In [1]:
```
# import libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import xgboost as xgb
from sklearn.metrics import accuracy_score, precision_score, mean_squared_error, confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

pd.options.mode.chained_assignment = None

import warnings

warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", message="Precision is ill-defined", category=UserWarning)
warnings.filterwarnings("ignore", message="The default value of numeric_only in DataFrame.mean is depreca
```

In [2]:
```
# Load the dataset
data = pd.read_csv('speed_data_data.csv')
data.head()
```

Out[2]:

	gender	age	income	goal	career	dec	attr	sinc	intel	fun	amb	shar	like	prob	met
0	0	21.0	69487.0	2.0	lawyer	1	6.0	9.0	7.0	7.0	6.0	5.0	7.0	6.0	2.0
1	0	21.0	69487.0	2.0	lawyer	1	7.0	8.0	7.0	8.0	5.0	6.0	7.0	5.0	1.0
2	0	21.0	69487.0	2.0	lawyer	1	5.0	8.0	9.0	8.0	5.0	7.0	7.0	NaN	1.0
3	0	21.0	69487.0	2.0	lawyer	1	7.0	6.0	8.0	7.0	6.0	8.0	7.0	6.0	2.0
4	0	21.0	69487.0	2.0	lawyer	1	5.0	6.0	7.0	7.0	6.0	6.0	6.0	6.0	2.0

In [3]:
```
# Check for missing values
missing_values = data.isnull().sum()
print("Missing values in each column:")
print(missing_values)
```

```
Missing values in each column:
gender       0
age         95
income    4099
goal        79
career      89
dec          0
attr       202
sinc       277
intel      296
fun        350
amb        712
shar      1067
like       240
prob       309
met        375
dtype: int64
```

In [4]:
```
data.shape
```

Out[4]:
```
(8378, 15)
```

In [5]:
```
data_filled = data.fillna(data.mean())
missing_values_after_fill = data_filled.isnull().sum()
print("Missing values in each column after filling with mean:")
print(missing_values_after_fill)
```

```
Missing values in each column after filling with mean:
gender      0
age         0
income      0
goal        0
career     89
dec         0
attr        0
sinc        0
intel       0
fun         0
amb         0
shar        0
like        0
prob        0
met         0
dtype: int64
```

In [6]:
```
data_cleaned = data_filled.dropna()
missing_values_after_drop = data_cleaned.isnull().sum()
print("Missing values in each column after dropping rows with missing values:")
print(missing_values_after_drop)
```

```
Missing values in each column after dropping rows with missing values:
gender    0
age       0
income    0
goal      0
career    0
dec       0
attr      0
sinc      0
intel     0
fun       0
amb       0
shar      0
like      0
prob      0
met       0
dtype: int64
```

In [7]:
```
# Encode categorical variables
label_encoders = {}
for col in ['goal', 'career']:
    label_encoders[col] = LabelEncoder()
    data_cleaned.loc[:, col] = label_encoders[col].fit_transform(data_cleaned.loc[:, col])

# Split features and target variable
X = data_cleaned.drop(['dec'], axis=1)
y = data_cleaned['dec']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)

# Train K-Nearest Neighbors Classifier
knn_classifier = KNeighborsClassifier()
knn_classifier.fit(X_train, y_train)

# Train Naive Bayes Classifier
```

```
nb_classifier = GaussianNB()
nb_classifier.fit(X_train, y_train)

# Train Support Vector Machine Classifier
svm_classifier = SVC()
svm_classifier.fit(X_train, y_train)

# Train Gradient Boosting Machine (XGBoost)
gbm_classifier = xgb.XGBClassifier()
gbm_classifier.fit(X_train, y_train)

# Make predictions
rf_pred = rf_classifier.predict(X_test)
knn_pred = knn_classifier.predict(X_test)
nb_pred = nb_classifier.predict(X_test)
svm_pred = svm_classifier.predict(X_test)
gbm_pred = gbm_classifier.predict(X_test)


# Evaluate accuracy
rf_accuracy = accuracy_score(y_test, rf_pred)
knn_accuracy = accuracy_score(y_test, knn_pred)
nb_accuracy = accuracy_score(y_test, nb_pred)
svm_accuracy = accuracy_score(y_test, svm_pred)
gbm_accuracy = accuracy_score(y_test, gbm_pred)

# Calculate precision for each model
rf_precision = precision_score(y_test, rf_pred)
knn_precision = precision_score(y_test, knn_pred)
nb_precision = precision_score(y_test, nb_pred)
svm_precision = precision_score(y_test, svm_pred)
gbm_precision = precision_score(y_test, gbm_pred)

# Calculate RMSE for each model
rf_rmse = np.sqrt(mean_squared_error(y_test, rf_pred))
knn_rmse = np.sqrt(mean_squared_error(y_test, knn_pred))
nb_rmse = np.sqrt(mean_squared_error(y_test, nb_pred))
svm_rmse = np.sqrt(mean_squared_error(y_test, svm_pred))
gbm_rmse = np.sqrt(mean_squared_error(y_test, gbm_pred))
```

```
# Create confusion matrix for each model
rf_conf_matrix = confusion_matrix(y_test, rf_pred)
knn_conf_matrix = confusion_matrix(y_test, knn_pred)
nb_conf_matrix = confusion_matrix(y_test, nb_pred)
svm_conf_matrix = confusion_matrix(y_test, svm_pred)
gbm_conf_matrix = confusion_matrix(y_test, gbm_pred)
```

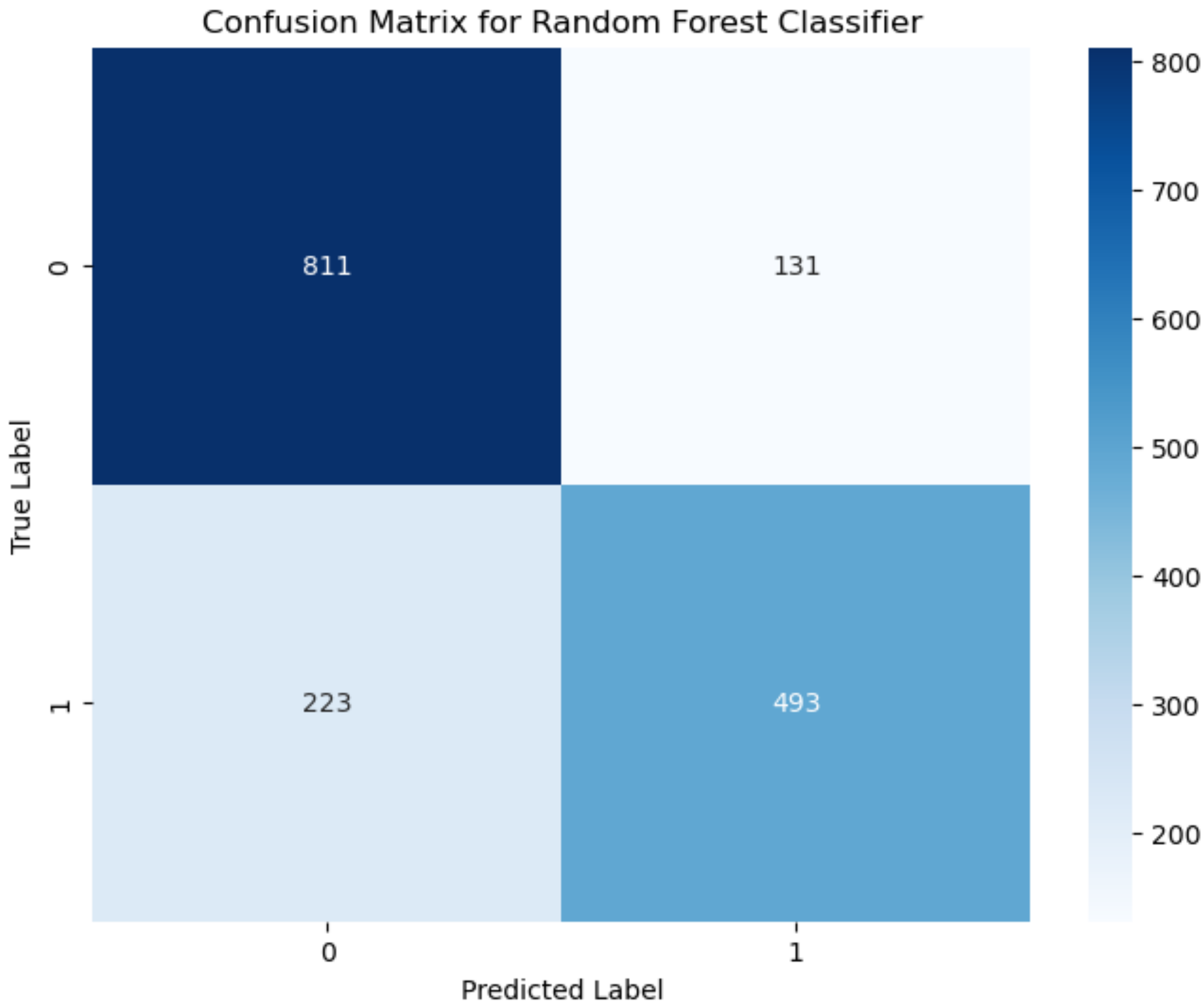
In [8]:

```
models = ['Random Forest', 'KNN', 'Naive Bayes', 'SVM', 'GBM']
accuracy = [rf_accuracy, knn_accuracy, nb_accuracy, svm_accuracy, gbm_accuracy]
precision = [rf_precision, knn_precision, nb_precision, svm_precision, gbm_precision]
rmse = [rf_rmse, knn_rmse, nb_rmse, svm_rmse, gbm_rmse]

# Create a DataFrame
metrics_df = pd.DataFrame({'Model': models,
                           'Accuracy': accuracy,
                           'Precision': precision,
                           'RMSE': rmse})

# Set Model column as index
metrics_df.set_index('Model', inplace=True)

print(metrics_df)
```

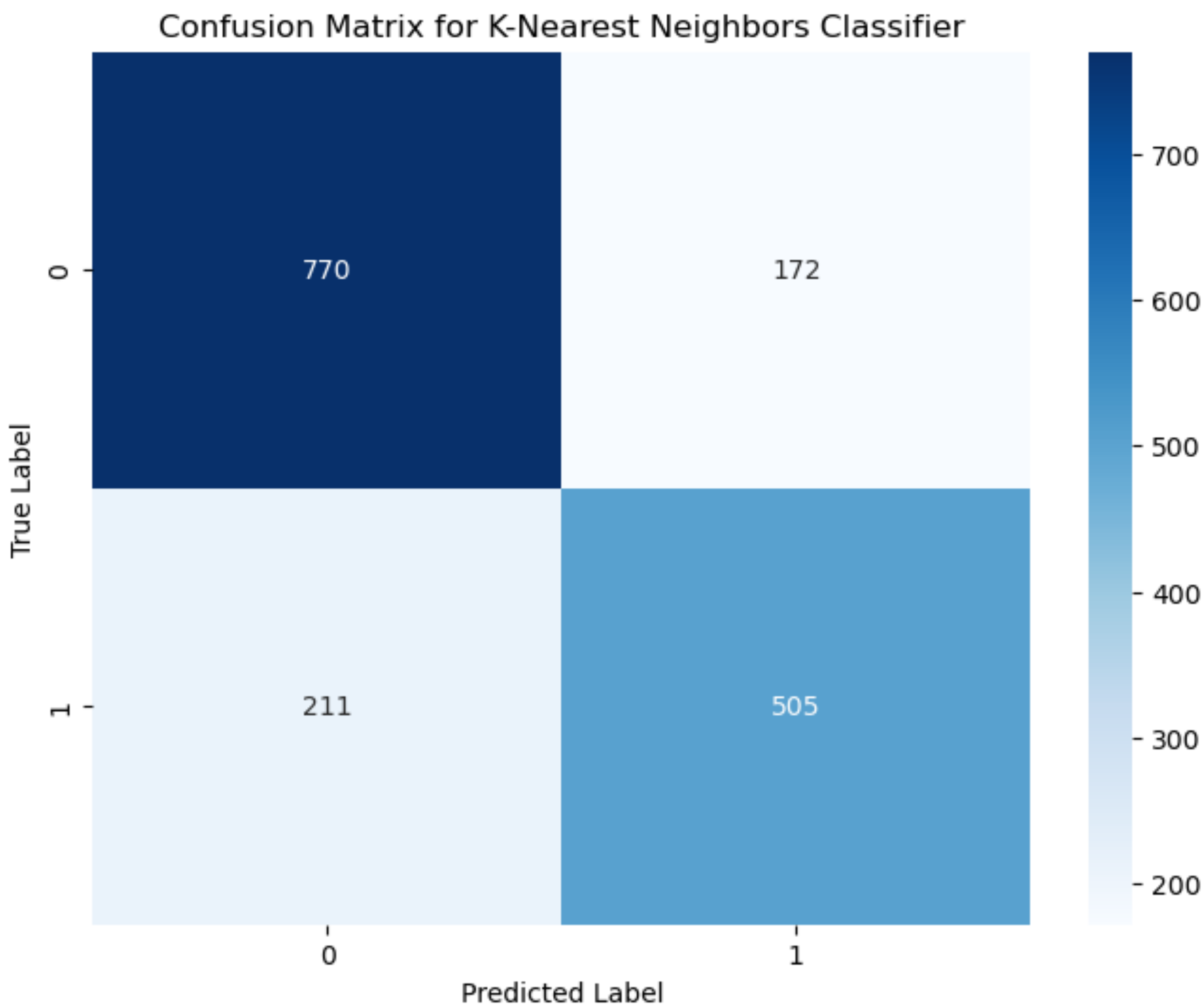
```
               Accuracy  Precision      RMSE
Model
Random Forest  0.786490   0.790064  0.462072
KNN            0.768999   0.745938  0.480626
Naive Bayes    0.713510   0.644311  0.535247
SVM            0.568154   0.000000  0.657150
GBM            0.817853   0.805310  0.426787
```

In [9]:

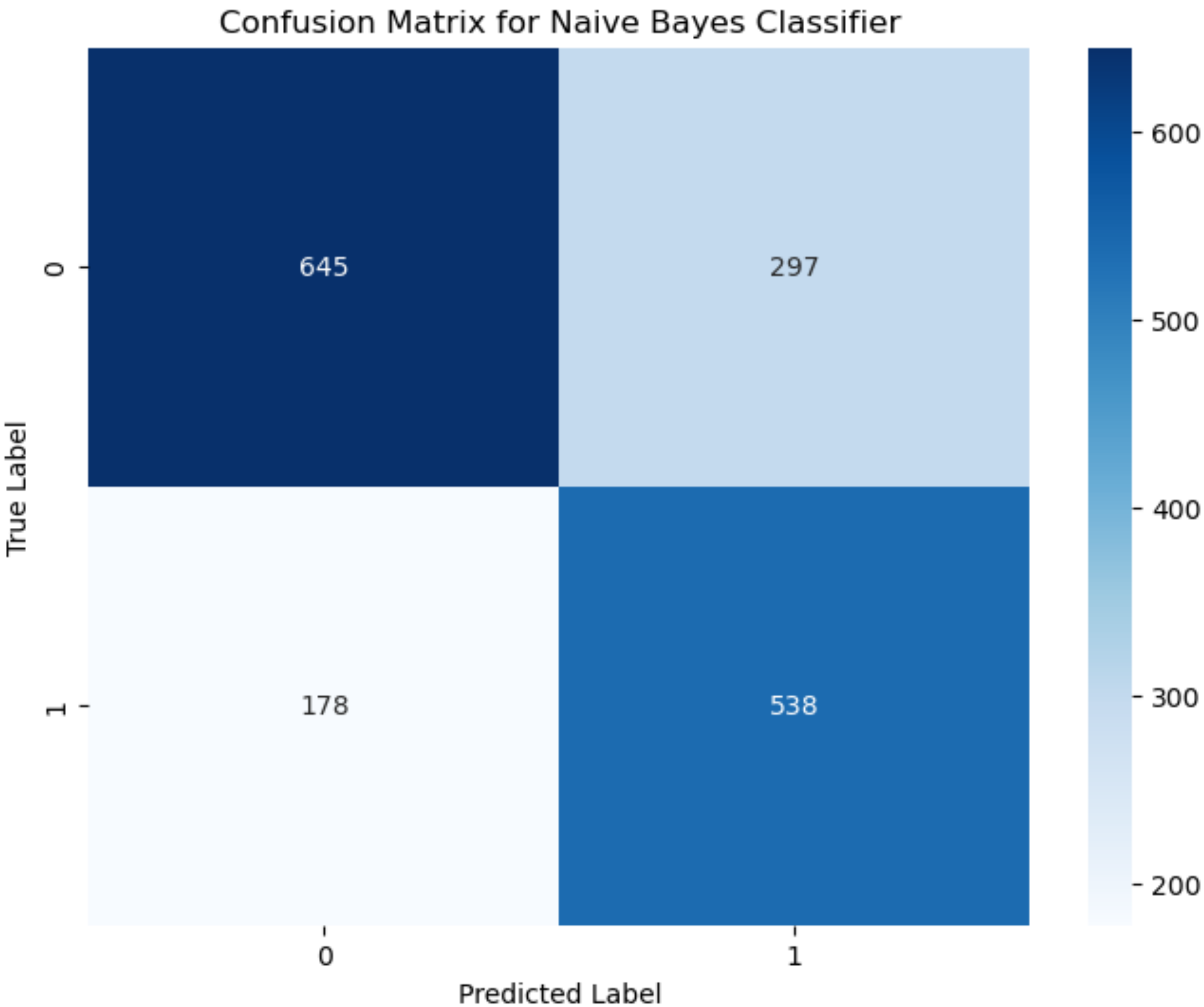
```
# Plot confusion matrix for Random Forest Classifier
plt.figure(figsize=(8, 6))
sns.heatmap(rf_conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix for Random Forest Classifier')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix for Random Forest Classifier
811
131
223
493
True Label
Predicted Label
0
1
0
1
800
700
600
500
400
300
200

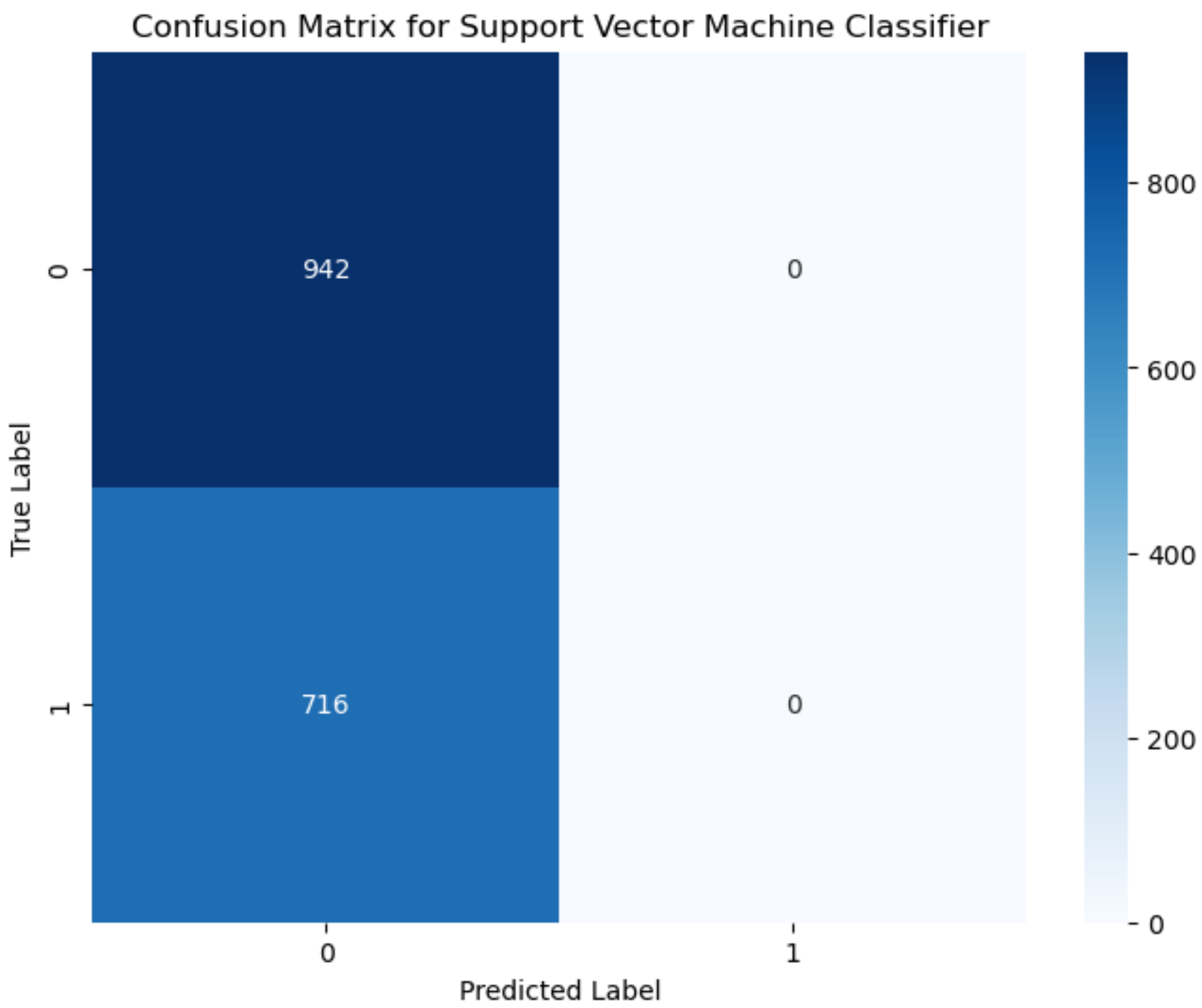
In [10]:
```
# Plot confusion matrix for K-Nearest Neighbors Classifier
plt.figure(figsize=(8, 6))
sns.heatmap(knn_conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix for K-Nearest Neighbors Classifier')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix for K-Nearest Neighbors Classifier
True Label
Predicted Label
0
1
770
172
211
505
700
600
500
400
300
200

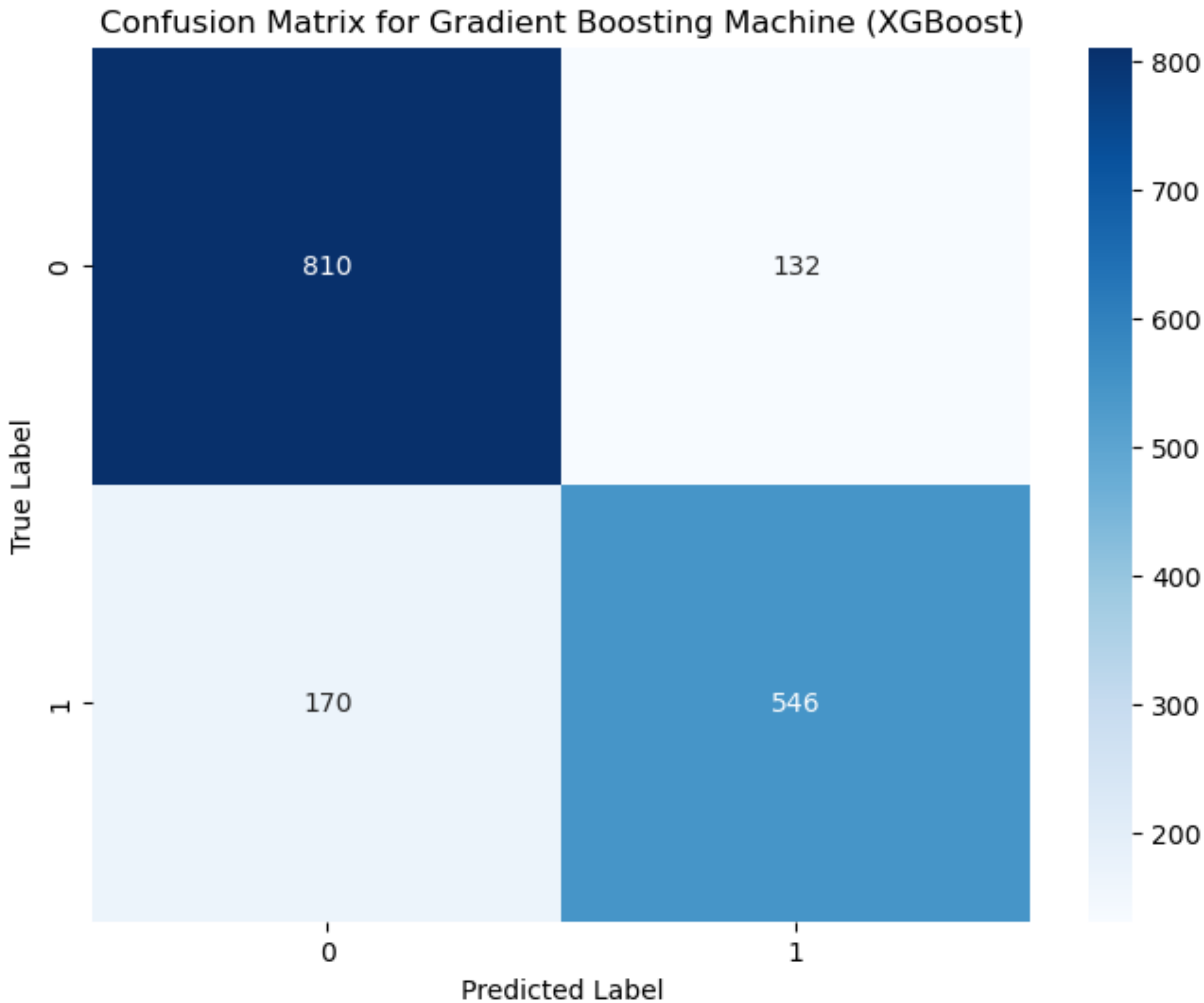
In [11]:
```
# Plot confusion matrix for Naive Bayes Classifier
plt.figure(figsize=(8, 6))
sns.heatmap(nb_conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix for Naive Bayes Classifier')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix for Naive Bayes Classifier
645
297
178
538
True Label
Predicted Label
0
1
0
1
600
500
400
300
200

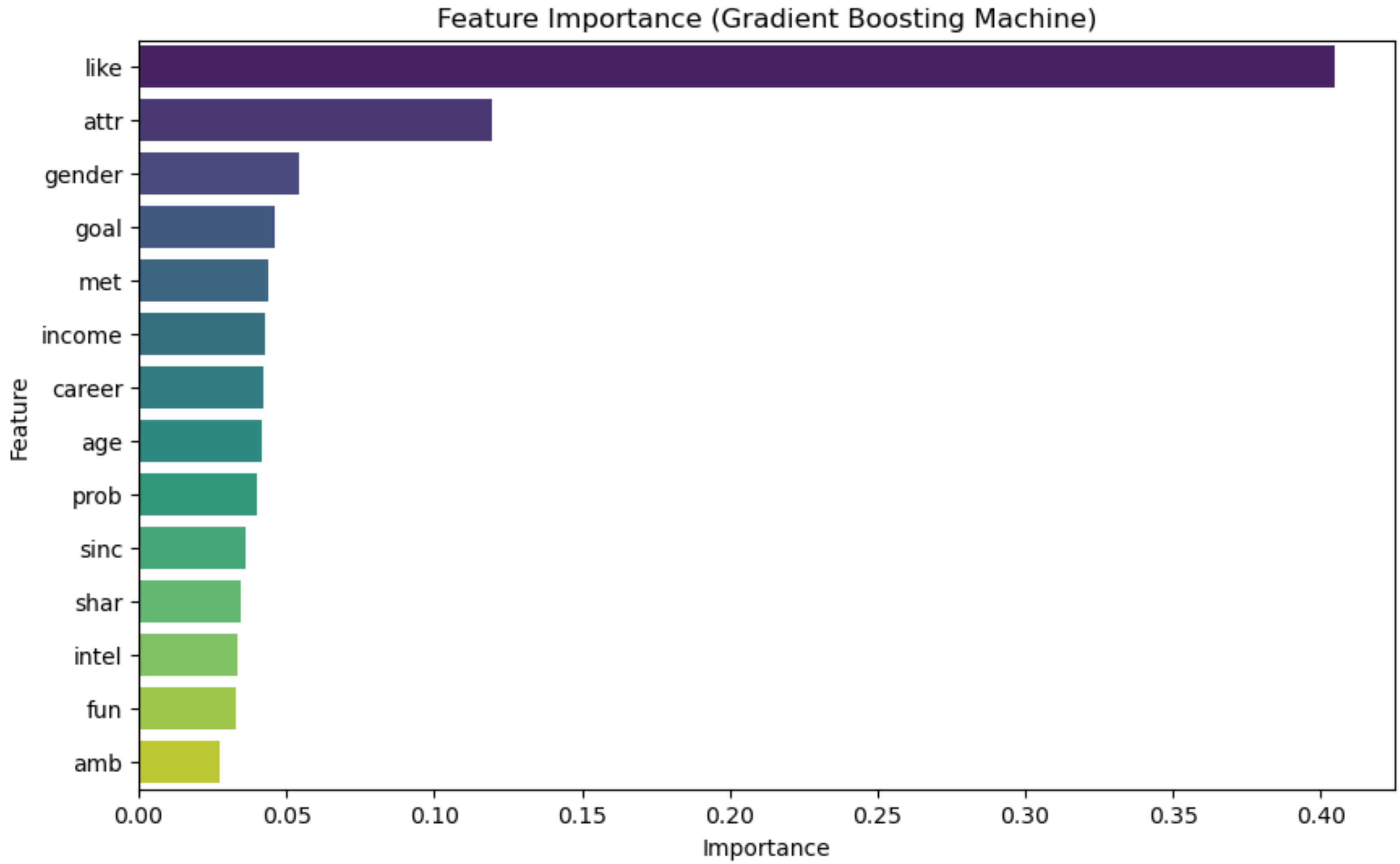
In [12]:
```
# Plot confusion matrix for Support Vector Machine Classifier
plt.figure(figsize=(8, 6))
sns.heatmap(svm_conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix for Support Vector Machine Classifier')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix for Support Vector Machine Classifier
942
0
716
0
True Label
Predicted Label
0
1
0
1
800
600
400
200
0

In [13]:
```
# Plot confusion matrix for Gradient Boosting Machine (XGBoost)
plt.figure(figsize=(8, 6))
sns.heatmap(gbm_conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix for Gradient Boosting Machine (XGBoost)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix for Gradient Boosting Machine (XGBoost)
810
132
170
546
0
1
True Label
0
1
Predicted Label
800
700
600
500
400
300
200

In [14]:
```
# Feature importance
feature_importance = gbm_classifier.feature_importances_

# Get feature names
feature_names = X.columns

# Create DataFrame to store feature importance
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': feature_importance})

# Sort DataFrame by importance in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Plot feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df, palette='viridis')
plt.title('Feature Importance (Gradient Boosting Machine)')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```


Feature Importance (Gradient Boosting Machine)
Feature
like
attr
gender
goal
met
income
career
age
prob
sinc
shar
intel
fun
amb
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
Importance

In [ ]: