Prediction of Liver Disease within Individuals

Load the dataset

In [1]:
```
import pandas as pd

file_path = 'Indian_Liver_Patients.csv'
data = pd.read_csv(file_path)
```

Explore the dataset

In [2]:
```
data.head()
```

Out[2]:

	Age	Gender	Total_Bilirubin	Direct_Bilirubin	Alkaline_Phosphotase	Alamine_Aminotrans
0	65	Female	0.7	0.1	187	
1	62	Male	10.9	5.5	699	
2	62	Male	7.3	4.1	490	
3	58	Male	1.0	0.4	182	
4	72	Male	3.9	2.0	195	

In [3]:
```
#Get number of records and columns
data.shape
```

Out[3]:
```
(583, 11)
```

In [4]:
```
#Get data types
data.dtypes
```

Out[4]:
```
Age                             int64
Gender                         object
Total_Bilirubin               float64
Direct_Bilirubin              float64
Alkaline_Phosphotase            int64
Alamine_Aminotransferase        int64
Aspartate_Aminotransferase      int64
Total_Protiens                float64
Albumin                       float64
Albumin_and_Globulin_Ratio    float64
Dataset                         int64
dtype: object
```

In [5]:
```python
#Get number of unique values in each column
data.nunique()
```

Out[5]:
```
Age                            72
Gender                          2
Total_Bilirubin               113
Direct_Bilirubin               80
Alkaline_Phosphotase          263
Alamine_Aminotransferase      152
Aspartate_Aminotransferase    177
Total_Protiens                 58
Albumin                        40
Albumin_and_Globulin_Ratio     69
Dataset                         2
dtype: int64
```

Perform column conversions

In [6]:
```python
#Rename the column 'Dataset' to 'Target' for identification convenience
data.rename(columns = {'Dataset':'Target'}, inplace = True)

#Replace values in the 'Target' column: 2 -> 0
data['Target'].replace({2: 0}, inplace = True)

data['Target'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 583 entries, 0 to 582
Series name: Target
Non-Null Count  Dtype
--------------  -----
583 non-null    int64
dtypes: int64(1)
memory usage: 4.7 KB
```

In [7]:
```python
#Get counts on the 'Target' variable
data['Target'].value_counts()
```

Out[7]:
```
Target
1    416
0    167
Name: count, dtype: int64
```

Handle duplicates

In [8]:
```python
#Check for dulpicated count of records
data.duplicated().sum()
```

Out[8]:
```
13
```

In [9]:
```python
#Drop them
data = data.drop_duplicates()
```

```
data.shape[0]
```

Out[9]: 570

Handle missing values

In [10]:
```
#Check for missing values
data.isnull().sum()
```

Out[10]:
```
Age                           0
Gender                        0
Total_Bilirubin               0
Direct_Bilirubin              0
Alkaline_Phosphotase          0
Alamine_Aminotransferase      0
Aspartate_Aminotransferase    0
Total_Protiens                0
Albumin                       0
Albumin_and_Globulin_Ratio    4
Target                        0
dtype: int64
```

In [11]:
```
#Impute the Albumin_and_Globulin_Ratio column with mean
data['Albumin_and_Globulin_Ratio'].fillna(data['Albumin_and_Globulin_Ratio'].mean()
#Verification
data.isnull().sum().sum()
```

Out[11]: 0

Encode categorical variables

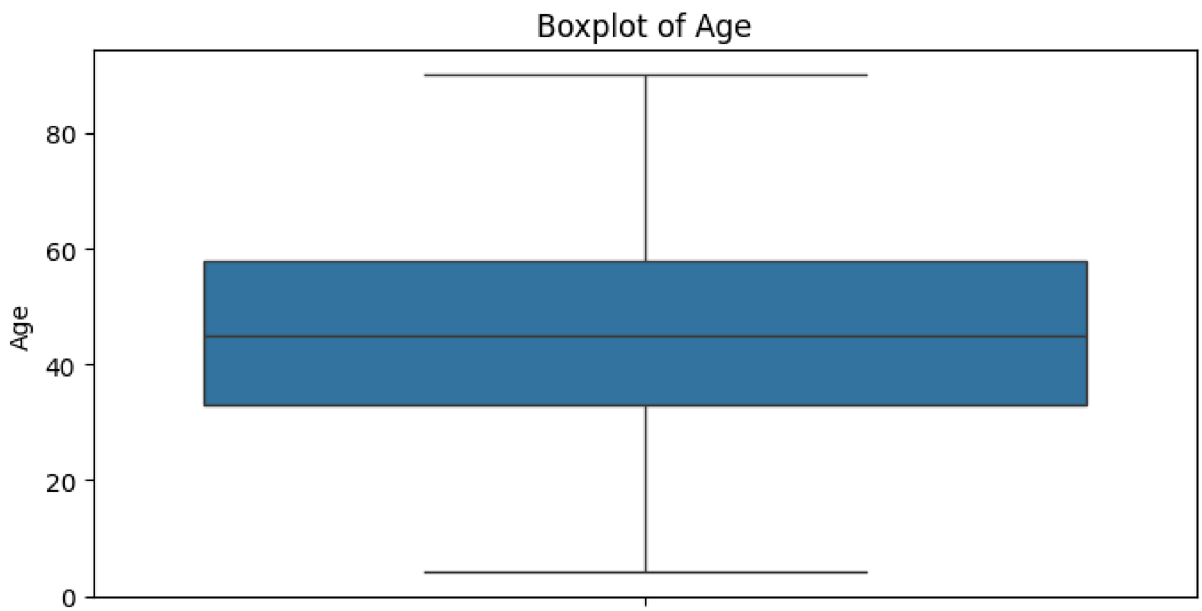
In [12]:
```
## 'Gender'
data['Gender'] = data['Gender'].map({'Female':0, 'Male':1})
#Verification
print(data['Gender'].unique())
print(data.dtypes)
```

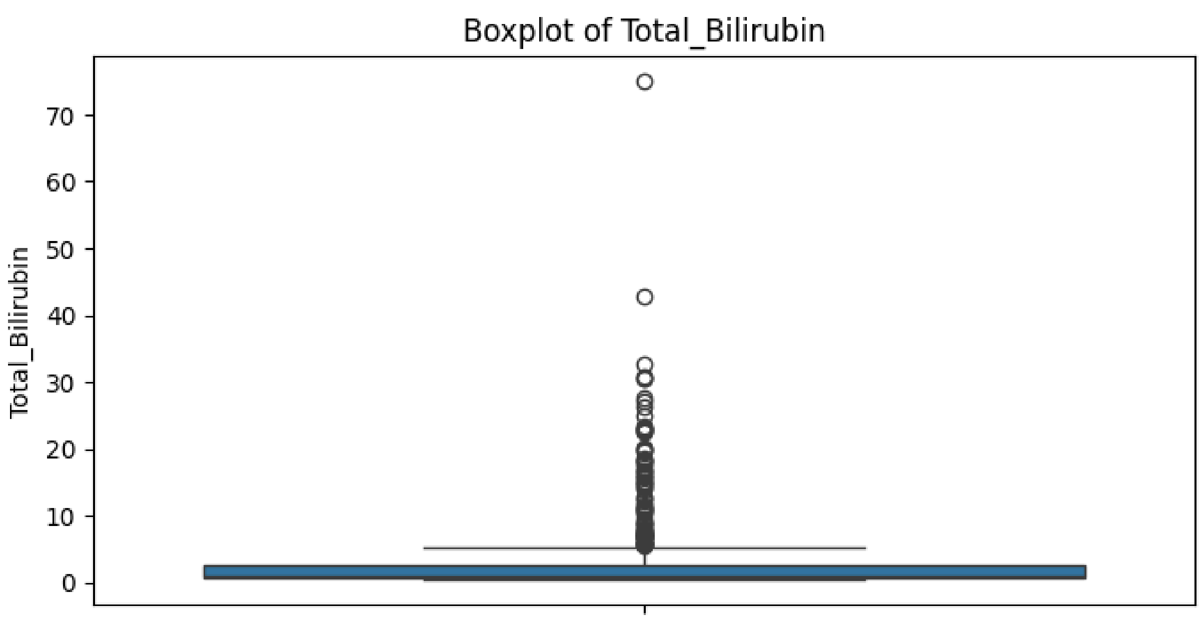
```
[0 1]
Age                             int64
Gender                          int64
Total_Bilirubin               float64
Direct_Bilirubin              float64
Alkaline_Phosphotase            int64
Alamine_Aminotransferase        int64
Aspartate_Aminotransferase      int64
Total_Protiens                float64
Albumin                       float64
Albumin_and_Globulin_Ratio    float64
Target                          int64
dtype: object
```

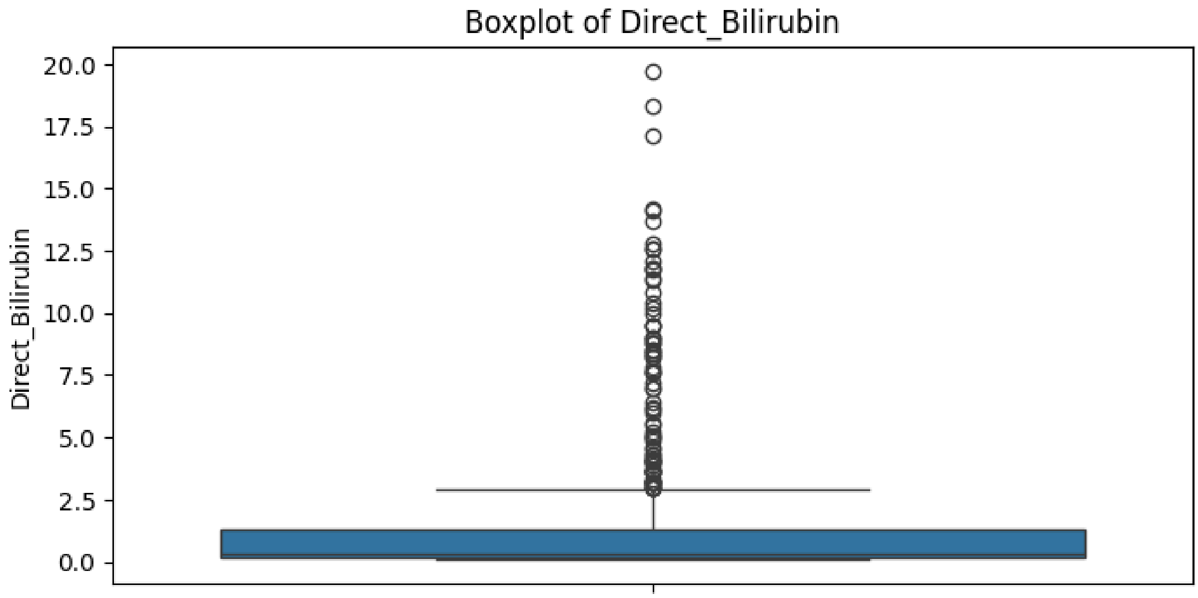
Check for outliers through boxplots

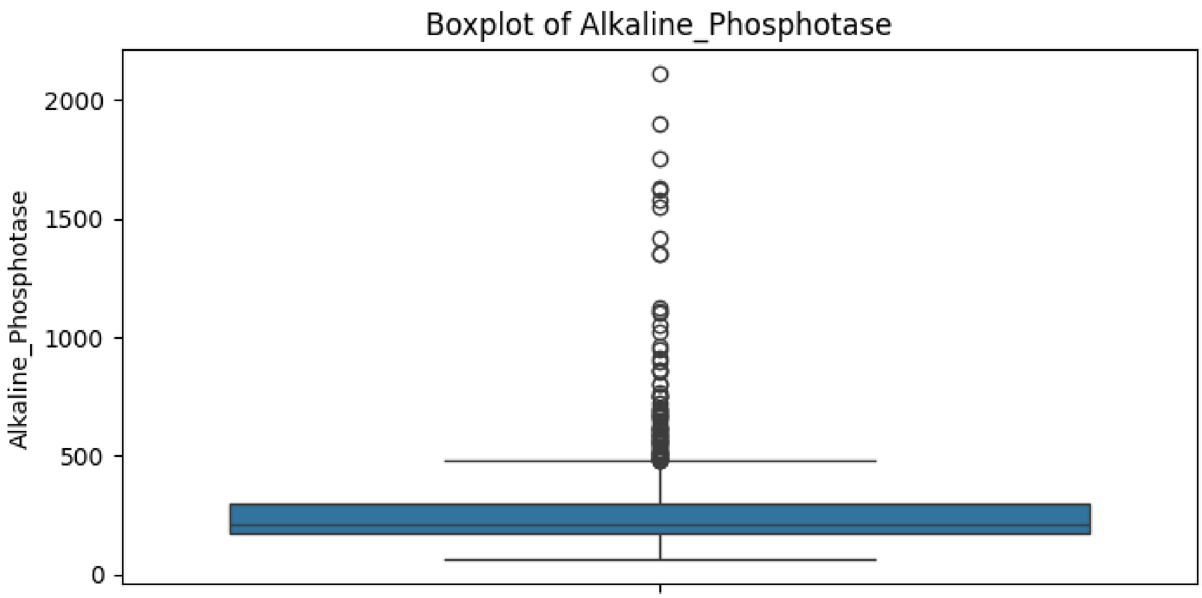
```
In [13]: numerical_cols = data.drop(columns = ['Gender', 'Target'])
```

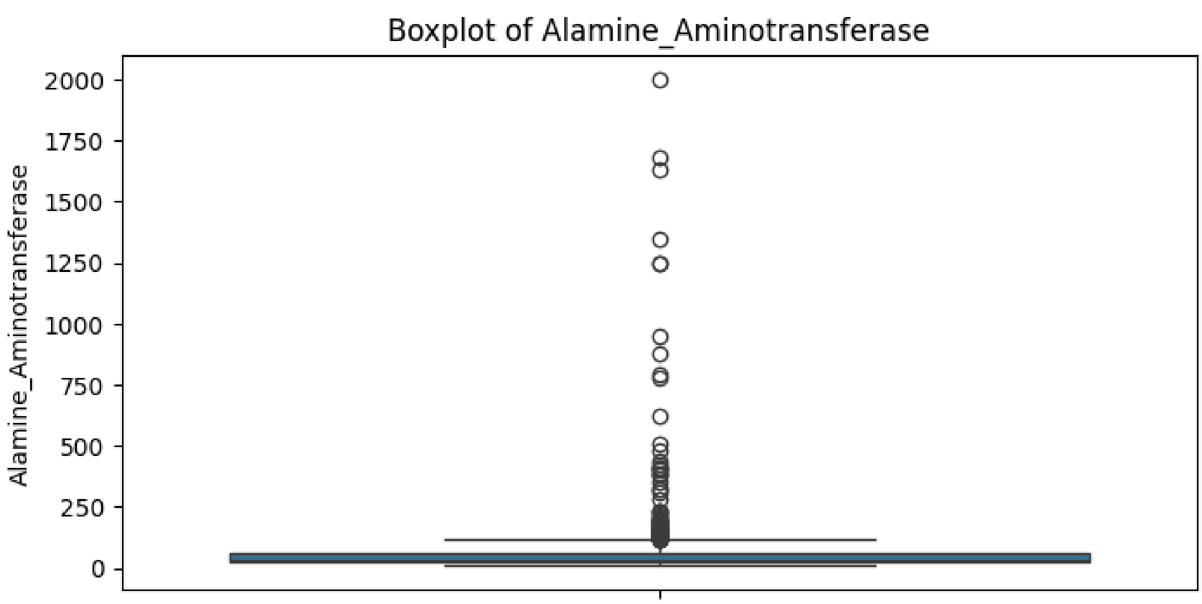
```
In [14]: import matplotlib.pyplot as plt
import seaborn as sns

for col in numerical_cols:
    plt.figure(figsize = (8, 4))
    sns.boxplot(data[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

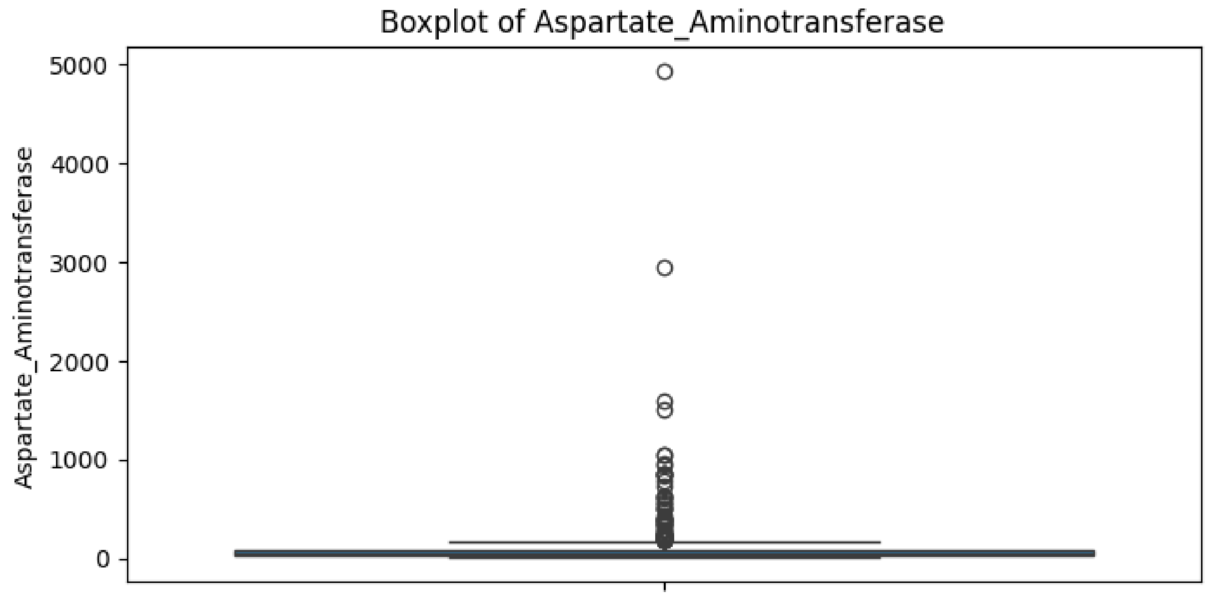


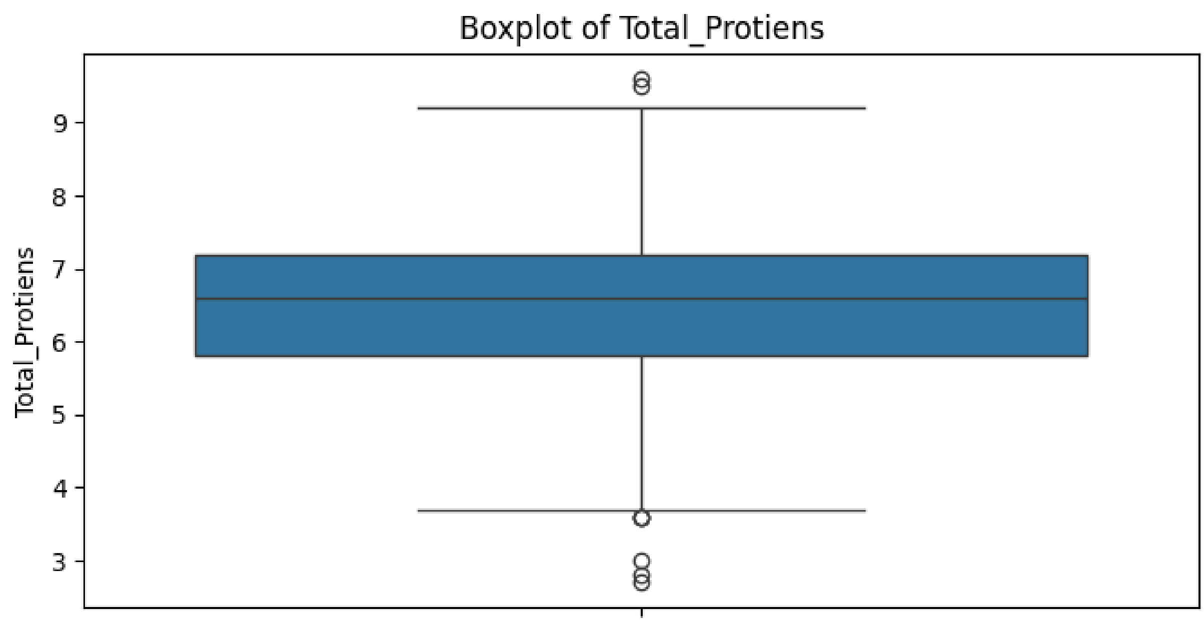


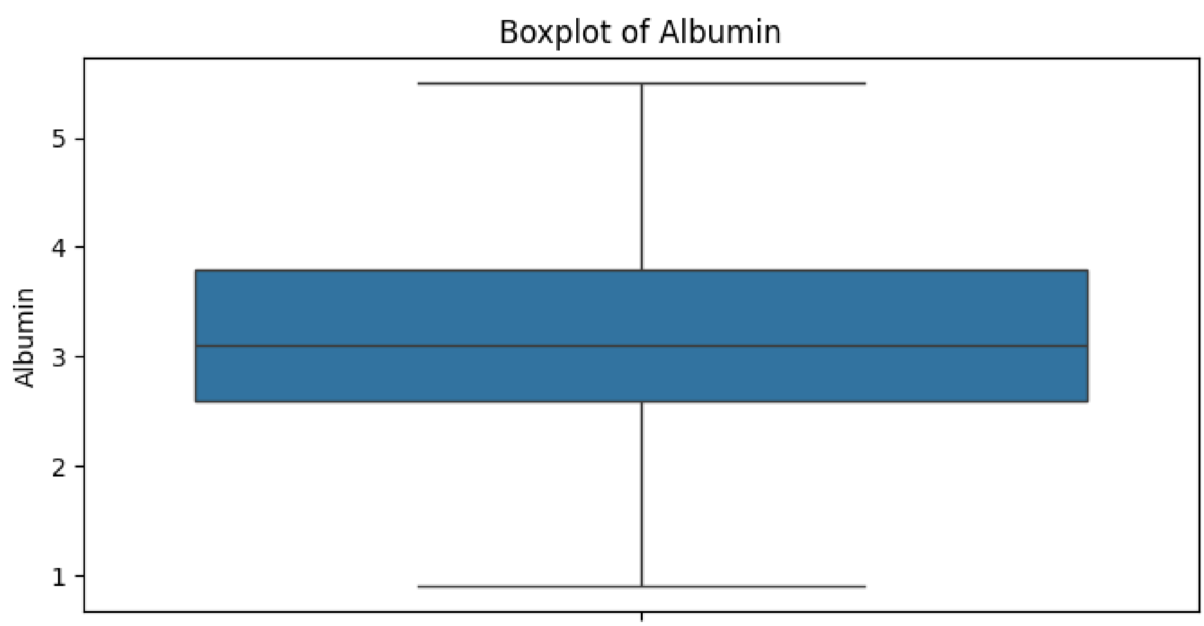

Boxplot of Direct_Bilirubin
Direct_Bilirubin
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

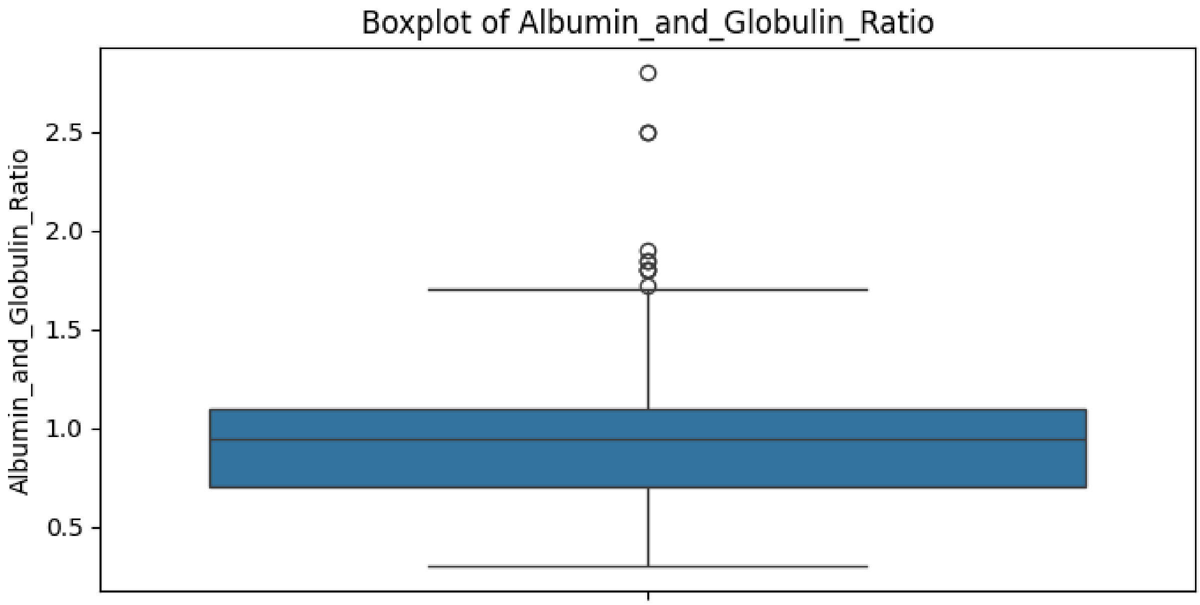

Boxplot of Alkaline_Phosphotase
Alkaline_Phosphotase
2000
1500
1000
500
0


Boxplot of Alamine_Aminotransferase
Alamine_Aminotransferase
2000
1750
1500
1250
1000
750
500
250
0


Boxplot of Aspartate_Aminotransferase
Aspartate_Aminotransferase
5000
4000
3000
2000
1000
0


Boxplot of Total_Protiens
Total_Protiens
9
8
7
6
5
4
3


Boxplot of Albumin
Albumin
5
4
3
2
1



In [15]:
```
#Detect considerable amount of oultiers
#Perform robust scaling
```

Numerical data - Robust scaling

In [16]:
```
from sklearn.preprocessing import RobustScaler

numerical_names = data.drop(columns = ['Gender', 'Target']).columns

scaler = RobustScaler()
data[numerical_names] = scaler.fit_transform(data[numerical_names])
data[numerical_names] = pd.DataFrame(data[numerical_names], columns = numerical_nam
data
```

Out[16]:

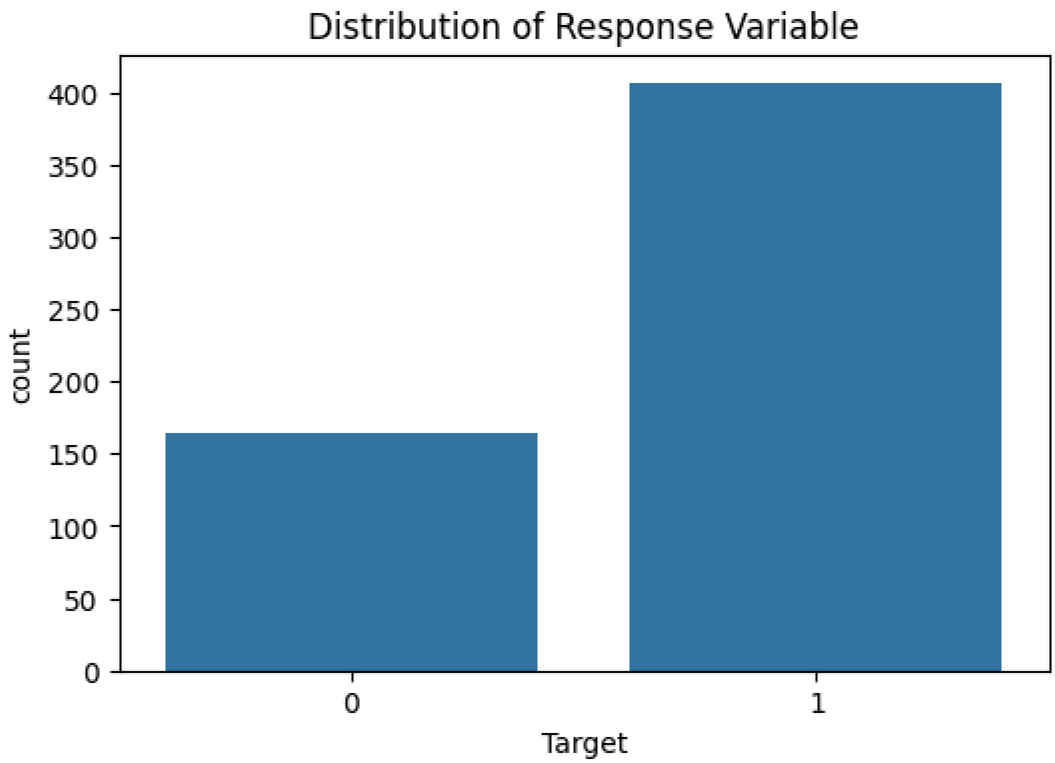
	Age	Gender	Total_Bilirubin	Direct_Bilirubin	Alkaline_Phosphotase	Alamine_Aminotr
0	0.80	0	-0.166667	-0.181818	-0.172131	
1	0.68	1	5.500000	4.727273	4.024590	
2	0.68	1	3.500000	3.454545	2.311475	
3	0.52	1	0.000000	0.090909	-0.213115	
4	1.08	1	1.611111	1.545455	-0.106557	
...	...	...	...	...	...	
578	0.60	1	-0.277778	-0.181818	2.393443	
579	-0.20	1	-0.222222	-0.181818	-0.901639	
580	0.28	1	-0.111111	-0.090909	0.303279	
581	-0.56	1	0.166667	0.181818	-0.196721	
582	-0.28	1	0.000000	0.000000	0.065574	

570 rows × 11 columns

Distribution of existence of liver disease

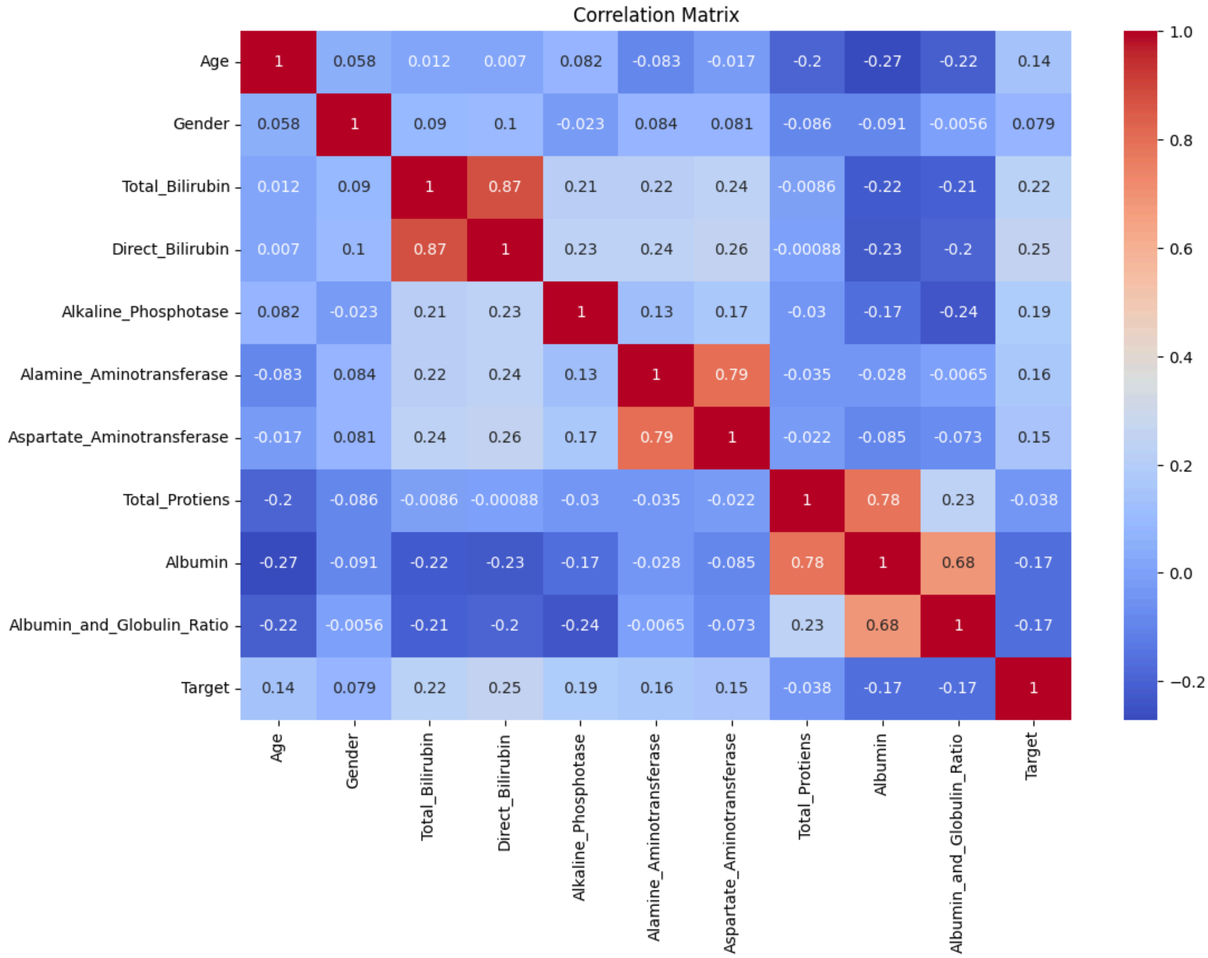
In [17]:

```
plt.figure(figsize = (6, 4))
sns.countplot(data = data, x = 'Target')
plt.title('Distribution of Response Variable')
plt.show()

#Detect heavy class imbalancement
```



Correlation matrix

In [18]:
```
plt.figure(figsize = (12, 8))
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot = True, cmap = 'coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



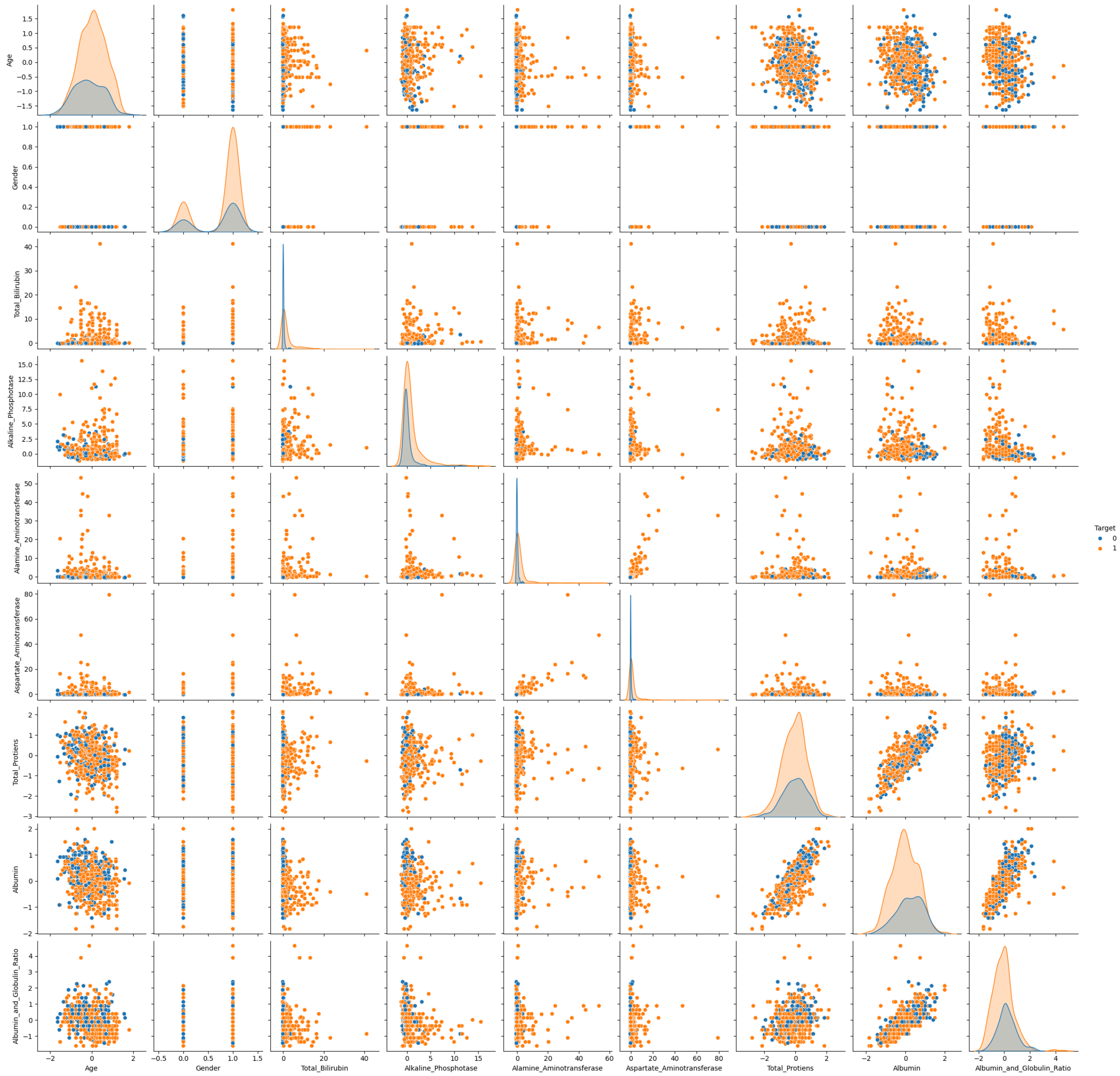
Drop one of the highly correlated columns

In [19]:
```
data = data.drop(columns = ['Direct_Bilirubin'])
data.shape
```

Out[19]: (570, 10)

Pair plot distributions

In [20]:
```
sns.pairplot(data, hue = 'Target', diag_kind = 'kde')
plt.show()
```



Split the data into train and test

In [21]:
```
from sklearn.model_selection import train_test_split
from collections import Counter

X = data.drop('Target', axis = 1)
y = data['Target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_s
print("Original class distribution:", Counter(y_train))
```

```
Original class distribution: Counter({1: 321, 0: 135})
```

Perform SMOTE on response variable

In [22]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state = 42)
```

```
X_train, y_train = smote.fit_resample(X_train, y_train)
print("SMOTE class distribution:", Counter(y_train))
```

```
SMOTE class distribution: Counter({1: 321, 0: 321})
```

In [23]:
```
X_train.shape
```

Out[23]:
```
(642, 9)
```

Train models

1. Logistic Regression model

In [24]:
```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(random_state = 42, penalty = 'l2')
lr.fit(X_train, y_train)
```

Out[24]:
```
LogisticRegression
LogisticRegression(random_state=42)
```

2. Random Forest Classifier model

In [25]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(random_state = 42)
rf.fit(X_train, y_train)
```

Out[25]:
```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

3. Support Vector Machine (SVM) model

In [26]:
```
from sklearn.svm import SVC

svm = SVC(random_state = 42)
svm.fit(X_train, y_train)
```

Out[26]:
```
SVC
SVC(random_state=42)
```

4. K Nearest Neighbors (KNN) Classifier Model

In [27]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors = 2)
knn.fit(X_train, y_train)
```

Out[27]:
```
KNeighborsClassifier

KNeighborsClassifier(n_neighbors=2)
```

5. XGBoost Classifier Model

In [28]:
```python
from xgboost import XGBClassifier

xgb = XGBClassifier(random_state = 42)
xgb.fit(X_train, y_train)
```

Out[28]:
```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds
=None,
              enable_categorical=False, eval_metric=None, feature_types
=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin
=None,
```

Hyperparameter tuning & Cross Validation for models

In [29]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import StratifiedKFold

cv = StratifiedKFold(n_splits = 10, shuffle = True, random_state = 42)
```

1. Logistic Regression model

In [30]:
```python
#Define hyperparameter grids
param_grid_lr = {
    'C': [0.01, 0.1, 1, 10], #Regularization strength; inversely proportional to C
    'solver': ['newton-cg', 'lbfgs', 'liblinear'], #Algorithm used in optimization
}

#Perform GridSearchCV
grid_search_lr = GridSearchCV(lr, param_grid_lr, cv = 5, n_jobs = -1, scoring = 'ac
grid_search_lr.fit(X_train, y_train)
```

```
best_lr = grid_search_lr.best_estimator_
best_lr_params = grid_search_lr.best_params_
print("LR best parameters: ", best_lr_params)
```

```
LR best parameters:  {'C': 0.1, 'solver': 'newton-cg'}
```

2. Random Forest Classifier model

In [31]:
```
#Define hyperparameter grids
param_grid_rf = {
    'n_estimators': [500, 600, 700], #No of trees in the forest
    'max_depth': [None, 10, 20], #Maximum depth of the tree
    #None means nodes are expanded until all leaves are pure
    'min_samples_split': [0.5, 1.0, 2, 5], #Minimum number of samples required to s
    'min_samples_leaf': [1, 2, 4], #Minimum number of samples required to be at a l
}

#Perform GridSearchCV
grid_search_rf = GridSearchCV(rf, param_grid_rf, cv = cv, n_jobs = -1, scoring = 'a
grid_search_rf.fit(X_train, y_train)
best_rf = grid_search_rf.best_estimator_
best_rf_params = grid_search_rf.best_params_
print("RF best parameters: ", best_rf_params)
```

```
RF best parameters:  {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split':
2, 'n_estimators': 600}
```

3. Support Vector Machine model

In [32]:
```
#Define hyperparameter grids
param_grid_svm = {
    'C': [800, 900, 1000, 1100], #Regularization strength; inversely proportional t
    'gamma': ['scale', 'auto'], #Kernel coefficient for 'rbf', 'poly' and 'sigmoid'
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid'], #Kernel type to be used
}

#Perform GridSearchCV
grid_search_svm = GridSearchCV(svm, param_grid_svm, cv = cv, n_jobs = -1, scoring =
grid_search_svm.fit(X_train, y_train)
best_svm = grid_search_svm.best_estimator_
best_svm_params = grid_search_svm.best_params_
print("SVM best parameters: ", best_svm_params)
```

```
SVM best parameters:  {'C': 900, 'gamma': 'auto', 'kernel': 'rbf'}
```

4. K Nearest Neighbours Model

In [33]:
```
#Define hyperparameter grids
param_grid_knn = {
    'n_neighbors': [1, 2, 3], #Number of default neighbors
    'weights': ['uniform', 'distance'], #Weight function used in prediction
    'metric': ['euclidean', 'manhattan', 'minkowski'], #Distance metric to use for
}
```

```
#Perform GridSearchCV
grid_search_knn = GridSearchCV(knn, param_grid_knn, cv = cv, n_jobs = -1, scoring =
grid_search_knn.fit(X_train, y_train)
best_knn = grid_search_knn.best_estimator_
best_knn_params = grid_search_knn.best_params_
print("KNN best parameters: ", best_knn_params)
```

```
KNN best parameters:  {'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'unifor
m'}
```

5. XGBoost Classifier Model

In [34]:
```
#Define hyperparameter grids
param_grid_xgb = {
    'n_estimators': [60, 70, 80, 90, 100],  # Number of trees
    'learning_rate': [0.01, 0.1, 0.5, 1],  # Learning rate
    'max_depth': [7, 8, 9, 10],  # Maximum depth of the tree
    'subsample': [0.5, 0.6, 0.7, 0.8],  # Subsample ratio of the training instance
    'colsample_bytree': [0.8, 0.9, 1.0],  # Subsample ratio of columns when constru
    'reg_alpha': [0, 0.1],  # L1 regularization
    'reg_lambda': [1, 0.1]  # L2 regularization
}

#Perform GridSearchCV
grid_search_xgb = GridSearchCV(xgb, param_grid_xgb, cv = cv, n_jobs = -1, scoring =
grid_search_xgb.fit(X_train, y_train)
best_xgb = grid_search_xgb.best_estimator_
best_xgb_params = grid_search_xgb.best_params_
print("XGB best parameters: ", best_xgb_params)
```

```
XGB best parameters:  {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth':
8, 'n_estimators': 70, 'reg_alpha': 0, 'reg_lambda': 0.1, 'subsample': 0.7}
```

Predictions & Evaluations on train data

In [35]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

1. Logistic Regression model

In [36]:
```
#Predict
y_pred_lr_tr = best_lr.predict(X_train)

#Evaluate
print("Logistic Regression Model (Training Data):")
print("Accuracy:", accuracy_score(y_train, y_pred_lr_tr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_train, y_pred_lr_tr))
```

```
Logistic Regression Model (Training Data):
Accuracy: 72.42990654205607
Confusion Matrix:
 [[275  46]
 [131 190]]
```

2. Random Forest Classifier model

In [37]:
```
#Predict
y_pred_rf_tr = best_rf.predict(X_train)

#Evaluate
print("Random Forest Classifier Model (Training Data):")
print("Accuracy:", accuracy_score(y_train, y_pred_rf_tr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_train, y_pred_rf_tr))
```

```
Random Forest Classifier Model (Training Data):
Accuracy: 100.0
Confusion Matrix:
 [[321   0]
 [  0 321]]
```

3. Support Vector Machine model

In [38]:
```
#Predict
y_pred_svm_tr = best_svm.predict(X_train)

#Evaluate
print("SVM Model (Training Data):")
print("Accuracy:", accuracy_score(y_train, y_pred_svm_tr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_train, y_pred_svm_tr))
```

```
SVM Model (Training Data):
Accuracy: 94.70404984423676
Confusion Matrix:
 [[319   2]
 [ 32 289]]
```

4. K Nearest Neighbours Model

In [39]:
```
#Predict
y_pred_knn_tr = best_knn.predict(X_train)

#Evaluate
print("KNN Model (Training Data):")
print("Accuracy:", accuracy_score(y_train, y_pred_knn_tr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_train, y_pred_knn_tr))
```

```
KNN Model (Training Data):
Accuracy: 100.0
Confusion Matrix:
 [[321   0]
 [  0 321]]
```

5. XGBoost Classifier Model

In [40]:
```
#Predict
y_pred_xgb_tr = best_xgb.predict(X_train)

#Evaluate
print("XGBoost Classifier Model (Training Data):")
print("Accuracy:", accuracy_score(y_train, y_pred_xgb_tr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_train, y_pred_xgb_tr))
```

```
XGBoost Classifier Model (Training Data):
Accuracy: 100.0
Confusion Matrix:
 [[321   0]
 [  0 321]]
```

Predictions & Evaluations on test data

1. Logistic Regression model

In [41]:
```
#Predict
y_pred_lr = best_lr.predict(X_test)

#Evaluate
print("Logistic Regression Model (Testing Data):")
print("Accuracy:", accuracy_score(y_test, y_pred_lr)*100)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr))
print("Classification Report:", classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Model (Testing Data):
Accuracy: 62.28070175438597
Confusion Matrix:
 [[22  7]
 [36 49]]
Classification Report:               precision    recall  f1-score   support

           0       0.38      0.76      0.51        29
           1       0.88      0.58      0.70        85

    accuracy                           0.62       114
   macro avg       0.63      0.67      0.60       114
weighted avg       0.75      0.62      0.65       114
```

2. Random Forest Classifier model

In [42]:
```
#Predict
y_pred_rf = best_rf.predict(X_test)

#Evaluate
print("Random Forest Classifier model (Testing Data):")
print("Accuracy:", accuracy_score(y_test, y_pred_rf)*100)
```

```
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
print("Classification Report:", classification_report(y_test, y_pred_rf))
```

```
Random Forest Classifier model (Testing Data):
Accuracy: 72.80701754385966
Confusion Matrix:
 [[17 12]
 [19 66]]
Classification Report:               precision    recall  f1-score   support

           0       0.47      0.59      0.52        29
           1       0.85      0.78      0.81        85

    accuracy                           0.73       114
   macro avg       0.66      0.68      0.67       114
weighted avg       0.75      0.73      0.74       114
```

3. Support Vector Machine model

In [43]:
```
#Predict
y_pred_svm = best_svm.predict(X_test)

#Evaluate
print("Support Vector Machine model (Testing Data):")
print("Accuracy:", accuracy_score(y_test, y_pred_svm)*100)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_svm))
print("Classification Report:", classification_report(y_test, y_pred_svm))
```

```
Support Vector Machine model (Testing Data):
Accuracy: 68.42105263157895
Confusion Matrix:
 [[17 12]
 [24 61]]
Classification Report:               precision    recall  f1-score   support

           0       0.41      0.59      0.49        29
           1       0.84      0.72      0.77        85

    accuracy                           0.68       114
   macro avg       0.63      0.65      0.63       114
weighted avg       0.73      0.68      0.70       114
```

4. K Nearest Neighbours Model

In [44]:
```
#Predict
y_pred_knn = best_knn.predict(X_test)

#Evaluate
print("K Nearest Neighbours Model (Testing Data):")
print("Accuracy:", accuracy_score(y_test, y_pred_knn)*100)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_knn))
print("Classification Report:", classification_report(y_test, y_pred_knn))
```

```
K Nearest Neighbours Model (Testing Data):
Accuracy: 66.66666666666666
Confusion Matrix:
 [[15 14]
 [24 61]]
Classification Report:               precision    recall  f1-score   support

           0       0.38      0.52      0.44        29
           1       0.81      0.72      0.76        85

    accuracy                           0.67       114
   macro avg       0.60      0.62      0.60       114
weighted avg       0.70      0.67      0.68       114
```

5. XGBoost Classifier Model

In [45]:
```python
#Predict
y_pred_xgb = best_xgb.predict(X_test)

#Evaluate
print("XGBoost Classifier Model (Testing Data):")
print("Accuracy:", accuracy_score(y_test, y_pred_xgb)*100)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
print("Classification Report:", classification_report(y_test, y_pred_xgb))
```

```
XGBoost Classifier Model (Testing Data):
Accuracy: 72.80701754385966
Confusion Matrix:
 [[16 13]
 [18 67]]
Classification Report:               precision    recall  f1-score   support

           0       0.47      0.55      0.51        29
           1       0.84      0.79      0.81        85

    accuracy                           0.73       114
   macro avg       0.65      0.67      0.66       114
weighted avg       0.74      0.73      0.73       114
```

Conclusion

In [46]:
```python
'''
According to the highest accuracy and other evaluation metrics like precision, reca
F1-score, the most suitable models would be RF and XGBoost. (with around 72% of acc
'''
```

Out[46]:
```
'\nAccording to the highest accuracy and other evaluation metrics like precision, 
recall and \nF1-score, the most suitable models would be RF and XGBoost. (with aro
und 72% of accuracy)\n'
```

Combine predictions of RF and XGBoost models using an ensemble method - Voting Classifier

In [47]:

```
from sklearn.ensemble import VotingClassifier

estimators = [('rf_clf', best_rf), ('xgb', best_xgb)]
voting_clf = VotingClassifier(estimators = estimators, voting = 'soft')
#"Soft" - For voting in averaging probabilities
voting_clf.fit(X_train, y_train)

#Make predictions
y_pred_voting_clf = voting_clf.predict(X_test)

#Evaluate the ensemble model
print("Voting Classifier Model:")
print("Accuracy:", accuracy_score(y_test, y_pred_voting_clf) * 100)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_voting_clf))
print("Classification Report:\n", classification_report(y_test, y_pred_voting_clf))
```

```
Voting Classifier Model:
Accuracy: 73.68421052631578
Confusion Matrix:
 [[16 13]
 [17 68]]
Classification Report:
               precision    recall  f1-score   support

           0       0.48      0.55      0.52        29
           1       0.84      0.80      0.82        85

    accuracy                           0.74       114
   macro avg       0.66      0.68      0.67       114
weighted avg       0.75      0.74      0.74       114
```

Predict a new observation (whether an individual is a patient or not)

In [48]:

```
import numpy as np

feature_names = ['Age', 'Gender', 'Total_Bilirubin', 'Alkaline_Phosphotase',
                 'Alamine_Aminotransferase', 'Aspartate_Aminotransferase', 'Total_P
                 'Albumin', 'Albumin_and_Globulin_Ratio']
new_obs = np.array([[0.5, 0, 0.3, 0.1, -0.1, 0.2, 0.3, 0.2, 0.1]])

new_obs_data = pd.DataFrame(new_obs, columns = feature_names)

#Predicting using RF and XGBoost models seperately
pred_rf = best_rf.predict(new_obs_data)
print("RF Prediction: ", pred_rf[0])
pred_xgb = best_xgb.predict(new_obs_data)
print("XGB Prediction: ", pred_xgb[0])
```

```
#Predicting using ensemble model
predict_voting = voting_clf.predict(new_obs_data)
print("Ensemble Model Prediction ", predict_voting[0])
```

```
RF Prediction:  1
XGB Prediction:  1
Ensemble Model Prediction  1
```

The combined model predicts that the individual with given diagnosis is a patient.