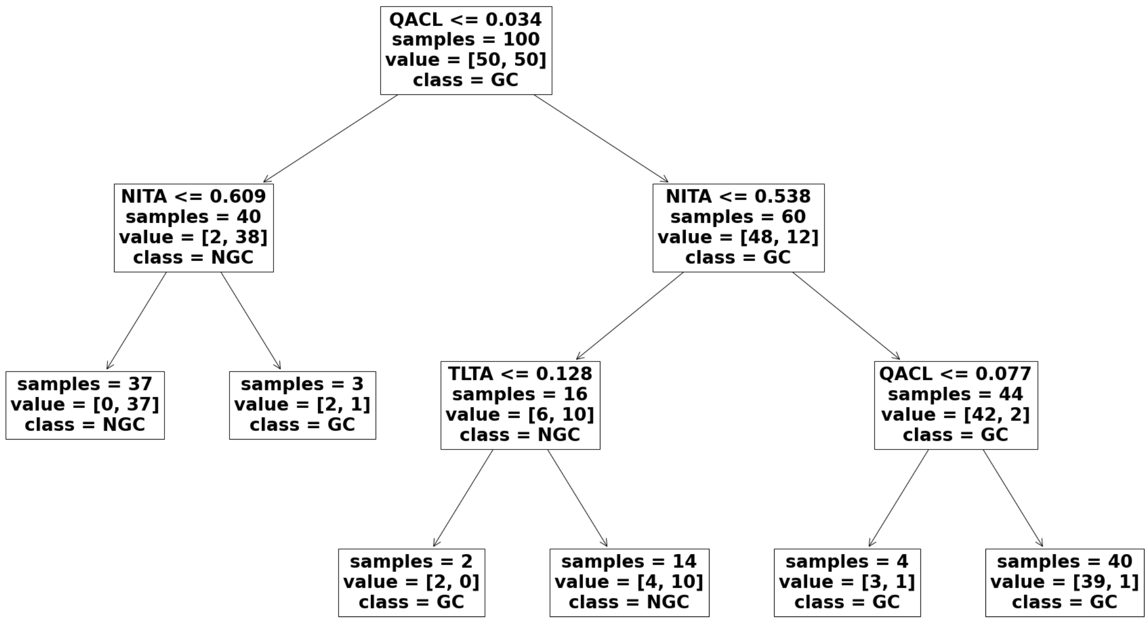
In [50]:
```
best_dt = dt_gscv.best_estimator_
```

In [51]:
```
best_dt.fit(norm_features, target)
```

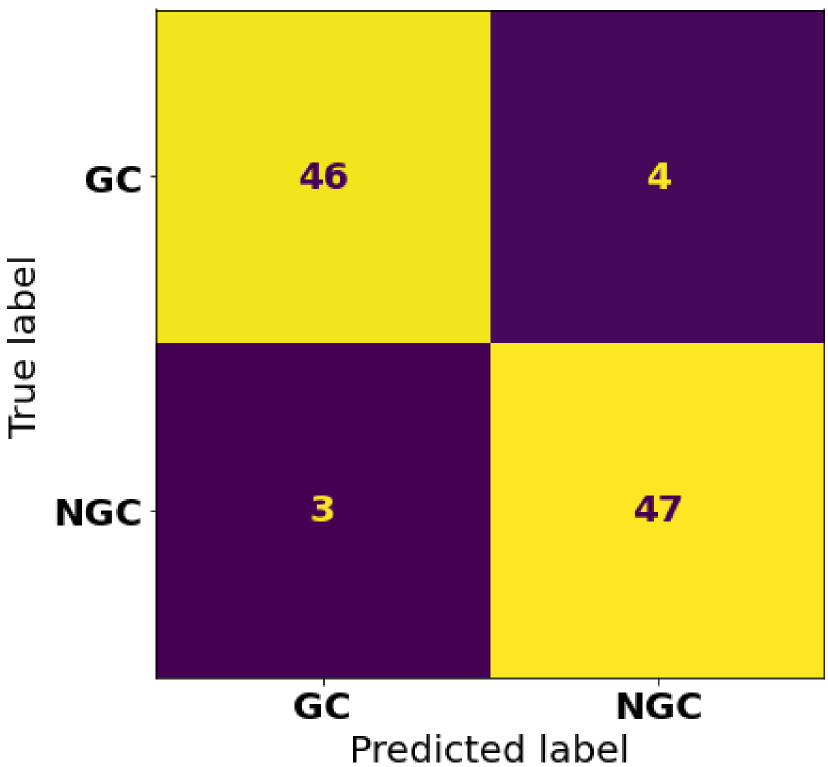
```
Out[51]: DecisionTreeClassifier(max_depth=3, max_features=2, min_samples_leaf=2,
                                random_state=42)
```

```
In [52]: dt_predictions = best_dt.predict(norm_features)
```

```
In [53]: plt.figure(figsize=(25,15))
         plot_tree(best_dt,feature_names=norm_features.columns.tolist(), class_names=["GC", "NGC"]
         plt.tight_layout()
         plt.savefig("tree", dpi=300)
         font = {'family': 'sans-serif',
             'weight': 'bold',
             'size': 20}
         plt.rc('font', **font)
         plt.show()
```




```
In [54]: plot_confusion_matrix(target, dt_predictions, fig_name="dt_conf_matrix", save=True)
```



In [55]:
```
precision_recall(target, dt_predictions)
```

```
kNN precision: 0.94
kNN recall: 0.92
```