In [1]:

```
#Import libraries

import numpy as np
import pandas as pd
import sys
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
import sklearn
import sklearn.model_selection as skm
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_curve, auc
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#Load the data csv files

train = pd.read_csv('Dataset_Training.csv')
test = pd.read_csv('Dataset_Test.csv')
```

Data Exploration and Preprocessing

In [3]:

```
#Check what the data looks like

train.head()
```

Out[3]:

	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	...	x22	x23	x24	x25	x26	x27	x28	x29	x30	y
0	17.99	10.38	122.80	1001.0	0.1184	0.2776	0.3001	0.14710	0.2419	0.07871	...	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890	0
1	19.69	21.25	130.00	1203.0	0.1096	0.1599	0.1974	0.12790	0.2069	0.05999	...	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	0.3613	0.08758	0
2	11.42	20.38	77.58	386.1	0.1425	0.2839	0.2414	0.10520	0.2597	0.09744	...	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300	0
3	20.29	14.34	135.10	1297.0	0.1003	0.1328	0.1980	0.10430	0.1809	0.05883	...	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	0.2364	0.07678	0
4	12.45	15.70	82.57	477.1	0.1278	0.1700	0.1578	0.08089	0.2087	0.07613	...	23.75	103.40	741.6	0.1791	0.5249	0.5355	0.1741	0.3985	0.12440	0

5 rows × 31 columns

In [4]:

```
# Check the shape of data

print("Train Data Shape:", train.shape)
print("Test Data Shape:", test.shape)
```

```
Train Data Shape: (519, 31)
Test Data Shape: (50, 31)
```

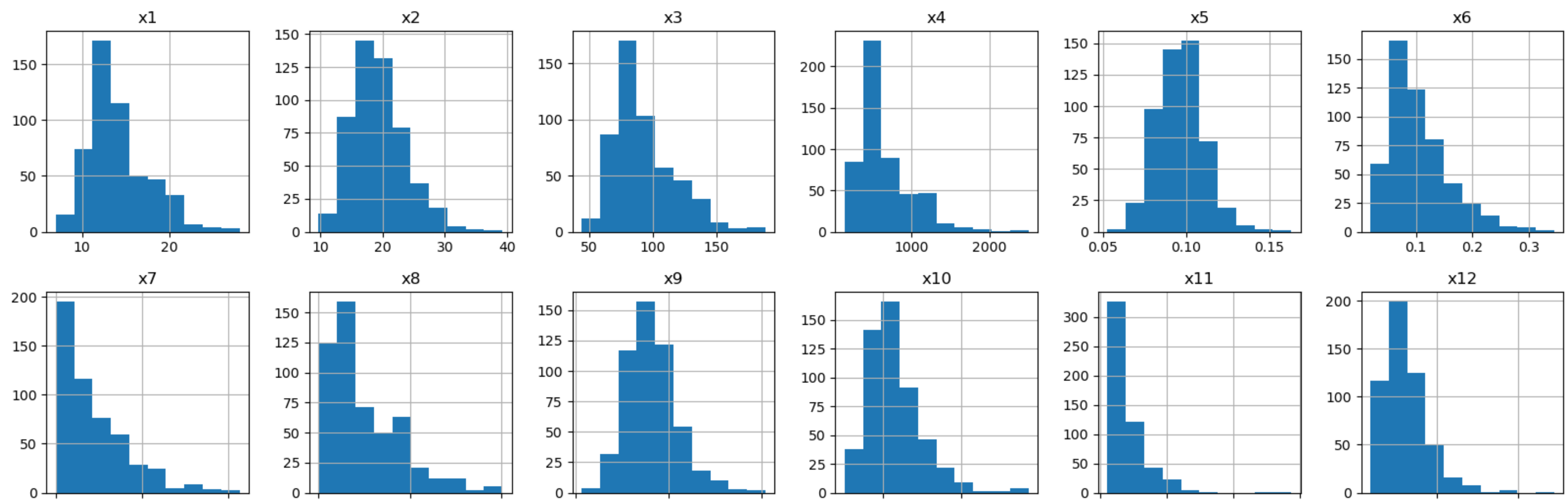
In [5]:

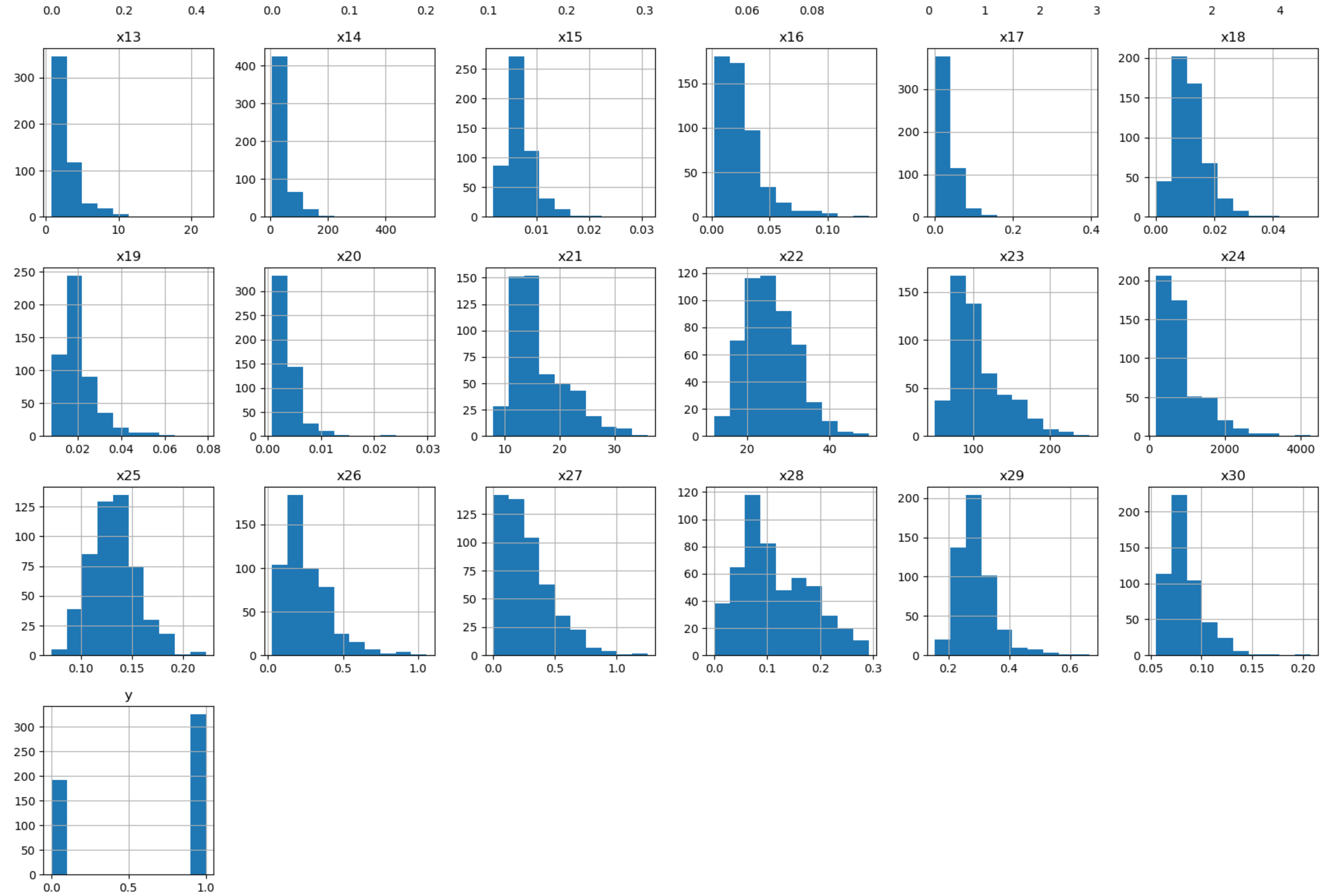
```
#Check for any missing data

print("Nulls in training data: ", train.isnull().sum().sum())
print("Nulls in test data: ", test.drop(['y'], axis = 1).isnull().sum().sum())
```

```
Nulls in training data:  0
Nulls in test data:  0
```

In [6]:

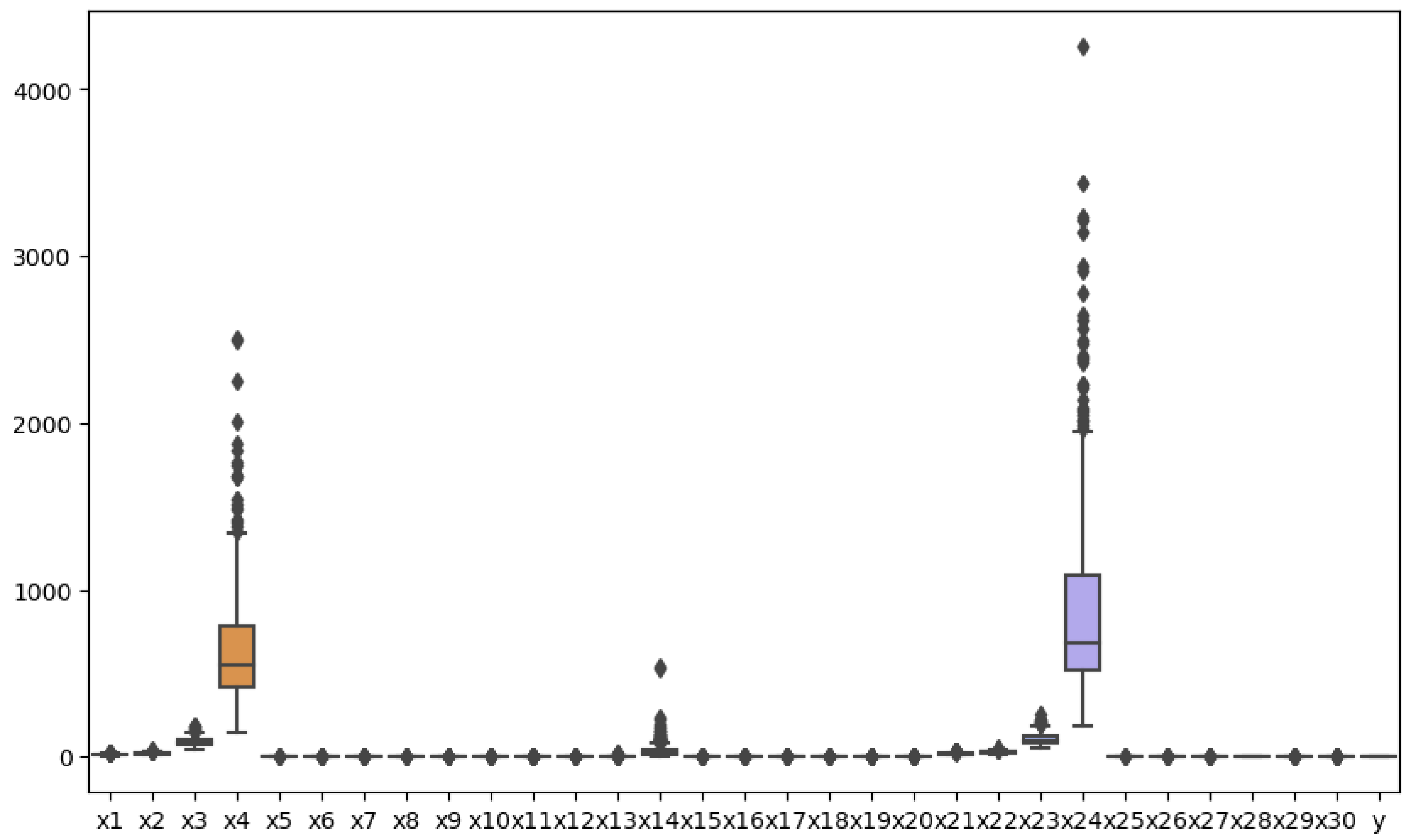
```
#Check how each feature is distributed

train.hist(figsize = (20, 20))
plt.show()
```





In [7]:

```
#Check outliers

plt.subplots(figsize=(10, 6))
sns.boxplot(data=train)
plt.show()
```



In [8]:

```
# Specify the column names to check for outliers
columns_to_check = ['x4', 'x24']

# Calculate the IQR for the specified columns
Q1 = train[columns_to_check].quantile(0.25)
Q3 = train[columns_to_check].quantile(0.75)
IQR = Q3 - Q1

# Determine the upper and lower thresholds for outlier detection
lower_threshold = Q1 - 2.5 * IQR
upper_threshold = Q3 + 2.5 * IQR

# Identify the potential outliers in the specified columns
```

```
outliers_mask = ((train[columns_to_check] < lower_threshold) | (train[columns_to_check] > upper_threshold)).any(axis=1)
outliers_data = train[outliers_mask]
outliers_data
```

Out[8]:

	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	...	x22	x23	x24	x25	x26	x27	x28	x29	x30	y
19	21.16	23.04	137.2	1404.0	0.09428	0.10220	0.1097	0.08632	0.1769	0.05278	...	35.59	188.0	2615.0	0.1401	0.2600	0.3155	0.2009	0.2822	0.07526	0
75	25.22	24.91	171.5	1878.0	0.10630	0.26650	0.3339	0.18450	0.1829	0.06782	...	33.62	211.7	2562.0	0.1573	0.6076	0.6476	0.2867	0.2355	0.10510	0
113	24.25	20.20	166.2	1761.0	0.14470	0.28670	0.4268	0.20120	0.2655	0.06877	...	23.99	180.9	2073.0	0.1696	0.4244	0.5803	0.2248	0.3222	0.08009	0
163	27.22	21.87	182.1	2250.0	0.10940	0.19140	0.2871	0.18780	0.1800	0.05770	...	32.85	220.8	3216.0	0.1472	0.4034	0.5340	0.2688	0.2856	0.08082	0
193	28.11	18.47	188.5	2499.0	0.11420	0.15160	0.3201	0.15950	0.1648	0.05525	...	18.47	188.5	2499.0	0.1142	0.1516	0.3201	0.1595	0.1648	0.05525	0
214	23.21	26.97	153.5	1670.0	0.09509	0.16820	0.1950	0.12370	0.1909	0.06309	...	34.51	206.0	2944.0	0.1481	0.4126	0.5820	0.2593	0.3103	0.08677	0
242	20.73	31.12	135.7	1419.0	0.09469	0.11430	0.1367	0.08646	0.1769	0.05674	...	47.16	214.0	3432.0	0.1401	0.2644	0.3442	0.1659	0.2868	0.08218	0
311	23.51	24.27	155.1	1747.0	0.10690	0.12830	0.2308	0.14100	0.1797	0.05506	...	30.73	202.4	2906.0	0.1515	0.2678	0.4819	0.2089	0.2593	0.07738	0
323	25.73	17.46	174.2	2010.0	0.11490	0.23630	0.3368	0.19130	0.1956	0.06121	...	23.58	229.3	3234.0	0.1530	0.5937	0.6451	0.2756	0.3690	0.08815	0
336	21.71	17.25	140.9	1546.0	0.09384	0.08562	0.1168	0.08465	0.1717	0.05054	...	26.44	199.5	3143.0	0.1363	0.1628	0.2861	0.1820	0.2510	0.06494	0
419	27.42	26.27	186.9	2501.0	0.10840	0.19880	0.3635	0.16890	0.2061	0.05623	...	31.37	251.2	4254.0	0.1357	0.4256	0.6833	0.2625	0.2641	0.07427	0
458	23.09	19.83	152.1	1682.0	0.09342	0.12750	0.1676	0.10030	0.1505	0.05484	...	23.87	211.5	2782.0	0.1199	0.3625	0.3794	0.2264	0.2908	0.07277	0
474	24.63	21.60	165.5	1841.0	0.10300	0.21060	0.2310	0.14710	0.1991	0.06739	...	26.93	205.7	2642.0	0.1342	0.4188	0.4658	0.2475	0.3157	0.09671	0

13 rows × 31 columns

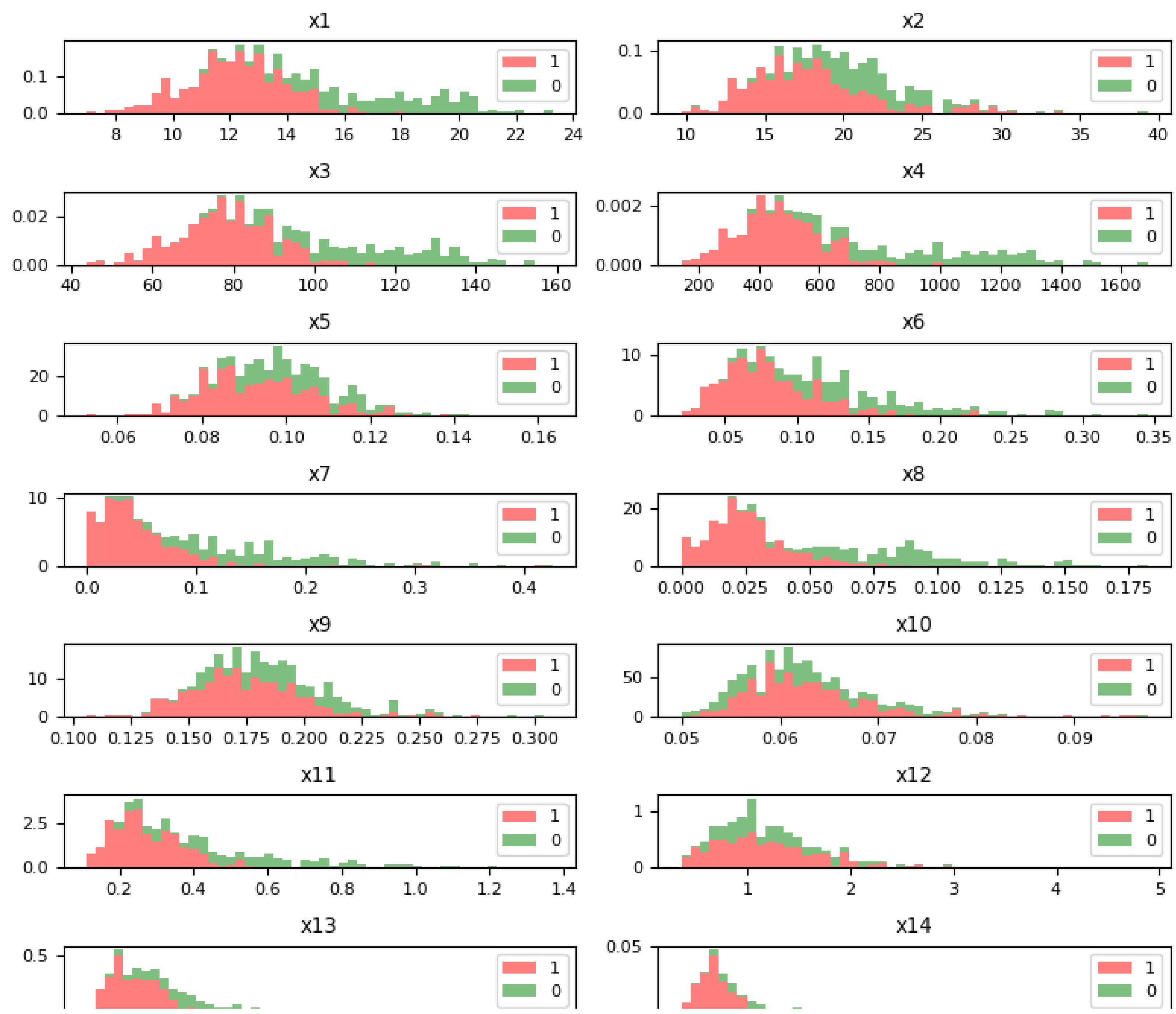
In [9]:

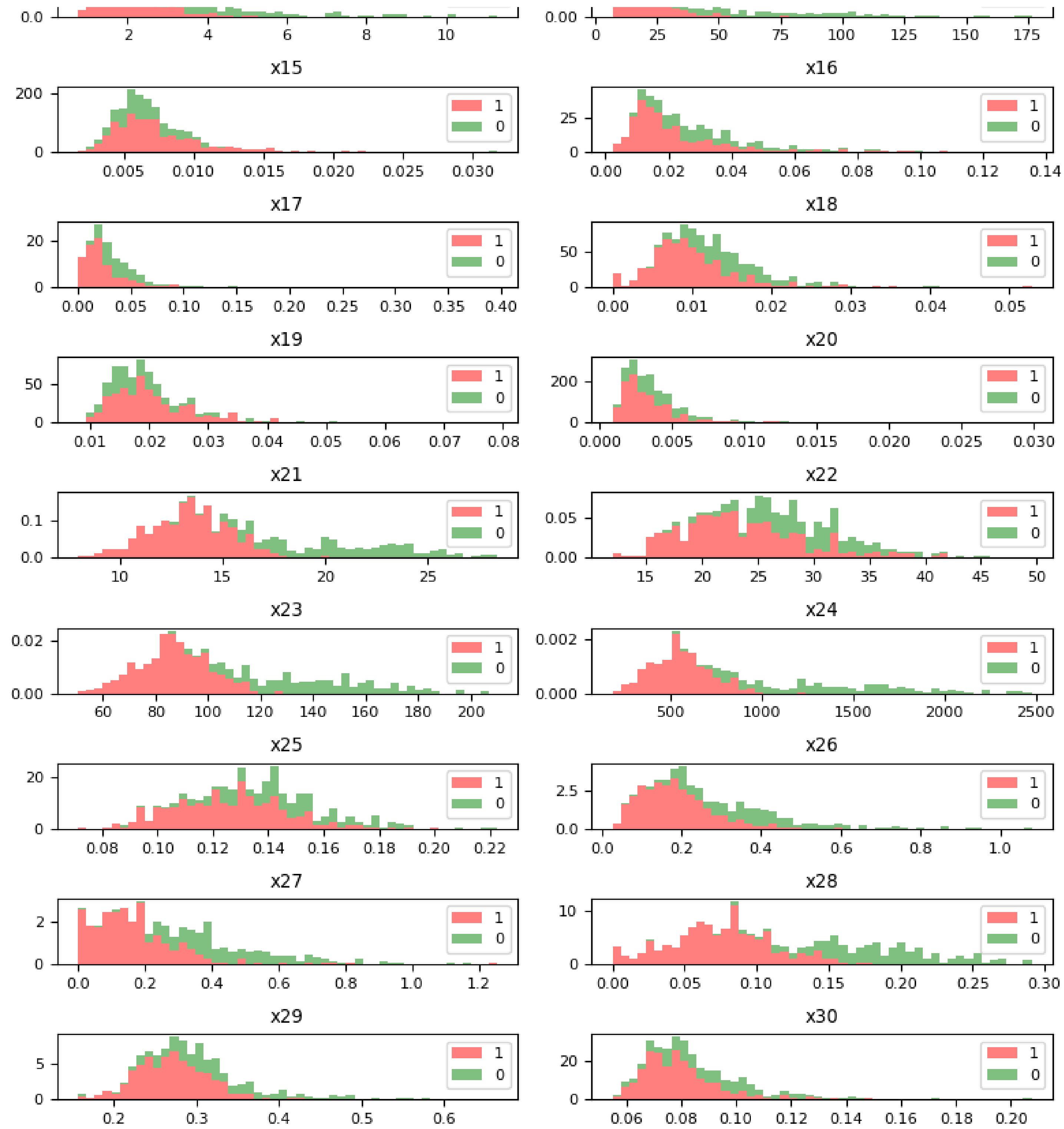
```
#Remove outliers

train = train[~outliers_mask]
train = train.reset_index(drop=True)
print(train.shape)
```

```
(506, 31)
```

In [10]:

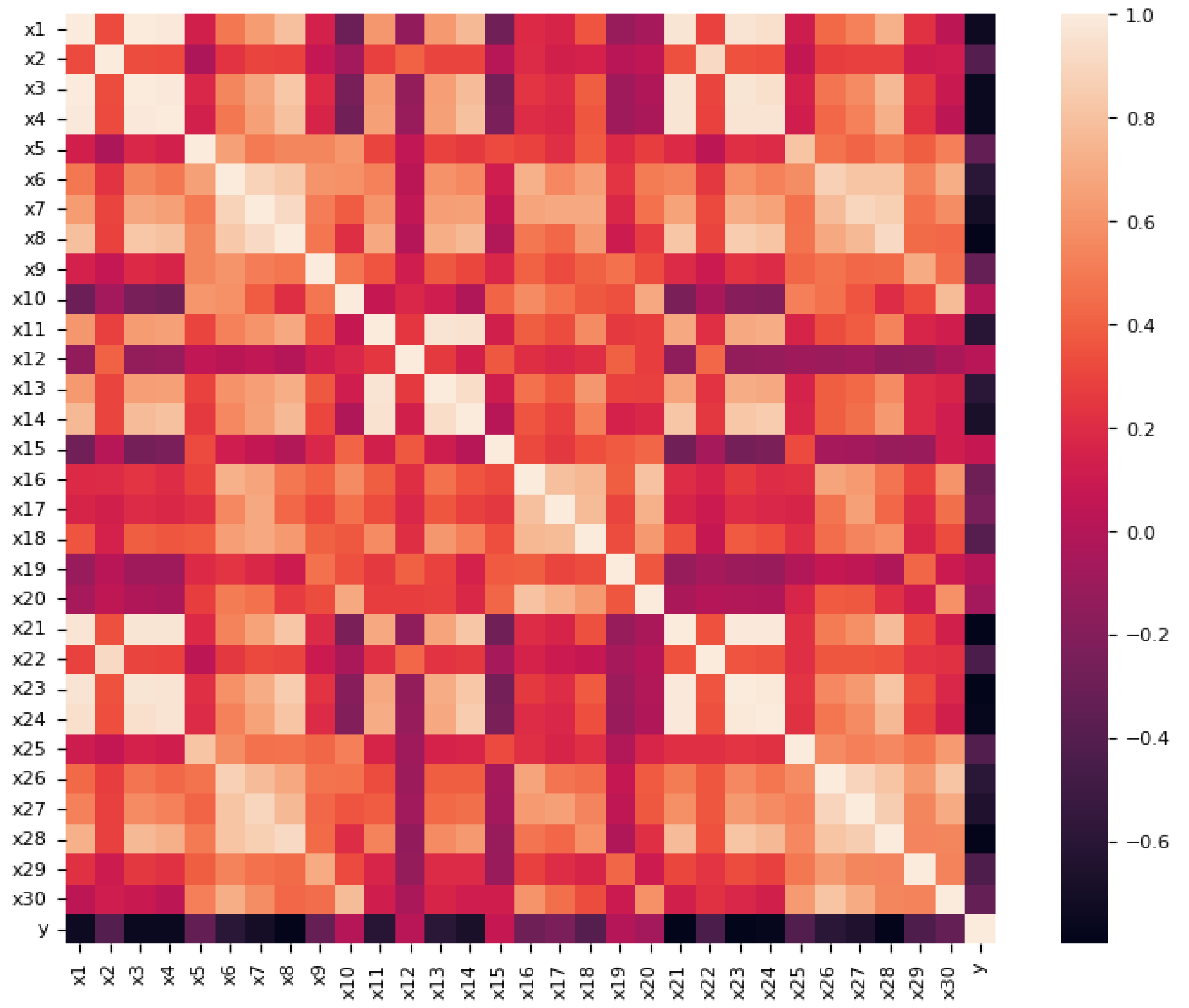
```
#Features vs classes in y

features = list(train.columns)
train1 = train[train['y'] ==1]
train0 = train[train['y'] ==0]

plt.rcParams.update({'font.size': 8})
fig, axes = plt.subplots(nrows=15, ncols=2, figsize=(8, 15))
axes = axes.ravel()
for idx, ax in enumerate(axes):
    ax.figure
    binwidth = (max(train[features[idx]]) - min(train[features[idx]])) / 50
    ax.hist([train1[features[idx]], train0[features[idx]]], bins=np.arange(min(train[features[idx]]), max(train[features[idx]]) +
binwidth, binwidth), alpha=0.5, stacked=True, density=True, label=['1', '0'], color=['r', 'g'])
    ax.legend(loc='upper right')
    ax.set_title(features[idx])
plt.tight_layout()
plt.show()
```





In [11]:

```
# Check if any of the features have strong correlation

corr = train.corr()
fig = plt.figure(figsize = (10, 7))

sns.heatmap(corr, vmax = 1, square = True)
plt.show()
```



Modelling

In [12]:

```
X_train = train.drop(['y'], axis = 1)
y_train = train['y']

X_test = test.drop(['y'], axis = 1)
y_test = test['y']
```

In [13]:

```
#Feature Scaling

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
```

Logistic Regression

In [14]:

```
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression(solver = 'liblinear', random_state = 0)
logreg.fit(x_train, y_train)

print("Score on training: ", logreg.score(x_train, y_train))

cross_val_scores = cross_val_score(logreg, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9861660079051383
Cross-Validation Scores: [0.97058824 0.97029703 0.98019802 0.97029703 0.99009901]
Mean CV Score: 0.9762958648806057
CV score Variance: 0.000062
```

In [15]:

```
logit = LogisticRegression(solver = 'liblinear',
                                random_state = 0)
param_grid = {'C' : [0.001, 0.01, 0.1, 1, 2, 5, 10, 100]}

grid = skm.GridSearchCV(estimator = logit, param_grid = param_grid , scoring = 'recall', verbose = 1, n_jobs = -1)
grid.fit(X_train, y_train)

best_parameters = grid.best_params_
print('The best parameters for using this model is', best_parameters)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
The best parameters for using this model is {'C': 2}
```

In [16]:

```
logreg_grid = LogisticRegression(C = best_parameters['C'], solver = 'liblinear',
                                random_state = 0)

logreg_grid.fit(x_train, y_train)

print("Score on training: ", logreg_grid.score(x_train, y_train))

cross_val_scores = cross_val_score(logreg_grid, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9861660079051383
Cross-Validation Scores: [0.97058824 0.97029703 0.98019802 0.97029703 0.99009901]
Mean CV Score: 0.9762958648806057
CV score Variance: 0.000062
```

K-Nearest Neighbours

In [17]:

```
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier(n_neighbors = 3)
knn_model.fit(x_train, y_train)
print("Score on training: ", knn_model.score(x_train, y_train))

cross_val_scores = cross_val_score(knn_model, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9762845849802372
Cross-Validation Scores: [0.96078431 0.95049505 0.98019802 0.96039604 0.94059406]
Mean CV Score: 0.9584934964084644
CV score Variance: 0.000173
```

In [18]:

```
knn2 = KNeighborsClassifier()
param_grid = {'n_neighbors': np.arange(1, 25)}
knn_gscv = skm.GridSearchCV(knn2, param_grid, cv=5)
knn_gscv.fit(x_train, y_train)
```

Out[18]:

```
GridSearchCV
estimator: KNeighborsClassifier
KNeighborsClassifier
```

In [19]:

```
knn_gscv.best_params_
```

Out[19]:

```
{'n_neighbors': 8}
```

In [20]:

```
knn = knn_gscv.best_estimator_
knn.fit(x_train, y_train)
print("Score on training: ", knn.score(x_train, y_train))

cross_val_scores = cross_val_score(knn, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9723320158102767
Cross-Validation Scores: [0.96078431 0.95049505 0.99009901 0.97029703 0.99009901]
Mean CV Score: 0.9723548825470782
CV score Variance: 0.000249
```

Naive Bayes

In [21]:

```
from sklearn.naive_bayes import GaussianNB

NB = GaussianNB()
NB.fit(x_train, y_train)
```

Out[21]:

```
GaussianNB
GaussianNB()
```

In [22]:

```
print("Score on training: ", NB.score(x_train, y_train))

cross_val_scores = cross_val_score(NB, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9446640316205533
Cross-Validation Scores: [0.92156863 0.91089109 0.95049505 0.97029703 0.91089109]
Mean CV Score: 0.9328285769753446
CV score Variance: 0.000561
```

Support Vector Machine

In [23]:

```
#Linear SVC

from sklearn.svm import LinearSVC
from sklearn.svm import SVC

svm = LinearSVC(C = 0.001, random_state = 0)
svm.fit(x_train, y_train)

print("Score on training: "+ str(svm.score(x_train, y_train)))
```

```
Score on training: 0.974308300395257
```

In [24]:

```
kfold = skm.KFold(5, random_state = 0, shuffle = True)

grid = skm.GridSearchCV(svm, {'C': [0.000001, 0.0001, 0.001, 0.01, 0.1, 1, 2, 5, 8, 10, 100]},
                        refit=True, cv=kfold, scoring='accuracy')
grid.fit(x_train, y_train)
grid.best_params_
```

Out[24]:

```
{'C': 0.1}
```

In [25]:

```
svm_grid = grid.best_estimator_
svm_grid.fit(x_train, y_train)
```

Out[25]:

```
▾          LinearSVC
LinearSVC(C=0.1, random_state=0)
```

In [26]:

```
print("Score on training: "+ str(svm_grid.score(x_train, y_train)))

cross_val_scores = cross_val_score(svm_grid, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9861660079051383
Cross-Validation Scores: [0.97058824 0.97029703 0.97029703 0.97029703 0.99009901]
Mean CV Score: 0.9743156668608037
CV score Variance: 0.000062
```

In [27]:

```
#Radial basis function kernel

svm_rbf = SVC(kernel = "rbf", gamma = 1, C=0.0001, random_state = 0)
svm_rbf.fit(x_train , y_train)
print("Score on training: "+ str(svm_rbf.score(x_train, y_train)))
```

```
Score on training: 0.6442687747035574
```

In [28]:

```
#Polynomial kernel function

svm_poly = SVC(kernel = "poly", gamma = 'scale', degree = 3, C=0.0001, random_state = 0)
svm_poly.fit(x_train , y_train)
print("Score on training: "+ str(svm_poly.score(x_train, y_train)))
```

```
Score on training: 0.6442687747035574
```

Linear Discriminant Analysis

In [29]:

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis()
lda_model = lda.fit(x_train, y_train)

lda_pred = lda_model.predict(x_train)
```

In [30]:

```
print("Score on training:", accuracy_score(y_train, lda_pred))

cross_val_scores = cross_val_score(lda_model, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9604743083003953
Cross-Validation Scores: [0.94117647 0.94059406 0.95049505 0.96039604 0.97029703]
Mean CV Score: 0.9525917297612114
CV score Variance: 0.000131
```

Quadratic Discriminant Analysis

In [31]:

```
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

qda = QuadraticDiscriminantAnalysis()
qda_model = qda.fit(x_train, y_train)
```

```
qda_pred = qda_model.predict(x_train)
```

In [32]:

```
print("Score on training:", accuracy_score(y_train, qda_pred))

cross_val_scores = cross_val_score(qda_model, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9723320158102767
Cross-Validation Scores: [0.97058824 0.91089109 0.95049505 0.97029703 0.95049505]
Mean CV Score: 0.95055329062318
CV score Variance: 0.000473
```

Decision Tree

In [33]:

```
from sklearn.tree import DecisionTreeClassifier as DTC

dtc = DTC(criterion = 'entropy', max_depth = 3, random_state = 0)
dtc.fit(x_train, y_train)
```

Out[33]:

```
▾                    DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
```

In [34]:

```
print("Score on training:", accuracy_score(y_train, dtc.predict(x_train)))

cross_val_scores = cross_val_score(dtc, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9545454545454546
Cross-Validation Scores: [0.90196078 0.9009901  0.92079208 0.92079208 0.92079208]
Mean CV Score: 0.9130654241894778
CV score Variance: 0.000090
```

In [35]:

```
DT = DTC(criterion='entropy', random_state = 0) # do not set max_depth
DT.fit(x_train, y_train)
print("Score on training:", accuracy_score(y_train, DT.predict(x_train)))
```

```
Score on training: 1.0
```

In [36]:

```
# compute the ccp_path parameter values on the training data for pruning the tree

ccp_path = DT.cost_complexity_pruning_path(x_train, y_train)
kfold = skm.KFold(10, random_state = 1, shuffle = True)
```

In [37]:

```
DT_grid = skm.GridSearchCV(DT, {'ccp_alpha': ccp_path.ccp_alphas},
             refit = True, cv = kfold, scoring='accuracy')
DT_grid.fit(x_train, y_train)
print("Score on training:", DT_grid.best_score_)

cross_val_scores = cross_val_score(DT_grid, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9486666666666667
Cross-Validation Scores: [0.89215686 0.9009901  0.95049505 0.93069307 0.89108911]
Mean CV Score: 0.9130848378955543
CV score Variance: 0.000556
```

Gradient Boosting Classifier

In [38]:

```
from sklearn.ensemble import GradientBoostingClassifier

gbc = GradientBoostingClassifier(n_estimators = 100, learning_rate = 0.01,
            max_depth = 3, random_state = 0)
```

```
gbc.fit(x_train, y_train)
```

Out[38]:

```
▾ GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=0.01, random_state=0)
```

In [39]:

```
print("Score on training: ", gbc.score(x_train, y_train))

cross_val_scores = cross_val_score(gbc, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training:  0.9822134387351779
Cross-Validation Scores: [0.91176471 0.9009901  0.96039604 0.92079208 0.94059406]
Mean CV Score: 0.9269073966220152
CV score Variance: 0.000449
```

Random Forests Classifier

In [40]:

```
from sklearn.ensemble import RandomForestClassifier as RF

# Bagging ensemble model using the random forest (RF) algorithm
RFC_bag = RF(max_features = X_train.shape[1],
        n_estimators = 10, criterion = 'entropy', random_state = 0, max_depth = 3).fit(x_train, y_train)

print("Score on training:", accuracy_score(y_train, RFC_bag.predict(x_train)))

cross_val_scores = cross_val_score(RFC_bag, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.974308300395257
Cross-Validation Scores: [0.94117647 0.92079208 0.97029703 0.94059406 0.95049505]
Mean CV Score: 0.9446709376820035
CV score Variance: 0.000258
```

In [41]:

```
RFC = RF(max_features = 15, random_state = 0,  max_depth = 3).fit(x_train, y_train)
print("Score on training:", accuracy_score(y_train, RFC.predict(x_train)))

cross_val_scores = cross_val_score(RFC, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

```
Score on training: 0.9802371541501976
Cross-Validation Scores: [0.92156863 0.93069307 0.98019802 0.98019802 0.96039604]
Mean CV Score: 0.9546107551931664
CV score Variance: 0.000601
```

In [42]:

```
feature_names = list(X_train.columns)
```

In [43]:

```
feature_imp = pd.DataFrame({'importance': RFC.feature_importances_}, index = feature_names)
imp_features = feature_imp.sort_values(by='importance', ascending = False).head(3)
top_features = imp_features.index.tolist()  # Get the index values of the top features as a list
x_subset = X_train[top_features]  # Subset X_train using the top features
```

In [44]:

```
RFs = RF(max_features = X_train.shape[1], random_state = 0, max_depth = 3).fit(x_subset, y_train)
print("Score on training:", accuracy_score(y_train, RFs.predict(x_subset)))

cross_val_scores = cross_val_score(RFs, x_train, y_train, cv = 5)
print("Cross-Validation Scores:", cross_val_scores)

mean_score = np.mean(cross_val_scores)
print("Mean CV Score:", mean_score)

variance = np.var(cross_val_scores)
variance = '{:.6f}'.format(variance)
print("CV score Variance:", variance)
```

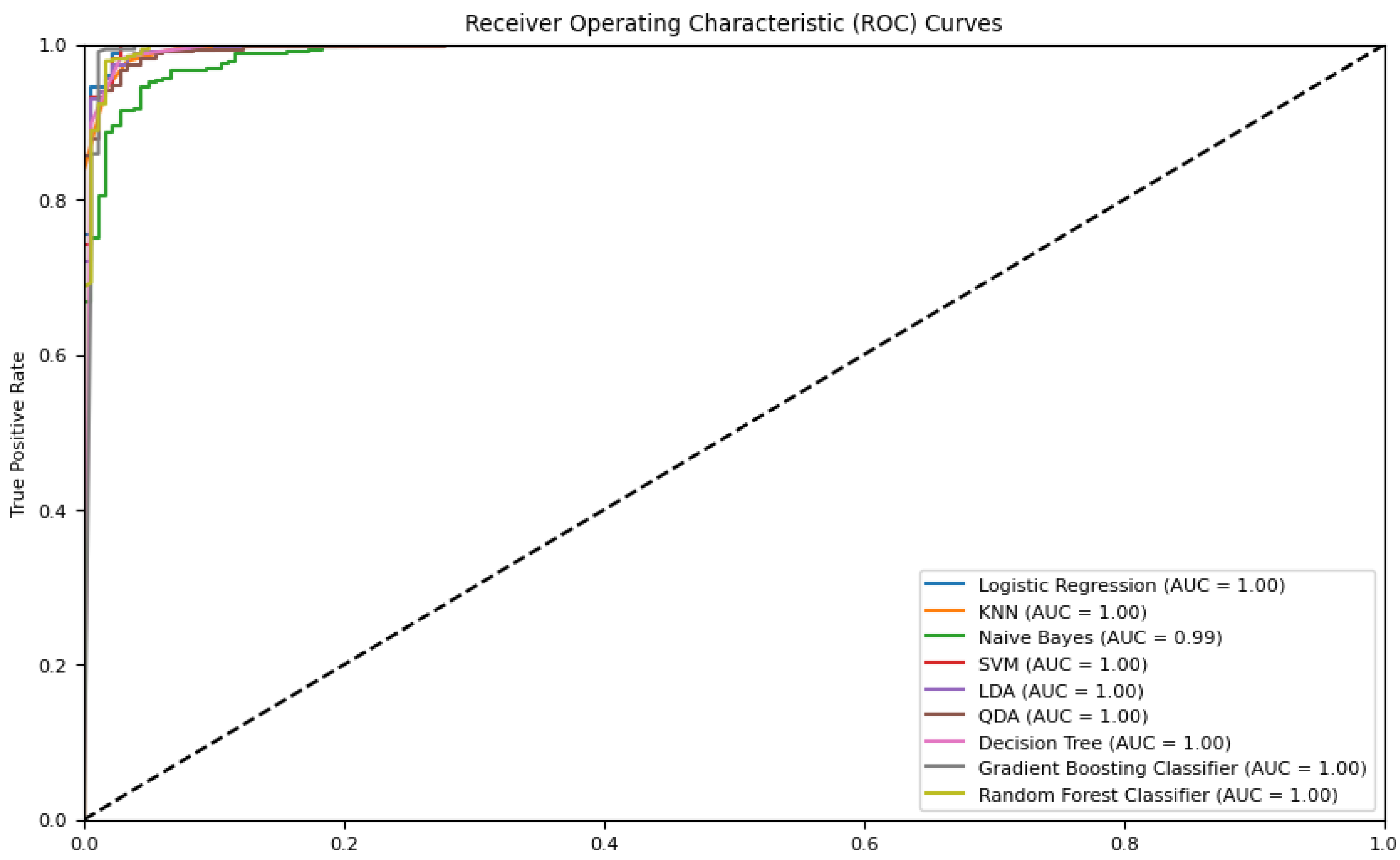
```
Score on training: 0.9604743083003953
```

```
Cross-validation Scores: [0.91176471 0.94059406 0.97029703 0.96039604 0.97029703]
Mean CV Score: 0.9506697728596389
CV score Variance: 0.000496
```

Model Comparison

In [45]:

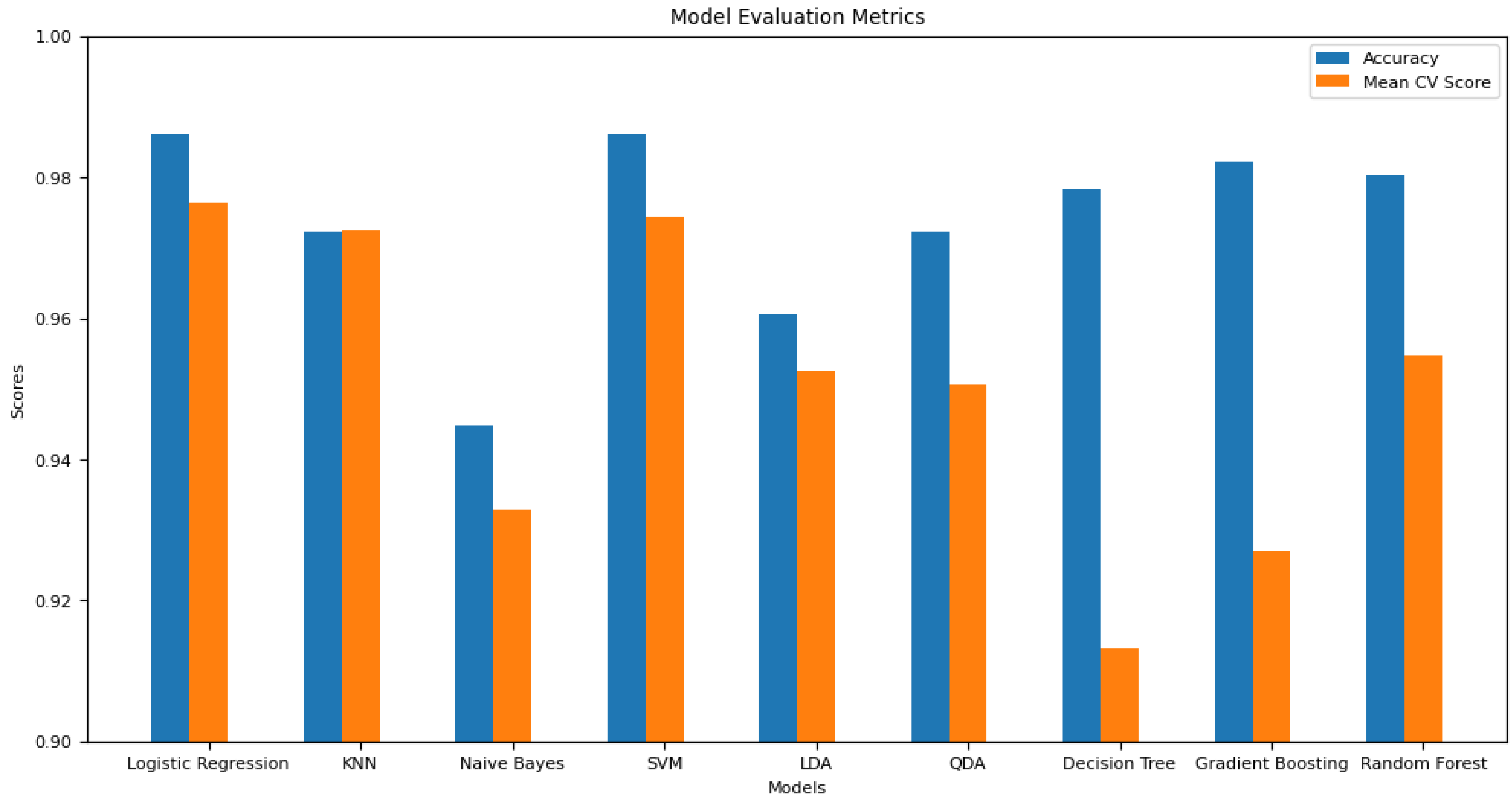
```python
from sklearn.calibration import CalibratedClassifierCV

clf = CalibratedClassifierCV(svm_grid)
clf.fit(x_train, y_train)

# Calculate the predicted probabilities for each model using x_train
y_pred_logreg = logreg_grid.predict_proba(x_train)[::,1]
y_pred_knn = knn.predict_proba(x_train)[::,1]
y_pred_NB = NB.predict_proba(x_train)[::,1]
y_pred_svm = clf.predict_proba(x_train)[::,1]
y_pred_lda = lda_model.predict_proba(x_train)[::,1]
y_pred_qda = qda_model.predict_proba(x_train)[::,1]
y_pred_DT = DT_grid.predict_proba(x_train)[::,1]
y_pred_gbc = gbc.predict_proba(x_train)[::,1]
y_pred_RFC = RFC.predict_proba(x_train)[::,1]

# Calculate AUC scores for each model using y_train and the corresponding predicted probabilities
auc_logreg = metrics.roc_auc_score(y_train, y_pred_logreg)
auc_knn = metrics.roc_auc_score(y_train, y_pred_knn)
auc_NB = metrics.roc_auc_score(y_train, y_pred_NB)
auc_svm = metrics.roc_auc_score(y_train, y_pred_svm)
auc_lda = metrics.roc_auc_score(y_train, y_pred_lda)
auc_qda = metrics.roc_auc_score(y_train, y_pred_qda)
auc_DT = metrics.roc_auc_score(y_train, y_pred_DT)
auc_gbc = metrics.roc_auc_score(y_train, y_pred_gbc)
auc_RFC = metrics.roc_auc_score(y_train, y_pred_RFC)

# Calculate the false positive rate (FPR), true positive rate (TPR), and threshold values for each model using y_train
fpr_logreg, tpr_logreg, thresholds_logreg = metrics.roc_curve(y_train, y_pred_logreg)
fpr_knn, tpr_knn, thresholds_knn = metrics.roc_curve(y_train, y_pred_knn)
fpr_NB, tpr_NB, thresholds_NB = metrics.roc_curve(y_train, y_pred_NB)
fpr_svm, tpr_svm, thresholds_svm = metrics.roc_curve(y_train, y_pred_svm)
fpr_lda, tpr_lda, thresholds_lda = metrics.roc_curve(y_train, y_pred_lda)
fpr_qda, tpr_qda, thresholds_qda = metrics.roc_curve(y_train, y_pred_qda)
fpr_DT, tpr_DT, thresholds_DT = metrics.roc_curve(y_train, y_pred_DT)
fpr_gbc, tpr_gbc, thresholds_gbc = metrics.roc_curve(y_train, y_pred_gbc)
fpr_RFC, tpr_RFC, thresholds_RFC = metrics.roc_curve(y_train, y_pred_RFC)

# Plot ROC curves
plt.figure(figsize=(10, 6))
plt.plot(fpr_logreg, tpr_logreg, label='Logistic Regression (AUC = %.2f)' % auc_logreg)
plt.plot(fpr_knn, tpr_knn, label='KNN (AUC = %.2f)' % auc_knn)
plt.plot(fpr_NB, tpr_NB, label='Naive Bayes (AUC = %.2f)' % auc_NB)
plt.plot(fpr_svm, tpr_svm, label='SVM (AUC = %.2f)' % auc_svm)
plt.plot(fpr_lda, tpr_lda, label='LDA (AUC = %.2f)' % auc_lda)
plt.plot(fpr_qda, tpr_qda, label='QDA (AUC = %.2f)' % auc_qda)
plt.plot(fpr_DT, tpr_DT, label='Decision Tree (AUC = %.2f)' % auc_DT)
plt.plot(fpr_gbc, tpr_gbc, label='Gradient Boosting Classifier (AUC = %.2f)' % auc_gbc)
plt.plot(fpr_RFC, tpr_RFC, label='Random Forest Classifier (AUC = %.2f)' % auc_RFC)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curves')
plt.legend(loc='lower right')
plt.show()

# Plot AUC scores
models = ['Logistic Regression', 'KNN', 'Naive Bayes', 'SVM', 'LDA', 'QDA', 'Decision Tree', 'Gradient Boosting', 'Random Forest'
]
```



False Positive Rate

In [46]:

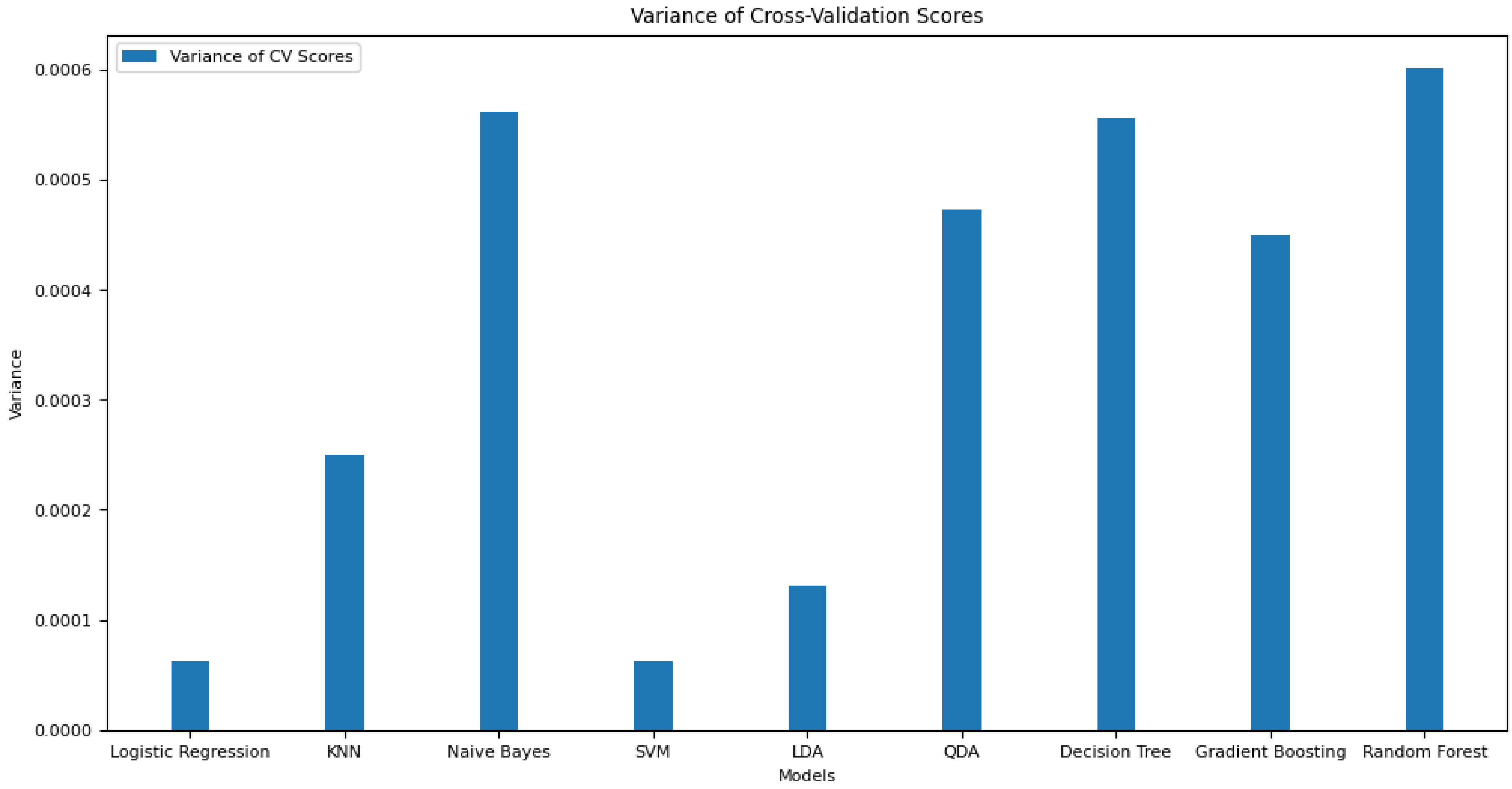
```
accuracy_scores = []
mean_cv_scores = []

# Calculate accuracy scores and cross-validation scores for each model
accuracy_scores.append(metrics.accuracy_score(y_train, logreg_grid.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, knn.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, NB.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, svm_grid.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, lda_model.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, qda_model.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, DT_grid.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, gbc.predict(x_train)))
accuracy_scores.append(metrics.accuracy_score(y_train, RFC.predict(x_train)))

mean_cv_scores.append(np.mean(cross_val_score(logreg_grid, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(knn, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(NB, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(svm_grid, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(lda_model, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(qda_model, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(DT_grid, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(gbc, x_train, y_train, cv=5)))
mean_cv_scores.append(np.mean(cross_val_score(RFC, x_train, y_train, cv=5)))

# Plot accuracy scores and mean cv scores
plt.figure(figsize=(12, 6))
x = np.arange(len(models))
bar_width = 0.25

plt.bar(x, accuracy_scores, width=bar_width, label='Accuracy')
plt.bar(x + bar_width, mean_cv_scores, width=bar_width, label='Mean CV Score')

plt.xlabel('Models')
plt.ylabel('Scores')
plt.title('Model Evaluation Metrics')
plt.xticks(x + bar_width, models)
plt.legend()
plt.ylim(0.9, 1.0)
plt.show()
```



In [47]:

```
variance_cv_scores = [
    np.var(cross_val_score(logreg_grid, x_train, y_train, cv=5)),
    np.var(cross_val_score(knn, x_train, y_train, cv=5)),
    np.var(cross_val_score(NB, x_train, y_train, cv=5)),
    np.var(cross_val_score(svm_grid, x_train, y_train, cv=5)),
    np.var(cross_val_score(lda_model, x_train, y_train, cv=5)),
    np.var(cross_val_score(qda_model, x_train, y_train, cv=5)),
    np.var(cross_val_score(DT_grid, x_train, y_train, cv=5)),
    np.var(cross_val_score(gbc, x_train, y_train, cv=5)),
    np.var(cross_val_score(RFC, x_train, y_train, cv=5))
]

plt.figure(figsize=(12, 6))
x = np.arange(len(models))
bar_width = 0.25

plt.bar(x, variance_cv_scores, width=bar_width, label='Variance of CV Scores')

plt.xlabel('Models')
plt.ylabel('Variance')
plt.title('Variance of Cross-Validation Scores')
plt.xticks(x, models)
plt.legend()
```

```
plt.show()
```



Predicting using best model

In [48]:

```
y_test = logreg_grid.predict(x_test)
test['y'] = y_test
test.to_csv('Test_predictions.csv')
```