Capstone Project

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Guidelines:

Using the dataset provided, create a binary classification.

Perform the following:

1. Perform an exploratory analysis (scaling, PCA, unbalanced)

2. Split the data (train, validation, test)

3. Perform 10-fold cross-validation and grid search (method of your choice)

4. Compare the different classification medthods (Logistic Regressin, KNN, SVM, RF, XGBOOST)

5. Show evaluation metrics (ROC-AUC, accuracy, f-1 score)

6. Submit the jupyter notebook using the following format: Colaste_SP901Capstone.ipnyb

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# #

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1. Perform Exploratory Analysis (Scaling, PCA, Unbalanced)

*** Preprocessing - Data Exploration

In [1]:

```
import pandas as pd
pd.options.display.max_rows = 10
pd.options.display.max_columns = None
```

```
# Load the dataset
df_cs = pd.read_csv('SP901_CS_completedata.csv', delimiter = ';')
dv = "\n--------------------"
```

In [2]:
```
# Data Shape, to know the number of rows and columns.
print(dv)
print(df_cs.shape)
```

```
--------------------
(197, 430)
```

In [3]:
```
# View Data --- Head, to see the first few rows.
print(dv)
display(df_cs.head())
```

```
--------------------
```

	PatientID	Failure.binary	Entropy_cooc.W.ADC	GLNU_align.H.PET	Min_hist.PET	Max_hist.PET	I
0	1	0	12.85352	46.256345	6.249117	17.825541	
1	2	1	12.21115	27.454540	11.005214	26.469077	
2	3	0	12.75682	90.195696	2.777718	6.877486	
3	4	1	13.46730	325.643330	6.296588	22.029843	
4	5	0	12.63733	89.579042	3.583846	7.922501	

In [4]:
```
# View Data --- Tail, to see the last few rows.
print(dv)
display(df_cs.tail())
```

```
--------------------
```

	PatientID	Failure.binary	Entropy_cooc.W.ADC	GLNU_align.H.PET	Min_hist.PET	Max_hist.PET
192	193	0	11.95184	32.691265	12.213982	33.473818
193	194	0	9.88702	60.481188	8.860044	21.524942
194	195	0	12.84907	82.701566	11.543354	39.525156
195	196	0	12.44606	72.223728	14.413852	49.234694
196	197	0	12.13425	109.304666	11.545814	39.527616

In [5]:
```
# Column Names,  to list the column names, which helps understand the features.
print(dv)
print(df_cs.columns)
```

```
---------------------
Index(['PatientID', 'Failure.binary', 'Entropy_cooc.W.ADC', 'GLNU_align.H.PET',
       'Min_hist.PET', 'Max_hist.PET', 'Mean_hist.PET', 'Variance_hist.PET',
       'Standard_Deviation_hist.PET', 'Skewness_hist.PET',
       ...
       'LZLGE.W.ADC', 'LZHGE.W.ADC', 'GLNU_area.W.ADC', 'ZSNU.W.ADC',
       'ZSP.W.ADC', 'GLNU_norm.W.ADC', 'ZSNU_norm.W.ADC', 'GLVAR_area.W.ADC',
       'ZSVAR.W.ADC', 'Entropy_area.W.ADC'],
      dtype='object', length=430)
```

In [6]:

```
print(dv)
print(df_cs.info())
```

```
---------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197 entries, 0 to 196
Columns: 430 entries, PatientID to Entropy_area.W.ADC
dtypes: float64(428), int64(2)
memory usage: 661.9 KB
None
```

In [7]:

```
print(dv)
display(df_cs.describe())
```

```
---------------------
```

	PatientID	Failure.binary	Entropy_cooc.W.ADC	GLNU_align.H.PET	Min_hist.PET	Max_hist.I
count	197.000000	197.000000	197.000000	197.000000	197.000000	197.000(
mean	99.000000	0.340102	12.278600	95.381938	8.513255	24.271
std	57.013156	0.474950	1.039816	86.089059	4.985543	14.779
min	1.000000	0.000000	9.532740	9.445031	1.484508	4.164
25%	50.000000	0.000000	11.558840	37.518193	5.151990	13.071
50%	99.000000	0.000000	12.278790	80.034684	7.388754	21.013
75%	148.000000	1.000000	12.977330	112.145185	11.005214	33.761
max	197.000000	1.000000	14.510471	559.351571	28.404496	79.985

In [8]:

```
# Missing Values, to see if any data needs to be filled or cleaned.
print(dv)
print(df_cs.isnull().sum().sort_values(ascending=False))
```

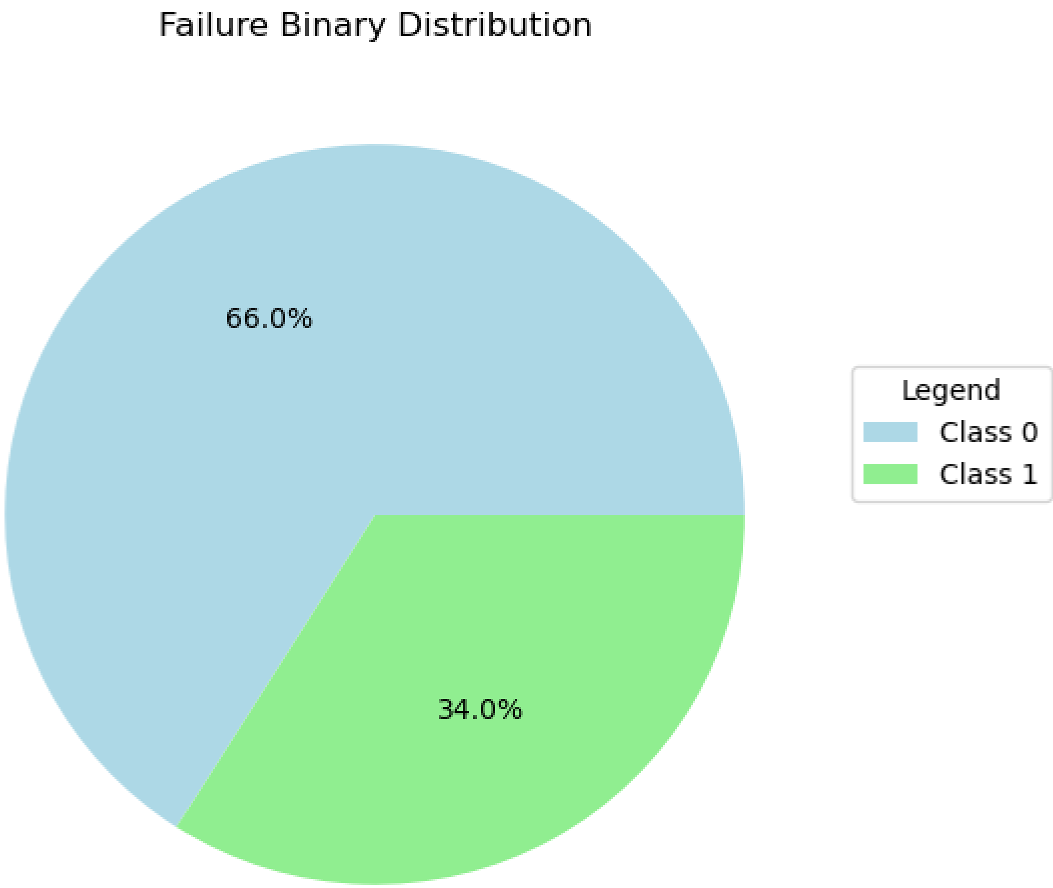
```
---------------------
PatientID              0
SZLGE.L.ADC            0
LGLZE.L.ADC            0
LZSE.L.ADC             0
SZSE.L.ADC             0
                      ..
SZSE.H.PET             0
Entropy_align.H.PET    0
RLVAR_align.H.PET      0
GLVAR_align.H.PET      0
Entropy_area.W.ADC     0
Length: 430, dtype: int64
```

In [9]:

```
import matplotlib.pyplot as plt

# Class Distribution
print(dv)
print(df_cs['Failure.binary'].value_counts())

# Create a pie chart
plt.figure(figsize=(6, 6))
class_counts = df_cs['Failure.binary'].value_counts(normalize=True)
colors = ['lightblue', 'lightgreen']

plt.pie(class_counts, labels=['', ''], autopct='%1.1f%%', colors=colors)
plt.title('Failure Binary Distribution')

# Create a custom legend
legend_labels = ['Class 0', 'Class 1']
legend_colors = colors
legend_texts = [f'{label}: {class_counts[i]:.1%}' for i, label in
enumerate(legend_labels)]
plt.legend(legend_texts, title="Legend", loc="lower left",
bbox_to_anchor=(1, 0.5), labels=legend_labels)

plt.show()
```

```
---------------------
Failure.binary
0    130
1     67
Name: count, dtype: int64
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_6676\2809638628.py:19: UserWarning: You
have mixed positional and keyword arguments, some input may be discarded.
  plt.legend(legend_texts, title="Legend", loc="lower left", bbox_to_anchor=(1, 0.
5), labels=legend_labels)
```



In [10]:

```
# Correlation, to check how columns are related.
df_cs_corr = df_cs.corr()

# Find row and column names where the cell value is greater than 0.9
# Excluding correlations where 'row' = 'column'
# Excluding repittion of row and column pairs
df_cs_corr_rows_column_names_p_nrows = 0  # Initialize a counter
df_cs_corr_rows_column_names_p = [
    (row, col)
    for i, row in enumerate(df_cs_corr.index)
    for j, col in enumerate(df_cs_corr.columns)
    if df_cs_corr.loc[row, col] > 0.9 and i < j
]
df_cs_corr_rows_column_names_p_nrows =
len(df_cs_corr_rows_column_names_p)

# Sort the list based on the correlation value in descending order
df_cs_corr_rows_column_names_p_sorted = sorted(
    df_cs_corr_rows_column_names_p,
    key=lambda x: df_cs_corr.loc[x[0], x[1]],
    reverse=True
```

```
)

# Print the df_cs_corr_rows_column_names_positive
print(dv)
print(f'No. of Correlation Pairs (>0.9):
{df_cs_corr_rows_column_names_p_nrows}')
print(dv)

data = []
for row, col in df_cs_corr_rows_column_names_p_sorted:
    value = df_cs_corr.loc[row, col]
    data.append([row, col, value])

df_corr_info = pd.DataFrame(data, columns=['Column 1', 'Column 2',
'Correlation Value'])
display(df_corr_info.T)

# Orignially, I wanted to have the output in a heatmap, but it was messy
and hard to interpret.
```

```
---------------------
No. of Correlation Pairs (>0.9): 6543
---------------------
```

	0	1	2	
Column 1	ratio_3ds_vol_norm.PET	DAVE_cooc.L.PET	SVAR_cooc.L.PET	DAVE_cooc.I
Column 2	Spherical_disproportion.PET	Dissimilarity_cooc.L.PET	Tendency_cooc.L.PET	Dissimilarity_cooc.I
Correlation Value	1.0	1.0	1.0	

In [11]:

```
# Find row and column names where the cell value is lesser than -0.9
df_cs_corr_rows_column_names_n_nrows = 0  # Initialize a counter
df_cs_corr_rows_column_names_n = [
    (row, col)
    for i, row in enumerate(df_cs_corr.index)
    for j, col in enumerate(df_cs_corr.columns)
    if df_cs_corr.loc[row, col] < -0.9 and i < j
]

df_cs_corr_rows_column_names_n_nrows =
len(df_cs_corr_rows_column_names_n)
```

```
# Sort the list based on the correlation value in descending order
df_cs_corr_rows_column_names_n_sorted = sorted(
    df_cs_corr_rows_column_names_n,
    key=lambda x: df_cs_corr.loc[x[0], x[1]],
    reverse=False
)

# Print the df_cs_corr_rows_column_names_negative
print(dv)
print(f'No. of Correlation Pairs (<0.9):
{df_cs_corr_rows_column_names_n_nrows}')
print(dv)

data = []
for row, col in df_cs_corr_rows_column_names_n_sorted:
    value = df_cs_corr.loc[row, col]
    data.append([row, col, value])

df_corr_info = pd.DataFrame(data, columns=['Column 1', 'Column 2',
'Correlation Value'])
display(df_corr_info.T)

# Orignially, I wanted to have the output in a heatmap, but it was messy
and hard to interpret.
```

```
--------------------
No. of Correlation Pairs (<0.9): 2

--------------------
```

	0	1
Column 1	IC1_d.W.ADC	IC1_d.H.ADC
Column 2	Strength_vdif.W.ADC	Strength_vdif.H.ADC
Correlation Value	-0.905982	-0.900776

*** Preprocessing - Scaling

Notes:

• We perform data splitting and early column dropping to enforce a clear separation between the training and testing datasets.

• This prevents any inadvertent mixing of the two sets during subsequent preprocessing such as in unbalancing, we are going to use SMOTE to have a balanced training dataset.

In [12]:
```
from sklearn.model_selection import train_test_split

X = df_cs.drop(columns = ['PatientID','Failure.binary'])
y = df_cs['Failure.binary']

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=10)
```

In [13]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [14]:
```
X_train_scaled
```

Out[14]:
```
array([[0.5110986 , 0.01858926, 0.12779277, ..., 0.07706133, 0.30413454,
        0.11383879],
       [0.25409576, 0.05861964, 0.08524072, ..., 0.08014984, 0.11883779,
        0.01018082],
       [0.69027625, 0.3642467 , 0.19051957, ..., 0.06503193, 1.        ,
        0.73666372],
       ...,
       [0.59437007, 0.05906897, 0.07529484, ..., 0.17936684, 0.19414418,
        0.1413953 ],
       [0.4676702 , 0.05564722, 0.16324178, ..., 0.21911267, 0.12100948,
        0.15073638],
       [0.60521824, 0.01730174, 0.1620983 , ..., 0.5074518 , 0.21778321,
        0.17002778]])
```

In [15]:
```
X_test_scaled
```

Out[15]:
```
array([[0.49814042, 0.25316123, 0.31353463, ..., 0.21587388, 0.30356077,
        0.15332686],
       [0.71481412, 0.16590426, 0.04034381, ..., 0.63834886, 0.17320183,
        0.20037628],
       [0.74634802, 0.34929967, 0.25045652, ..., 0.23891675, 0.2378936 ,
        0.16820558],
       ...,
       [0.49760975, 0.17974009, 0.39203375, ..., 0.50328194, 0.43261154,
        0.88143861],
       [0.67850839, 0.22770409, 0.14566099, ..., 0.20688953, 0.24971312,
        0.15802374],
       [0.68893497, 0.1975524 , 0.11973483, ..., 0.20271659, 0.21533898,
        0.14670968]])
```

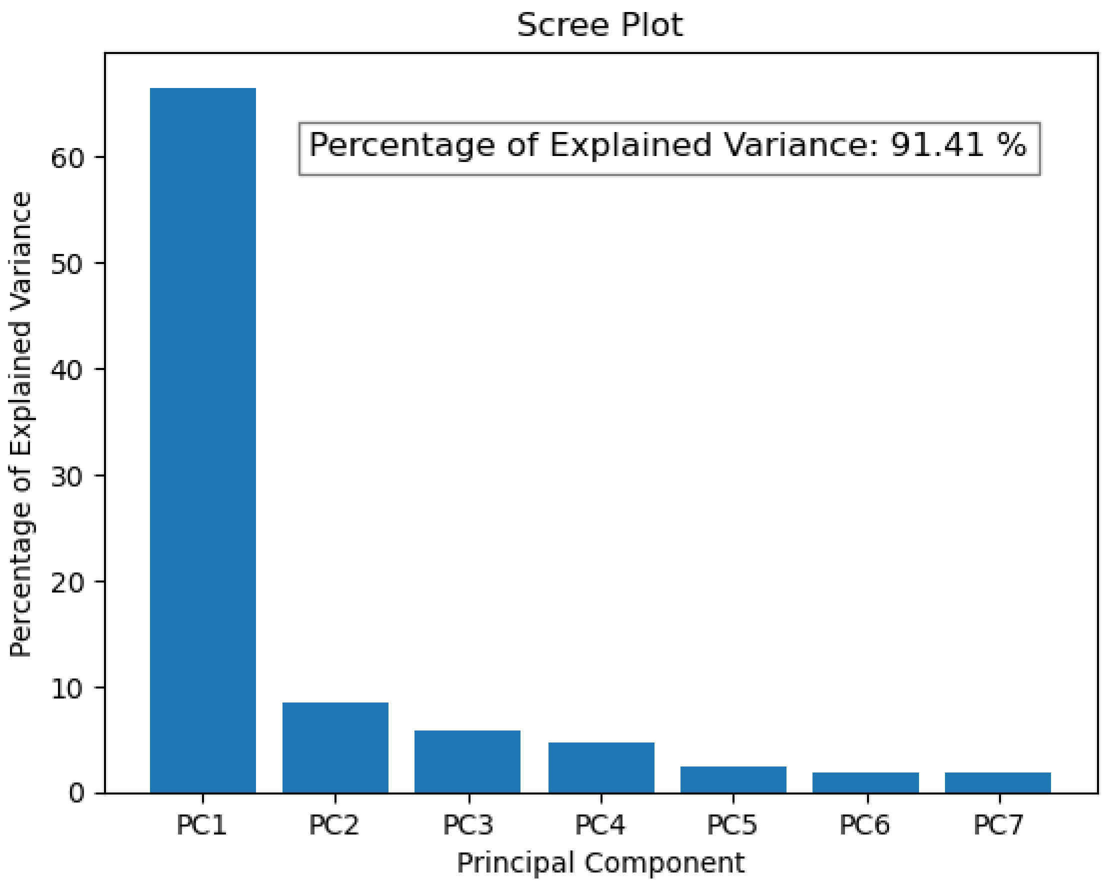
*** Preprocessing - Principal component analysis (PCA)

Notes:

We used 'n_components = 7' to retain a high percentage of the original dataset's variance as this retains a 91.41% of explained variance as shown in the below chart.

In [16]:

```
import numpy as np
from sklearn.decomposition import PCA

pca = PCA(n_components = 7)
pca.fit(X_train_scaled)

a = pca.explained_variance_ratio_.sum()*100

X_train_pca = pca.transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

per_var = np.round(pca.explained_variance_ratio_*100, decimals = 1)
labels = ['PC'+ str(X_train_scaled) for X_train_scaled in range(1,
len(per_var)+1)]

# Scree plot
plt.bar(x=range(1, len(per_var) + 1), height=per_var, tick_label=labels)
plt.ylabel('Percentage of Explained Variance')
plt.xlabel('Principal Component')
plt.title('Scree Plot')

# Textbox
textbox_x = 1.8
textbox_y = 60
textbox_text = f"Percentage of Explained Variance: {a:.2f} %"
plt.rcParams['font.family'] = 'DejaVu Sans'
plt.text(textbox_x, textbox_y, textbox_text, fontsize=12,
bbox=dict(facecolor='white', alpha=0.5))

plt.show()
```



*** Preprocessing - Unbalanced

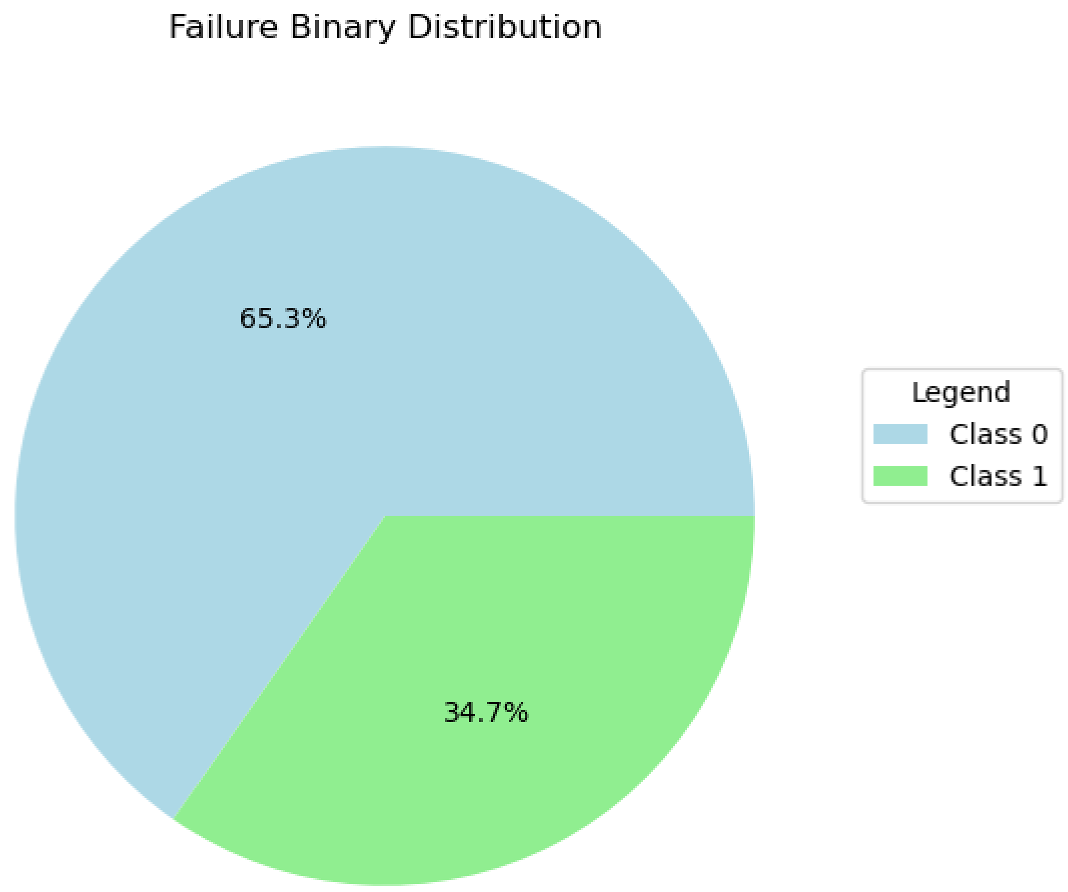
In [17]:

```
# Class Distribution
print(dv)
print(y_train.value_counts())

# Create a pie chart
plt.figure(figsize=(6, 6))
class_counts = y_train.value_counts(normalize=True)*100
colors = ['lightblue', 'lightgreen']

plt.pie(class_counts, labels=['', ''], autopct='%1.1f%%', colors=colors)
plt.title('Failure Binary Distribution')

# Create a custom legend
legend_labels = ['Class 0', 'Class 1']
legend_colors = colors
legend_texts = [f'{label}: {class_counts[i]:.1%}' for i, label in
enumerate(legend_labels)]
plt.legend(legend_texts, title="Legend", loc="lower left",
bbox_to_anchor=(1, 0.5), labels=legend_labels)
```

```
plt.show()
```

```
---------------------
Failure.binary
0    96
1    51
Name: count, dtype: int64
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_6676\2437434084.py:17: UserWarning: You have mixed positional and keyword arguments, some input may be discarded.
  plt.legend(legend_texts, title="Legend", loc="lower left", bbox_to_anchor=(1, 0.5), labels=legend_labels)
```



Notes:

Since the Failure Binary Distribution is unbalanced, we made use of SMOTE to have authentic samples added in the training dataset --- making it balanced.

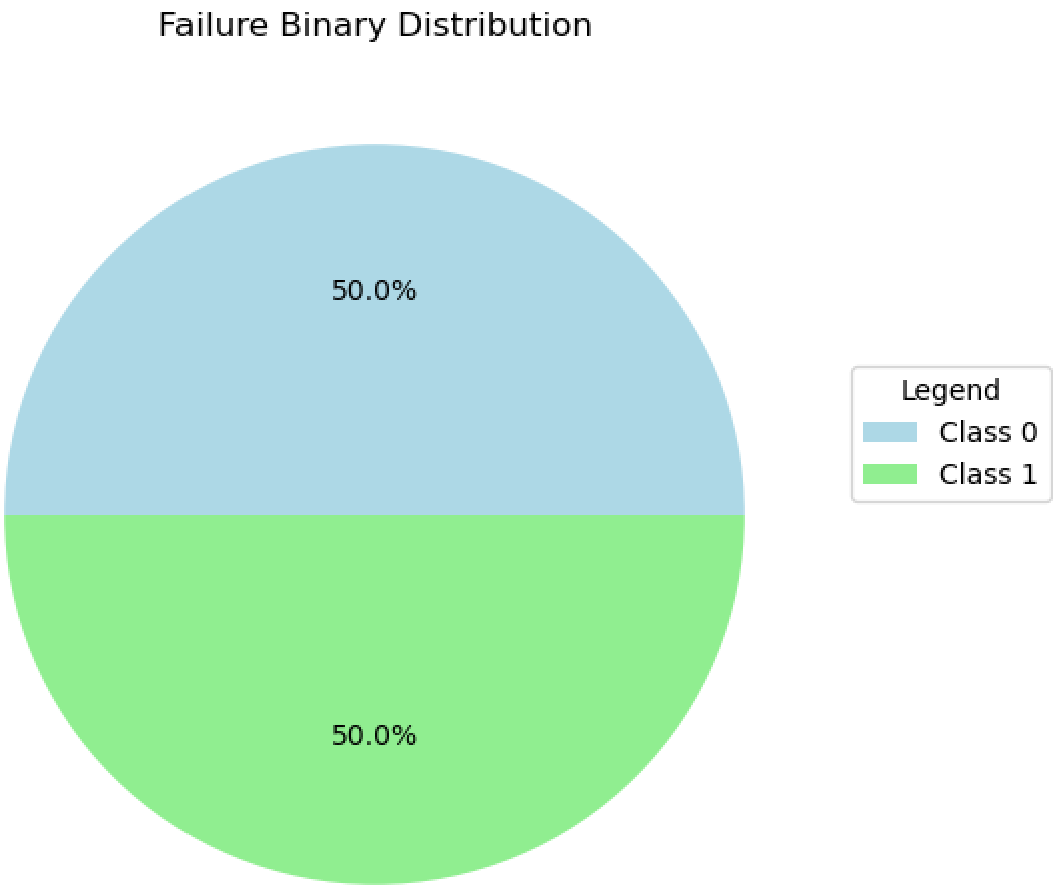
In [18]:

```
# Create an instance of SMOTE
from imblearn.over_sampling import SMOTE
oversampler = SMOTE()

# Resample data
X_train_over_pca, y_train_over = oversampler.fit_resample(X_train_pca, y_train)
```

```python
print(dv)
print(y_train_over.value_counts())

# Create a pie chart
plt.figure(figsize=(6, 6))
class_counts = y_train_over.value_counts(normalize=True)*100
colors = ['lightblue', 'lightgreen']

plt.pie(class_counts, labels=['', ''], autopct='%1.1f%%', colors=colors)
plt.title('Failure Binary Distribution')

# Create a custom legend
legend_labels = ['Class 0', 'Class 1']
legend_colors = colors
legend_texts = [f'{label}: {class_counts[i]:.1%}' for i, label in
enumerate(legend_labels)]
plt.legend(legend_texts, title="Legend", loc="lower left",
bbox_to_anchor=(1, 0.5), labels=legend_labels)

plt.show()
```

```
--------------------
Failure.binary
1    96
0    96
Name: count, dtype: int64
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_6676\2101566368.py:23: UserWarning: You
have mixed positional and keyword arguments, some input may be discarded.
  plt.legend(legend_texts, title="Legend", loc="lower left", bbox_to_anchor=(1, 0.
5), labels=legend_labels)
```



#

#

----

2. Split the Data (Train, Validation, Test)

Note:

• The current training and test datasets are outputs from the preprocessing.

• Dataset Proportion from Original Dataset: Train Size = 0.75, Test Size = 0.25

#

Current Training Datasets:

X_train_over_pca

*** from X_train dataset that undergone scaling, PCA and unbalance SMOTE.

#

y_train_over

*** from y_train dataset that undergone unbalance SMOTE.

#

#

Current Test Dataset:

X_test_pca

*** from X_test dataset that undergone scaling and PCA.

#

y_test

*** have not undergone any preprocessing

In [19]:
```
# Test Set with the size of 0.25 from the Original Dataset was already
extracted before scaling.
# Lacking is validation dataset which will be extracted from
"X_train_over_pca".
validation_size = 0.15

# Split the data into a training set and validation data set
X_train_temp, X_validation, y_train_temp, y_validation =
train_test_split(X_train_over_pca, y_train_over,
test_size=validation_size, random_state=10, stratify=y_train_over)
```

UPDATED:

#

Updated Overall Training Datasets:

- X_train_temp
- y_train_temp

#

Updated Overall Validation Datasets:

- X_validation
- y_validation

#

Updated Overall Test Datasets:

- X_test_pca

- y_test

#

#

----

3. Perform 10-Fold Cross-Validation and Grid Search

In [20]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

***10-fold Cross-Validation (Method: Logistic Regression)

In [21]:
```
# Create a Logistic Regression model and fit it to the training data
logreg = LogisticRegression().fit(X_train_temp, y_train_temp)

# Perform 10-fold cross-validation and get the scores
scores = cross_val_score(logreg, X_train_temp, y_train_temp,
cv=KFold(n_splits=10))

# Print the cross-validation scores
print(f'Cross-validation Scores: \n {scores}')
```

```
Cross-validation Scores:
 [0.47058824 0.70588235 0.70588235 0.75       0.625      0.4375
 0.375      0.8125     0.5625     0.625     ]
```

***Grid Search (Method: Logistic Regression)

In [22]:
```
# Initialize variables to keep track of the best score and corresponding
parameters
best_score = 0
best_parameters = None
```

```python
# Define the hyperparameter values to search over
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
}

# Iterate over each combination of hyperparameters
for C in param_grid['C']:
    for solver in param_grid['solver']:
        # Create a Logistic Regression model with the current
hyperparameters
        clf = LogisticRegression(C=C, solver=solver, max_iter=1000)
        clf.fit(X_train_temp, y_train_temp)

        # Evaluate the model on the validation set
        score = clf.score(X_validation, y_validation)

        # If the current model's score is better than the previous best,
update the best score and parameters
        if score > best_score:
            best_score = score
            best_parameters = {'C': C, 'Solver': solver}

# Print the best score and the corresponding best parameters
print("Best Score: {:.2f}".format(best_score))
print("Best Parameters: {}".format(best_parameters))
```

```
Best Score: 0.52
Best Parameters: {'C': 0.01, 'Solver': 'newton-cg'}
```

#

#

----

4. Compare the Different Classification Methods

Note:

I have a total of six (6) different classification models due to XGBOOST as I am not sure (from the instructions of the project capstone) if it was referring to the standard gradiant boosting or to the extreme gradiant boosting since based on the course ipnyb handouts, I have not found an example of extreme gradiant boosting --- only standard gradiant boosting.

*** Logistic Regression

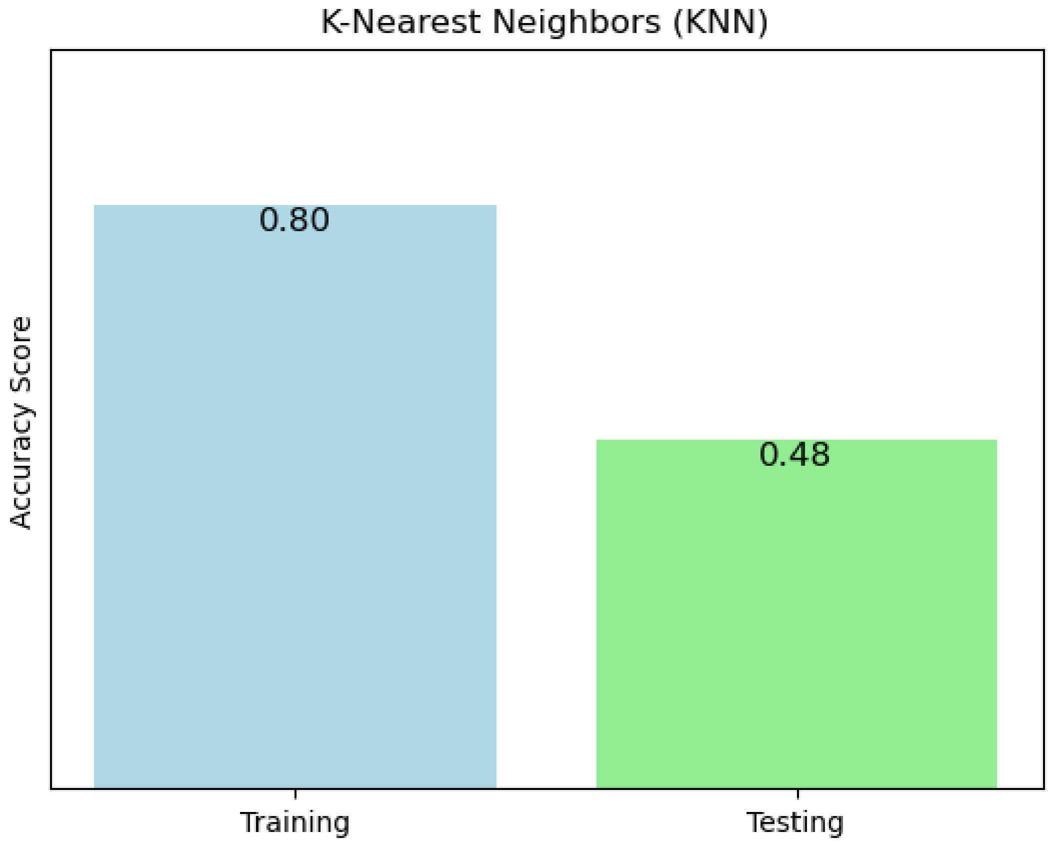
In [23]:
```
from sklearn.linear_model import LogisticRegression

# Create a classification model and fit it to the training data
lrc = LogisticRegression()
lrc.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
lrc_train_score = lrc.score(X_train_temp, y_train_temp)
lrc_test_score = lrc.score(X_test_pca, y_test)

# Model scores
scores = [lrc_train_score, lrc_test_score]
labels = ['Training', 'Testing']

# Create the column chart
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
plt.ylabel('Accuracy Score')
plt.title('Logistic Regression')
plt.yticks([])
plt.ylim(0, 1.02)

# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```

*** K-Nearest Neighbors (KNN)

In [24]:

```
from sklearn.neighbors import KNeighborsClassifier

# Create a classification model and fit it to the training data
knn = KNeighborsClassifier()
knn.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
knn_train_score = knn.score(X_train_temp, y_train_temp)
knn_test_score = knn.score(X_test_pca, y_test)

# Model scores
scores = [knn_train_score, knn_test_score]
labels = ['Training', 'Testing']

# Create the column chart
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
plt.ylabel('Accuracy Score')
plt.title('K-Nearest Neighbors (KNN)')
plt.yticks([])
plt.ylim(0, 1.02)
```

```python
# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```

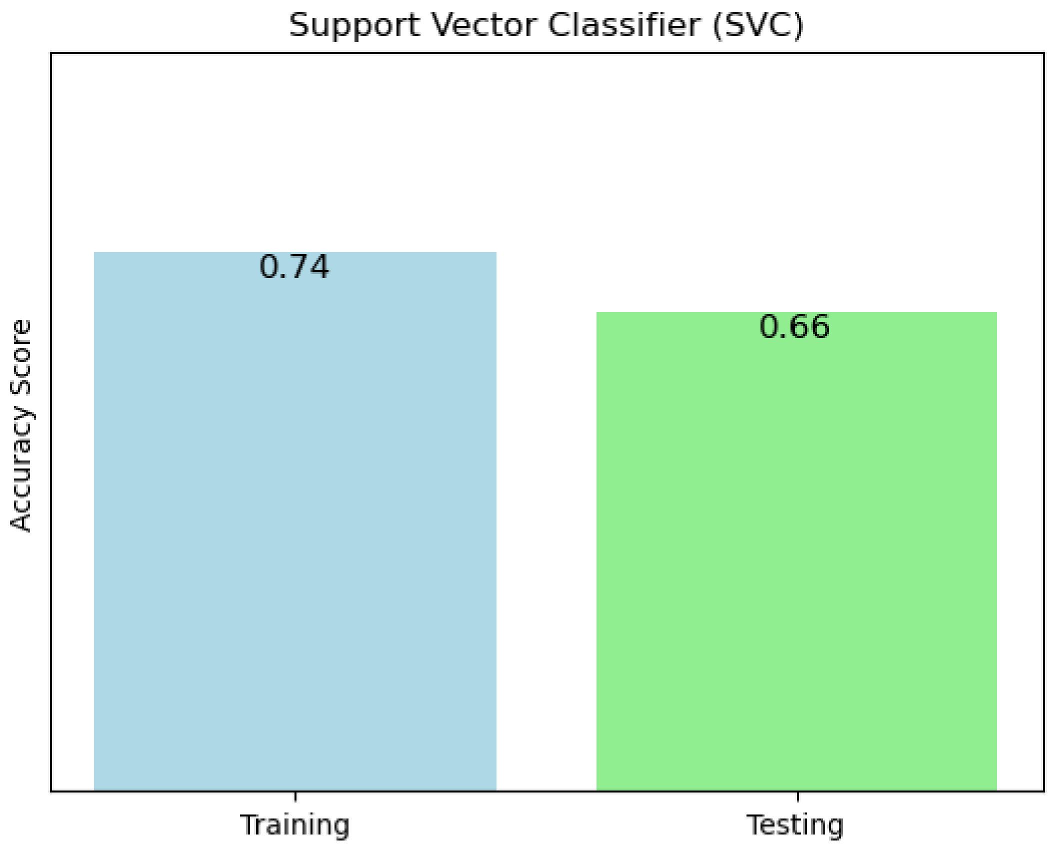


*** Support Vector Classifier (SVC)

In [25]:

```python
from sklearn.svm import SVC

# Create a classification model and fit it to the training data
svc = SVC()
svc.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
svc_train_score = svc.score(X_train_temp, y_train_temp)
svc_test_score = svc.score(X_test_pca, y_test)

# Model scores
scores = [svc_train_score, svc_test_score]
labels = ['Training', 'Testing']

# Create the column chart
```

```python
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
plt.ylabel('Accuracy Score')
plt.title('Support Vector Classifier (SVC)')
plt.yticks([])
plt.ylim(0, 1.02)

# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```

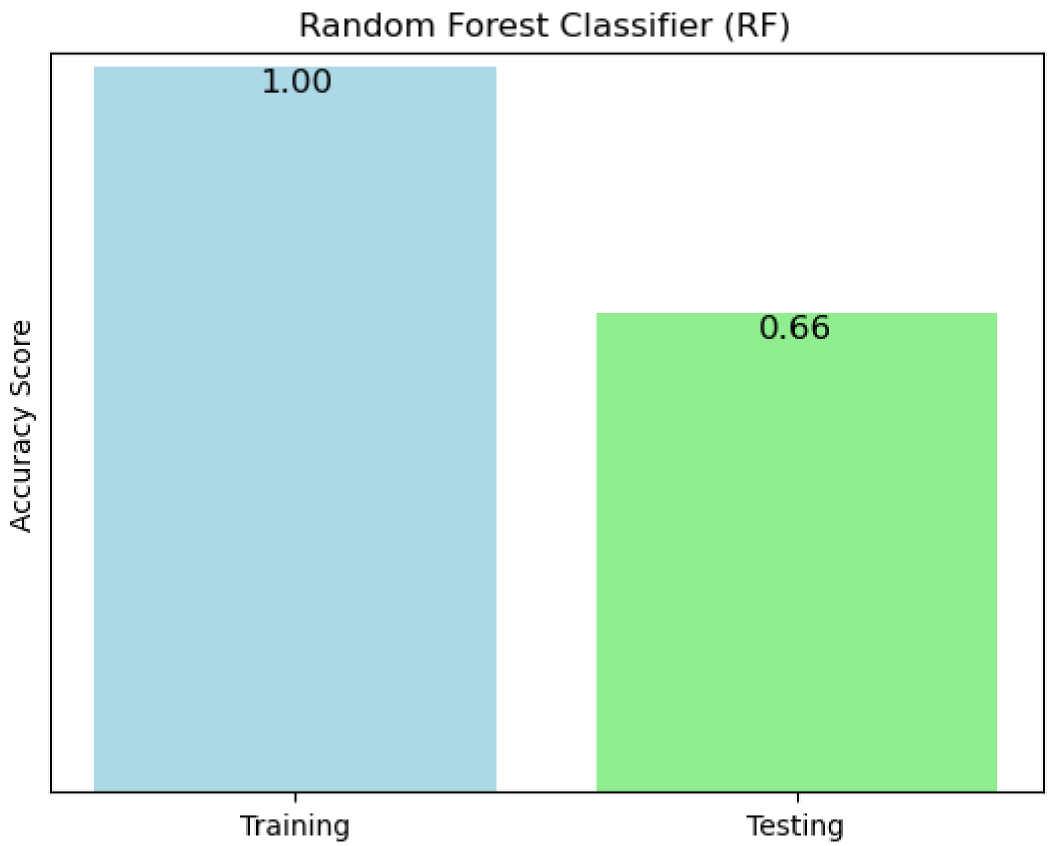


*** Random Forest Classifier (RF)

In [26]:

```python
from sklearn.ensemble import RandomForestClassifier

# Create a classification model and fit it to the training data
rfc = RandomForestClassifier()
rfc.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
rfc_train_score = rfc.score(X_train_temp, y_train_temp)
rfc_test_score = rfc.score(X_test_pca, y_test)
```

```
# Model scores
scores = [rfc_train_score, rfc_test_score]
labels = ['Training', 'Testing']

# Create the column chart
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
plt.ylabel('Accuracy Score')
plt.title('Random Forest Classifier (RF)')
plt.yticks([])
plt.ylim(0, 1.02)

# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```

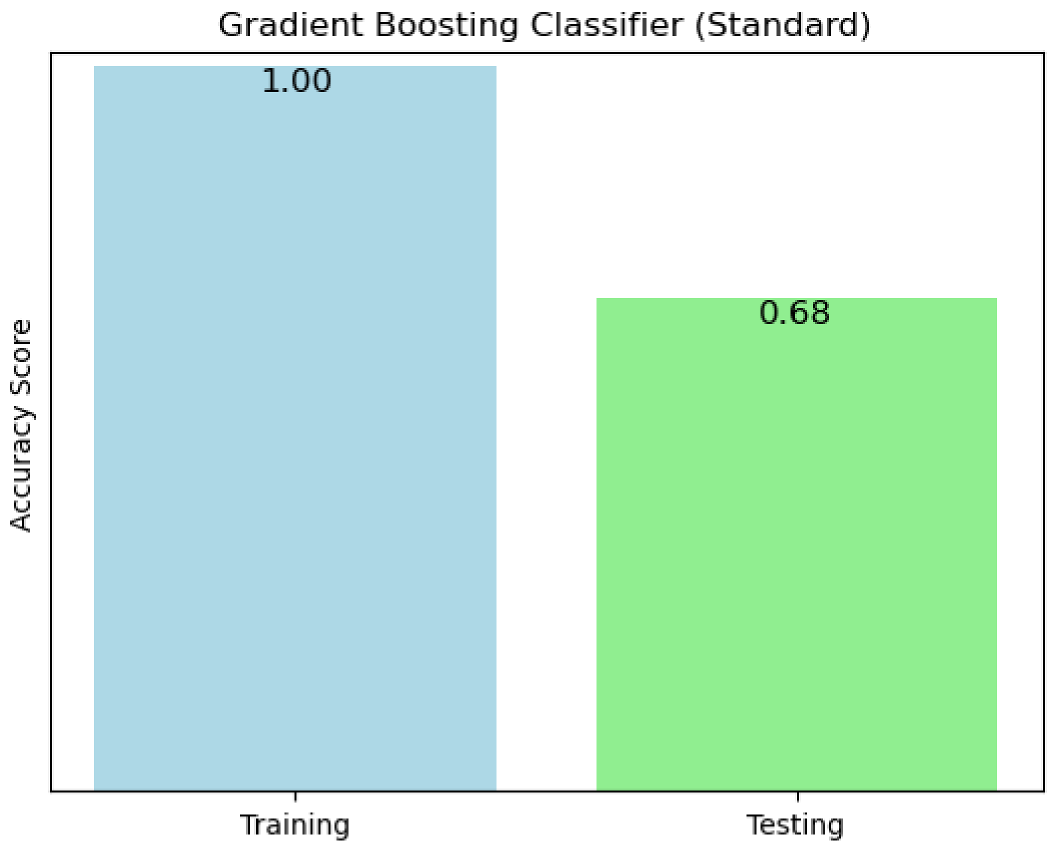


*** Gradient Boosting Classifier (Standard)

In [27]:

```
from sklearn.ensemble import GradientBoostingClassifier

# Create a classification model and fit it to the training data
```

```python
grb = GradientBoostingClassifier()
grb.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
grb_train_score = grb.score(X_train_temp, y_train_temp)
grb_test_score = grb.score(X_test_pca, y_test)

# Model scores
scores = [grb_train_score, grb_test_score]
labels = ['Training', 'Testing']

# Create the column chart
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
plt.ylabel('Accuracy Score')
plt.title('Gradient Boosting Classifier (Standard)')
plt.yticks([])
plt.ylim(0, 1.02)

# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```



- **Extreme Gradient Boosting Classifier (XGBOOST)**

Note:

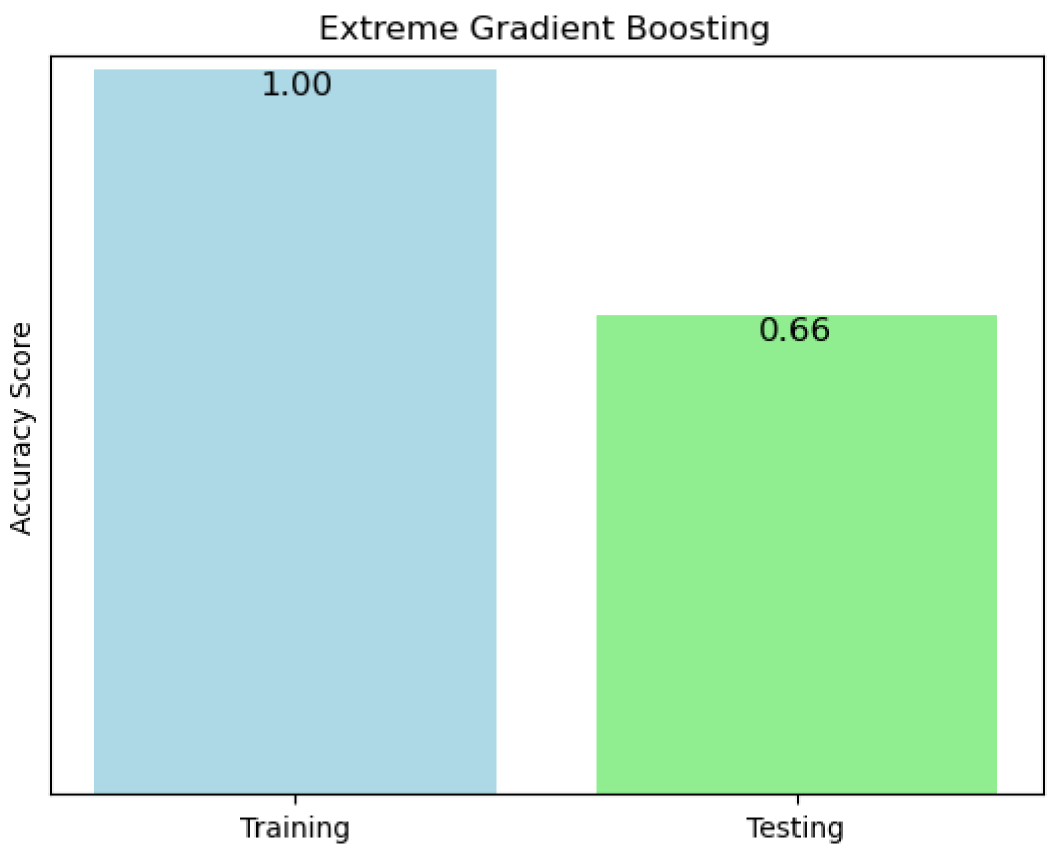
Extreme Gradient Boosting Classifier (XGBOOST) has a separate library from GradientBoostingClassifier. This means you need to install the below code to have this section of the notebook work.

pip install xgboost

In [28]:

```
from xgboost import XGBClassifier

# Create a classification model and fit it to the training data
xgrb = XGBClassifier()
xgrb.fit(X_train_temp, y_train_temp)

# Calculate the accuracy scores for the training and test sets
xgrb_train_score = xgrb.score(X_train_temp, y_train_temp)
xgrb_test_score = xgrb.score(X_test_pca, y_test)

# Model scores
scores = [xgrb_train_score, xgrb_test_score]
labels = ['Training', 'Testing']

# Create the column chart
plt.bar(labels, scores, color=['lightblue', 'lightgreen'])
```

```
plt.ylabel('Accuracy Score')
plt.title('Extreme Gradient Boosting')
plt.yticks([])
plt.ylim(0, 1.02)

# Display the scores on the columns
for i, score in enumerate(scores):
    plt.text(i, score, f'{score:.2f}', ha='center', va='top',
fontsize=12, color='black')

plt.show()
```



#

#

----

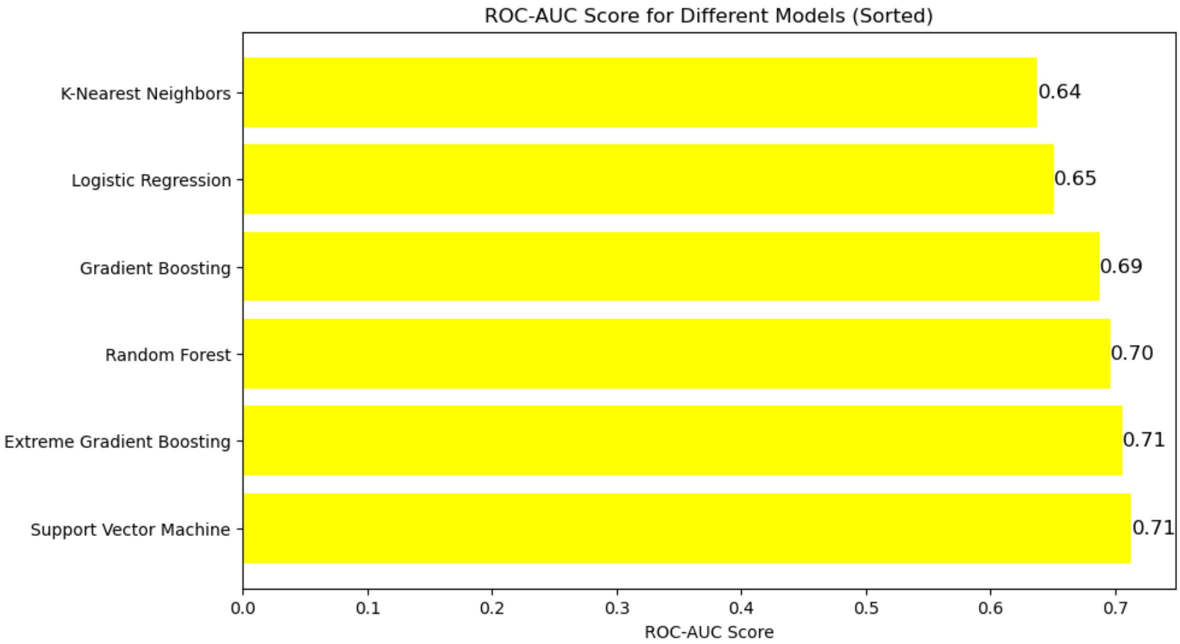
4. Evaluation Metrics (ROC-AUC, Accuracy, F-1 Score)

*** ROC-AUC

In [29]:

```
from sklearn.metrics import roc_auc_score

auc_lrc = roc_auc_score(y_test, lrc.decision_function(X_test_pca))
auc_knn = roc_auc_score(y_test, knn.predict_proba(X_test_pca)[:, 1])
auc_svc = roc_auc_score(y_test, svc.decision_function(X_test_pca))
auc_rfc = roc_auc_score(y_test, rfc.predict_proba(X_test_pca)[:, 1])
auc_grb = roc_auc_score(y_test, grb.predict_proba(X_test_pca)[:, 1])
auc_xgrb = roc_auc_score(y_test, xgrb.predict_proba(X_test_pca)[:, 1])

# Find the model with the highest ROC-AUC score
model = np.array([
    ['Logistic Regression', auc_lrc],
    ['K-Nearest Neighbors', auc_knn],
    ['Support Vector Machine', auc_svc],
    ['Random Forest', auc_rfc],
    ['Gradient Boosting', auc_grb],
    ['Extreme Gradient Boosting', auc_xgrb]
])

# Extract model names and accuracy scores
model_names = model[:, 0]
accuracy_scores = model[:, 1].astype(float)

# Sort the data based on accuracy scores in descending order
sorted_indices = np.argsort(accuracy_scores)[::-1]
model_names = model_names[sorted_indices]
accuracy_scores = accuracy_scores[sorted_indices]

# Create the bar chart
plt.figure(figsize=(10, 6))
plt.barh(model_names, accuracy_scores, color= 'Yellow')
plt.xlabel('ROC-AUC Score')
plt.title('ROC-AUC Score for Different Models (Sorted)')
plt.grid(axis='x', linestyle=' ', alpha=0.6)

# Display the accuracy scores on the bars
```

```
for i, accuracy in enumerate(accuracy_scores):
    plt.text(accuracy, i, f'{accuracy:.2f}', va='center', fontsize=12,
color='black')

plt.show()
```

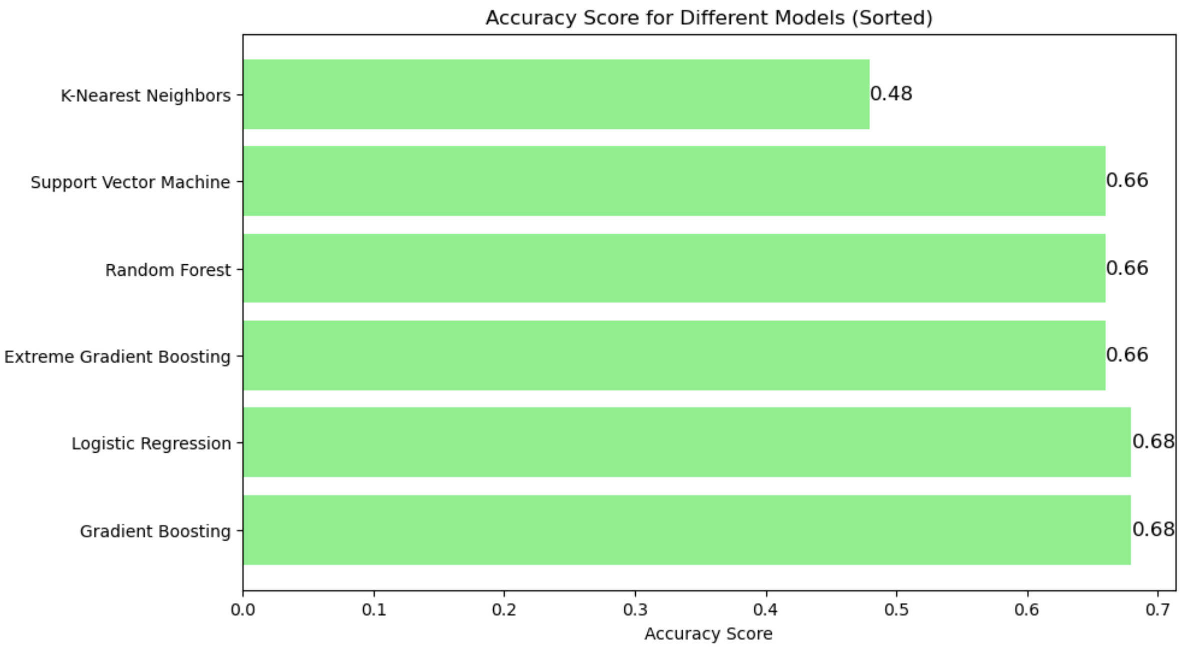


*** Accuracy

In [30]:

```
from sklearn.metrics import accuracy_score

ac_lrc = accuracy_score(y_test, lrc.predict(X_test_pca))
ac_knn = accuracy_score(y_test, knn.predict(X_test_pca))
ac_svc = accuracy_score(y_test, svc.predict(X_test_pca))
ac_rfc = accuracy_score(y_test, rfc.predict(X_test_pca))
ac_grb = accuracy_score(y_test, grb.predict(X_test_pca))
ac_xgrb = accuracy_score(y_test, xgrb.predict(X_test_pca))

# Find the model with the highest ROC-AUC score
model = np.array([
    ['Logistic Regression', ac_lrc],
    ['K-Nearest Neighbors', ac_knn],
    ['Support Vector Machine', ac_svc],
    ['Random Forest', ac_rfc],
    ['Gradient Boosting', ac_grb],
    ['Extreme Gradient Boosting', ac_xgrb]
])

# Extract model names and accuracy scores
```

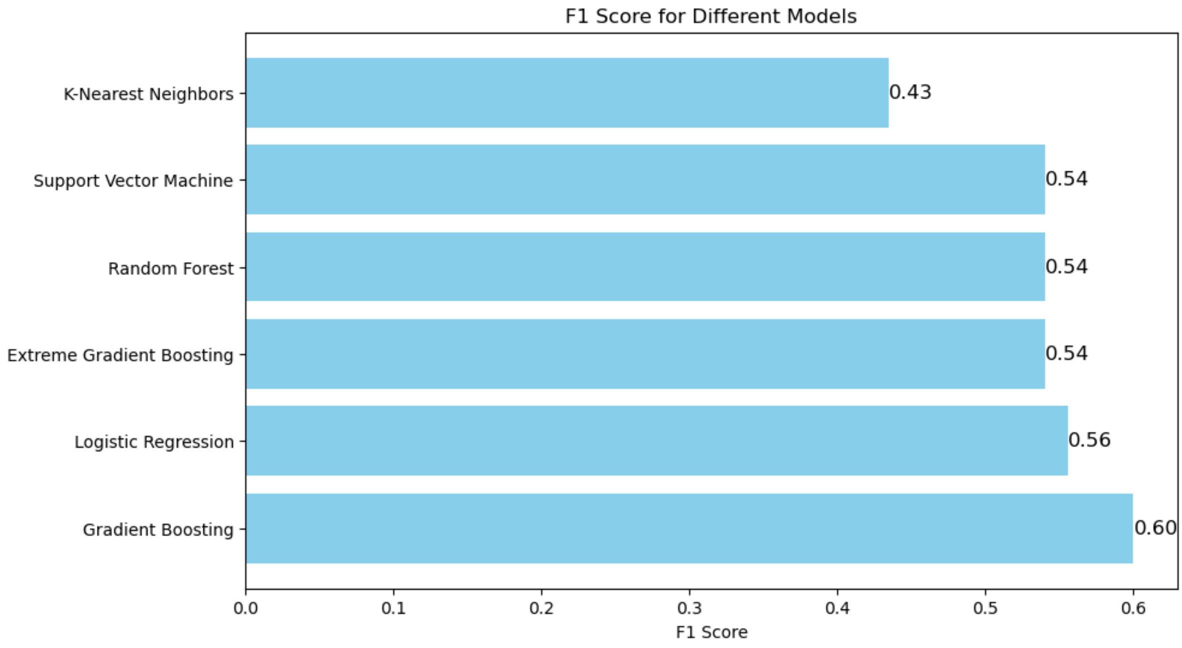
```
model_names = model[:, 0]
accuracy_scores = model[:, 1].astype(float)

# Sort the data based on accuracy scores in descending order
sorted_indices = np.argsort(accuracy_scores)[::-1]
model_names = model_names[sorted_indices]
accuracy_scores = accuracy_scores[sorted_indices]

# Create the bar chart
plt.figure(figsize=(10, 6))
plt.barh(model_names, accuracy_scores, color='lightgreen')
plt.xlabel('Accuracy Score')
plt.title('Accuracy Score for Different Models (Sorted)')
plt.grid(axis='x', linestyle=' ', alpha=0.6)

# Display the accuracy scores on the bars
for i, accuracy in enumerate(accuracy_scores):
    plt.text(accuracy, i, f'{accuracy:.2f}', va='center', fontsize=12,
color='black')

plt.show()
```



*** F-1 Score

In [31]:
```
from sklearn.metrics import f1_score

fscore_lrc = f1_score(y_test, lrc.predict(X_test_pca))
fscore_knn = f1_score(y_test, knn.predict(X_test_pca))
```

```
fscore_svc = f1_score(y_test, svc.predict(X_test_pca))
fscore_rfc = f1_score(y_test, rfc.predict(X_test_pca))
fscore_grb = f1_score(y_test, grb.predict(X_test_pca))
fscore_xgrb = f1_score(y_test, xgrb.predict(X_test_pca))

# Find the model with the highest ROC-AUC score
model = np.array([
    ['Logistic Regression', fscore_lrc],
    ['K-Nearest Neighbors', fscore_knn],
    ['Support Vector Machine', fscore_svc],
    ['Random Forest', fscore_rfc],
    ['Gradient Boosting', fscore_grb],
    ['Extreme Gradient Boosting', fscore_xgrb]
])

# Extract model names and F1 scores
model_names = model[:, 0]
fscores = model[:, 1].astype(float)

# Sort the data based on F1 scores in descending order
sorted_indices = np.argsort(fscores)[::-1]
model_names = model_names[sorted_indices]
fscores = fscores[sorted_indices]

# Bar chart
plt.figure(figsize=(10, 6))
plt.barh(model_names, fscores, color='skyblue')
plt.xlabel('F1 Score')
plt.title('F1 Score for Different Models')
plt.grid(axis='x', linestyle=' ', alpha=0.6)

# Display the F1 scores on the bars
for i, fscore in enumerate(fscores):
    plt.text(fscore, i, f'{fscore:.2f}', va='center', fontsize=12,
color='black')

plt.show()
```



Evaluation Summary:

Of all the models or techniques, Gradient Boosting turned out to be the best in terms of three important things: (1) how well it correctly identified positive cases, (2) how well it separated different classes, and (3) how often it was right.

This means that if we have a similar problem or dataset in the future, using Gradient Boosting is a smart choice because it's better at giving us accurate and reliable results among the models or techniques that we have contested.