In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.impute import KNNImputer
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, confusion_matrix, classification_
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassif
from sklearn.metrics import roc_auc_score, classification_report, confusion_
```

LOADING DATA

In [2]:
```
got_character = pd.read_excel('./datasets/GOT_character_predictions.xlsx')

got_dictionary = pd.read_excel('./datasets/GOT_data_dictionary.xlsx')


# Display print out of dataset to understand the data

print(got_character.head())
print(got_dictionary.head())
```

```
   S.No            name title  male               culture  dateOfBirth mother
\
0  1739   Imry Florent   Ser     1                   NaN          NaN    NaN
1  1233  Merianne Frey   NaN     0                   NaN        288.0    NaN
2   998            Dolf   NaN     0  Vale mountain clans          NaN    NaN
3    64           Quill   NaN     1              Braavosi          NaN    NaN
4   334           Bandy   NaN     0              Northmen          NaN    NaN

  father heir           house  ... isAliveMother  isAliveFather  isAliveHeir
\
0    NaN  NaN  House Florent  ...           NaN            NaN          NaN
1    NaN  NaN     House Frey  ...           NaN            NaN          NaN
2    NaN  NaN    Stone Crows  ...           NaN            NaN          NaN
3    NaN  NaN            NaN  ...           NaN            NaN          NaN
4    NaN  NaN    House Stark  ...           NaN            NaN          NaN

   isAliveSpouse  isMarried  isNoble   age  numDeadRelations  popularity  \
0            NaN          0        1   NaN                 0    0.183946
1            NaN          0        0  17.0                 0    0.083612
2            NaN          0        0   NaN                 0    0.016722
3            NaN          0        0   NaN                 0    0.016722
4            NaN          0        0   NaN                 0    0.020067

   isAlive
0        0
1        1
2        1
3        1
4        1

[5 rows x 26 columns]
         S.No          Character number (by order of appearance)
0         name                                     Character name
1        title          Honorary title(s) given to each character
2         male                                1 = male, 0 = female
3      culture        Indicates the cultural group of a character
4  dateOfBirth  Known dates of birth for each character (measu...
```

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

Out[3]:

	S.No	name	title	male	culture	dateOfBirth	mother	father	heir	house	...
0	1739	Imry Florent	Ser	1	NaN	NaN	NaN	NaN	NaN	House Florent	...
1	1233	Merianne Frey	NaN	0	NaN	288.0	NaN	NaN	NaN	House Frey	...
2	998	Dolf	NaN	0	Vale mountain clans	NaN	NaN	NaN	NaN	Stone Crows	...
3	64	Quill	NaN	1	Braavosi	NaN	NaN	NaN	NaN	NaN	...
4	334	Bandy	NaN	0	Northmen	NaN	NaN	NaN	NaN	House Stark	...

5 rows × 26 columns

In [4]:
```
got_dictionary.head()
```

Out[4]:

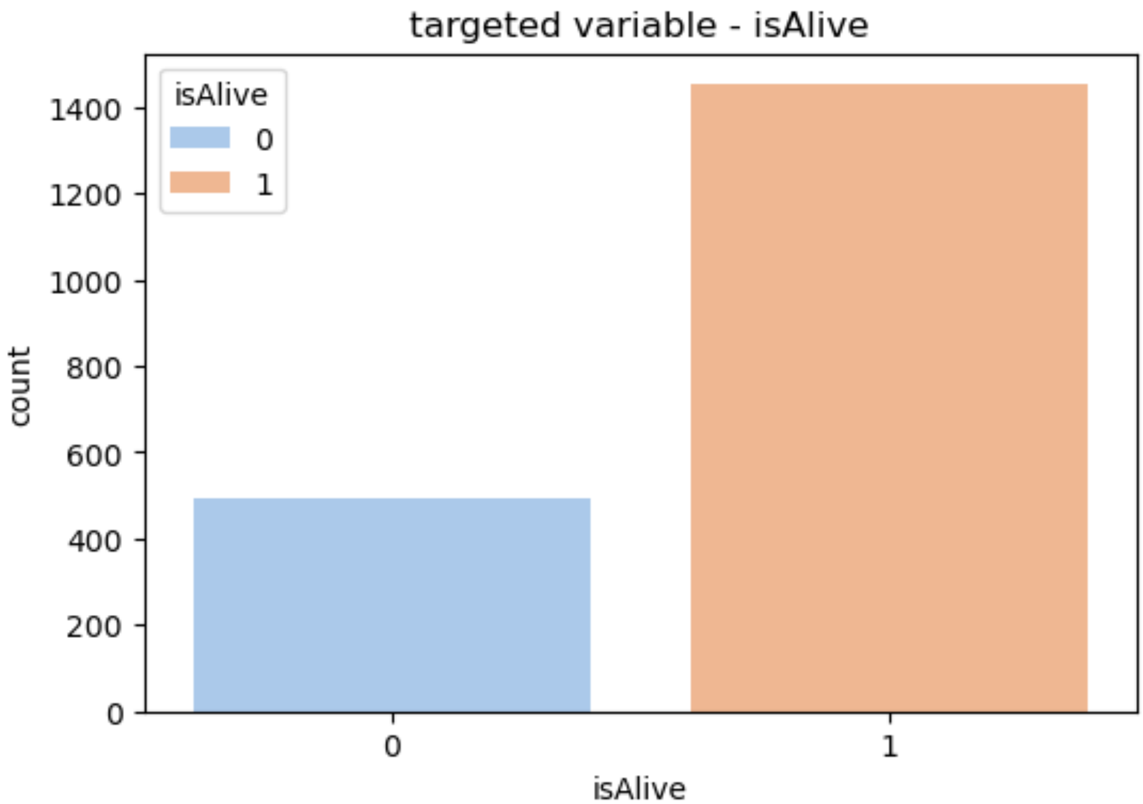
	S.No	Character number (by order of appearance)
0	name	Character name
1	title	Honorary title(s) given to each character
2	male	1 = male, 0 = female
3	culture	Indicates the cultural group of a character
4	dateOfBirth	Known dates of birth for each character (measu...

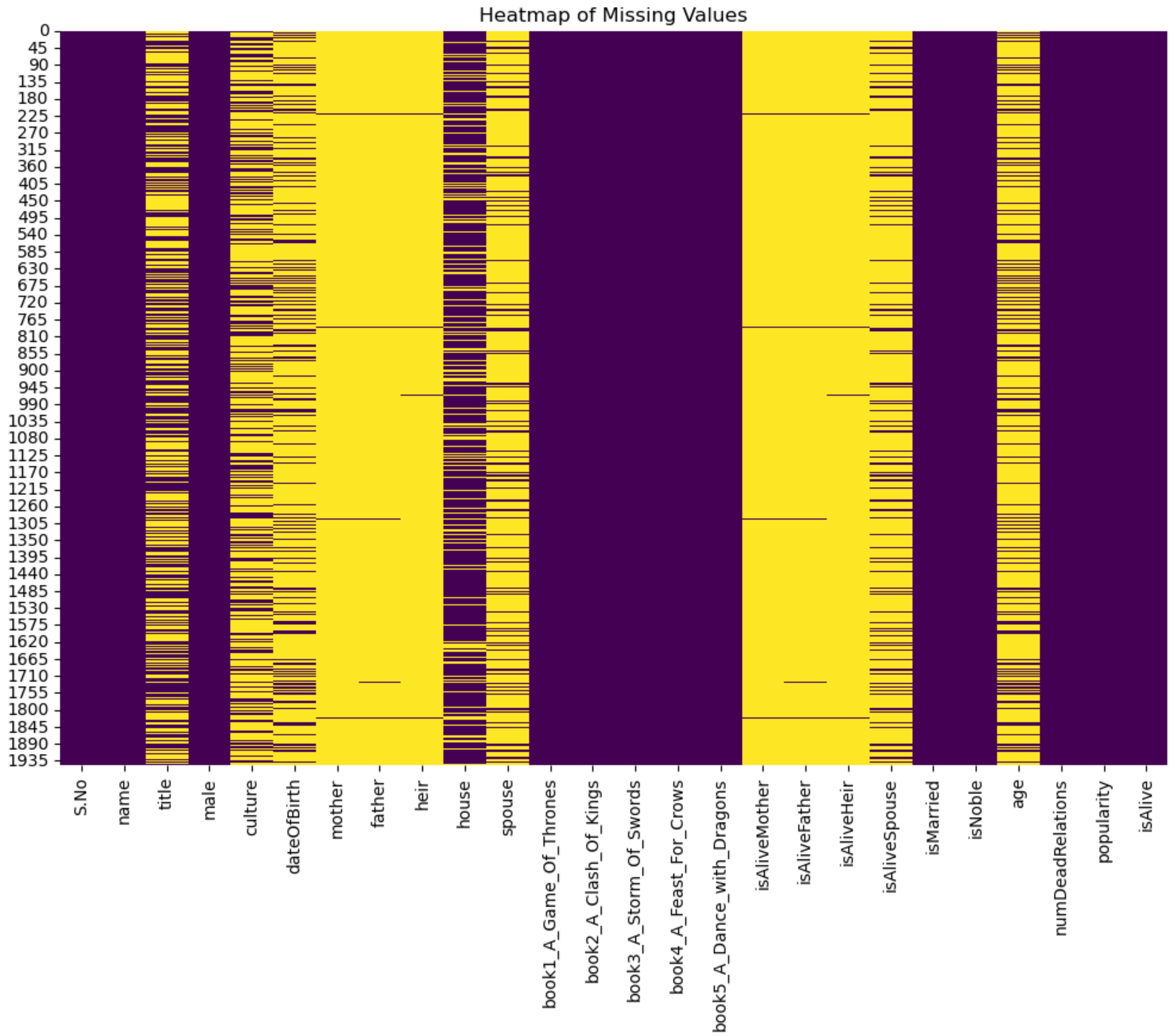
EDA & DP

In [5]:
```
# Description statitics with Data
got_character.info()
got_character.describe()

# Projection - targeted variable distribution which is 'isAlive'
plt.figure(figsize=(6, 4))
sns.countplot(data=got_character, x='isAlive',hue= 'isAlive', palette='paste
plt.title('targeted variable - isAlive')
plt.show()

# Detecting the missing values in the data

missing_values = got_character.isnull().sum()
```

```python
# Projecting missing values

plt.figure(figsize=(12, 8))
sns.heatmap(got_character.isnull(), cbar=False, cmap='viridis')
plt.title('Heatmap of Missing Values')
plt.show()

missing_values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1946 entries, 0 to 1945
Data columns (total 26 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   S.No                        1946 non-null   int64  
 1   name                        1946 non-null   object 
 2   title                       938 non-null    object 
 3   male                        1946 non-null   int64  
 4   culture                     677 non-null    object 
 5   dateOfBirth                 433 non-null    float64
 6   mother                      21 non-null     object 
 7   father                      26 non-null     object 
 8   heir                        23 non-null     object 
 9   house                       1519 non-null   object 
 10  spouse                      276 non-null    object 
 11  book1_A_Game_Of_Thrones     1946 non-null   int64  
 12  book2_A_Clash_Of_Kings      1946 non-null   int64  
 13  book3_A_Storm_Of_Swords     1946 non-null   int64  
 14  book4_A_Feast_For_Crows     1946 non-null   int64  
 15  book5_A_Dance_with_Dragons  1946 non-null   int64  
 16  isAliveMother               21 non-null     float64
 17  isAliveFather               26 non-null     float64
 18  isAliveHeir                 23 non-null     float64
 19  isAliveSpouse               276 non-null    float64
 20  isMarried                   1946 non-null   int64  
 21  isNoble                     1946 non-null   int64  
 22  age                         433 non-null    float64
 23  numDeadRelations            1946 non-null   int64  
 24  popularity                  1946 non-null   float64
 25  isAlive                     1946 non-null   int64  
dtypes: float64(7), int64(11), object(8)
memory usage: 395.4+ KB
```


targeted variable - isAlive
isAlive
0
1
count
0
200
400
600
800
1000
1200
1400
0
1
isAlive


Heatmap of Missing Values
0
45
90
135
180
225
270
315
360
405
450
495
540
585
630
675
720
765
810
855
900
945
990
1035
1080
1125
1170
1215
1260
1305
1350
1395
1440
1485
1530
1575
1620
1665
1710
1755
1800
1845
1890
1935
S.No
name
title
male
culture
dateOfBirth
mother
father
heir
house
spouse
book1_A_Game_Of_Thrones
book2_A_Clash_Of_Kings
book3_A_Storm_Of_Swords
book4_A_Feast_For_Crows
book5_A_Dance_with_Dragons
isAliveMother
isAliveFather
isAliveHeir
isAliveSpouse
isMarried
isNoble
age
numDeadRelations
popularity
isAlive

Out[5]:
```
S.No                              0
name                              0
title                          1008
male                              0
culture                        1269
dateOfBirth                    1513
mother                         1925
father                         1920
heir                           1923
house                           427
spouse                         1670
book1_A_Game_Of_Thrones           0
book2_A_Clash_Of_Kings            0
book3_A_Storm_Of_Swords           0
book4_A_Feast_For_Crows           0
book5_A_Dance_with_Dragons        0
isAliveMother                  1925
isAliveFather                  1920
isAliveHeir                    1923
isAliveSpouse                  1670
isMarried                         0
isNoble                           0
age                            1513
numDeadRelations                  0
popularity                        0
isAlive                           0
dtype: int64
```

ADDRESSING THE MISSING VALUES

In [6]:
```
print(got_character.columns)
```

```
Index(['S.No', 'name', 'title', 'male', 'culture', 'dateOfBirth', 'mother',
       'father', 'heir', 'house', 'spouse', 'book1_A_Game_Of_Thrones',
       'book2_A_Clash_Of_Kings', 'book3_A_Storm_Of_Swords',
       'book4_A_Feast_For_Crows', 'book5_A_Dance_with_Dragons',
       'isAliveMother', 'isAliveFather', 'isAliveHeir', 'isAliveSpouse',
       'isMarried', 'isNoble', 'age', 'numDeadRelations', 'popularity',
       'isAlive'],
      dtype='object')
```

In [7]:
```
# Drop columns with excessive missing values
drop_these_columns = ['mother', 'father', 'heir', 'isAliveMother', 'isAliveF
got_character = got_character.drop(columns=drop_these_columns)

# Impute missing values for 'age' with the median
got_character['age'].fillna(got_character['age'].median(), inplace=True)
```

```
# Impute missing values for 'culture' and 'house' with the most used value
got_character['culture'].fillna(got_character['culture'].mode()[0], inplace=
got_character['house'].fillna(got_character['house'].mode()[0], inplace=True

# Drop any remaining rows with missing values
got_character = got_character.dropna()

# Confirm no missing values remain
any_missing_values_after = got_character.isnull().sum()

# Display the cleaned data and check for missing values
got_character.head()
any_missing_values_after.head()
```

Out[7]:

```
S.No       0
name       0
title      0
male       0
culture    0
dtype: int64
```

FEATURE ENGINEERING

In [8]:

```
# Feature Engineering

# 1. Age Group
bins = [0, 13, 19, 60, 100]
labels = ['Child', 'Teenager', 'Adult', 'Senior']
got_character['age_group'] = pd.cut(got_character['age'], bins=bins, labels=

# 2. Total Books Appeared
got_character['total_books_appeared'] = got_character[['book1_A_Game_Of_Thro

# 3. Renowned Family (formerly Family Popularity)
renowned_family = got_character.groupby('house')['popularity'].transform('me
got_character['renowned_family'] = renowned_family


# Display the first few rows to confirm the new features
got_character.head()
got_character[['age_group', 'total_books_appeared', 'renowned_family']].heac
```

Out[8]:

	age_group	total_books_appeared	renowned_family
25	Adult	5	0.478261
27	Adult	0	0.246656
36	Adult	5	0.498328
51	Adult	5	0.979933
90	Senior	5	0.147157

Train and Test

In [9]:

```
# Categorical variables encoded
le = LabelEncoder()
got_character['title'] = le.fit_transform(got_character['title'])
got_character['culture'] = le.fit_transform(got_character['culture'])
got_character['house'] = le.fit_transform(got_character['house'])
got_character['spouse'] = le.fit_transform(got_character['spouse'])
got_character['age_group'] = le.fit_transform(got_character['age_group'])

# Define the features and target variable
X = got_character.drop(columns=['S.No', 'name', 'isAlive'])
y = got_character['isAlive']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize models
logreg = LogisticRegression(random_state=42)
ridge = RidgeClassifier(random_state=42)
knn = KNeighborsClassifier()
decision_tree = DecisionTreeClassifier(random_state=42)
random_forest = RandomForestClassifier(random_state=42)
gbm = GradientBoostingClassifier(random_state=42)

# Train the models
logreg.fit(X_train_scaled, y_train)
ridge.fit(X_train_scaled, y_train)
knn.fit(X_train_scaled, y_train)
decision_tree.fit(X_train, y_train)
random_forest.fit(X_train, y_train)
```

```
gbm.fit(X_train, y_train)

# Evaluate the models
models = {
    'Logistic Regression': logreg,
    'Ridge Classifier': ridge,
    'K-Nearest Neighbors': knn,
    'Decision Tree': decision_tree,
    'Random Forest': random_forest,
    'GBM': gbm
}

for model_name, model in models.items():
    if model_name in ['Logistic Regression', 'Ridge Classifier', 'K-Nearest
        predictions = model.predict(X_test_scaled)
    else:
        predictions = model.predict(X_test)

    roc_auc = roc_auc_score(y_test, predictions)
    print(f"{model_name} ROC AUC: {roc_auc}")

    class_report = classification_report(y_test, predictions)
    print(f"Classification Report for {model_name}:")
    print(class_report)
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, predictions))
    print("\n" + "-"*60 + "\n")
```

```
Logistic Regression ROC AUC: 0.494949494949494949
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.44      0.44      0.44         9
           1       0.55      0.55      0.55        11

    accuracy                           0.50        20
   macro avg       0.49      0.49      0.49        20
weighted avg       0.50      0.50      0.50        20

Confusion Matrix:
[[4 5]
 [5 6]]

------------------------------------------------------------

Ridge Classifier ROC AUC: 0.6313131313131313
Classification Report for Ridge Classifier:
              precision    recall  f1-score   support

           0       0.67      0.44      0.53         9
```

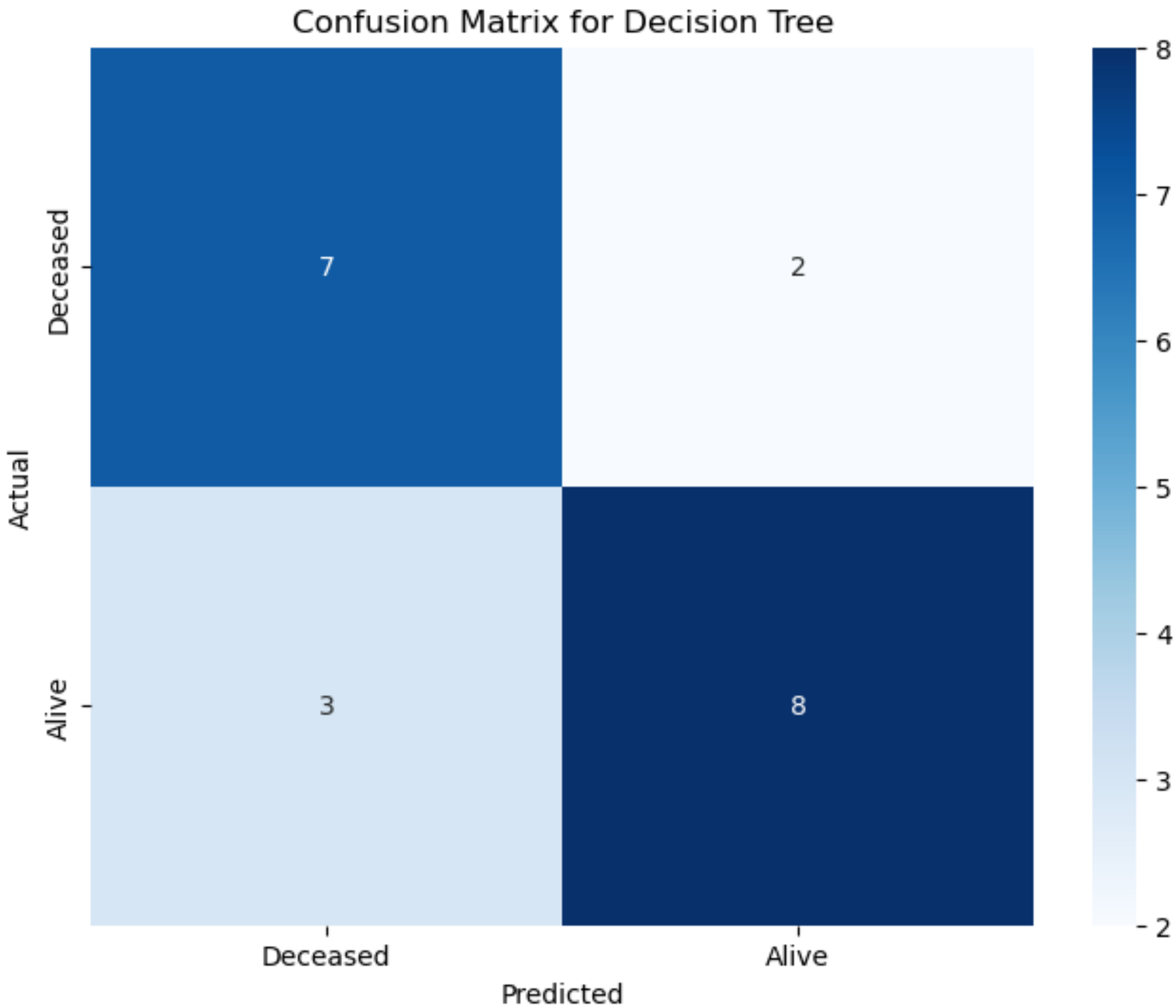
```
           1       0.64      0.82      0.72        11

    accuracy                           0.65        20
   macro avg       0.65      0.63      0.63        20
weighted avg       0.65      0.65      0.64        20

Confusion Matrix:
[[4 5]
 [2 9]]

------------------------------------------------------------

K-Nearest Neighbors ROC AUC: 0.6868686868686869
Classification Report for K-Nearest Neighbors:
              precision    recall  f1-score   support

           0       0.71      0.56      0.63         9
           1       0.69      0.82      0.75        11

    accuracy                           0.70        20
   macro avg       0.70      0.69      0.69        20
weighted avg       0.70      0.70      0.69        20

Confusion Matrix:
[[5 4]
 [2 9]]

------------------------------------------------------------

Decision Tree ROC AUC: 0.7525252525252525
Classification Report for Decision Tree:
              precision    recall  f1-score   support

           0       0.70      0.78      0.74         9
           1       0.80      0.73      0.76        11

    accuracy                           0.75        20
   macro avg       0.75      0.75      0.75        20
weighted avg       0.76      0.75      0.75        20

Confusion Matrix:
[[7 2]
 [3 8]]

------------------------------------------------------------

Random Forest ROC AUC: 0.696969696969697
Classification Report for Random Forest:
              precision    recall  f1-score   support
```

```
           0       0.67      0.67      0.67         9
           1       0.73      0.73      0.73        11

    accuracy                           0.70        20
   macro avg       0.70      0.70      0.70        20
weighted avg       0.70      0.70      0.70        20

Confusion Matrix:
[[6 3]
 [3 8]]

------------------------------------------------------------

GBM ROC AUC: 0.696969696969697
Classification Report for GBM:
              precision    recall  f1-score   support

           0       0.67      0.67      0.67         9
           1       0.73      0.73      0.73        11

    accuracy                           0.70        20
   macro avg       0.70      0.70      0.70        20
weighted avg       0.70      0.70      0.70        20

Confusion Matrix:
[[6 3]
 [3 8]]

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

FINAL MODEL SELECTION

In [10]:

```
# Decision Tree ROC AUC: 0.7525252525252525


predictions = decision_tree.predict(X_test)

# confusion matrix
conf_matrix = confusion_matrix(y_test, predictions)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['De
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Decision Tree')
plt.show()
```



Hyper Tunning The Selected Model

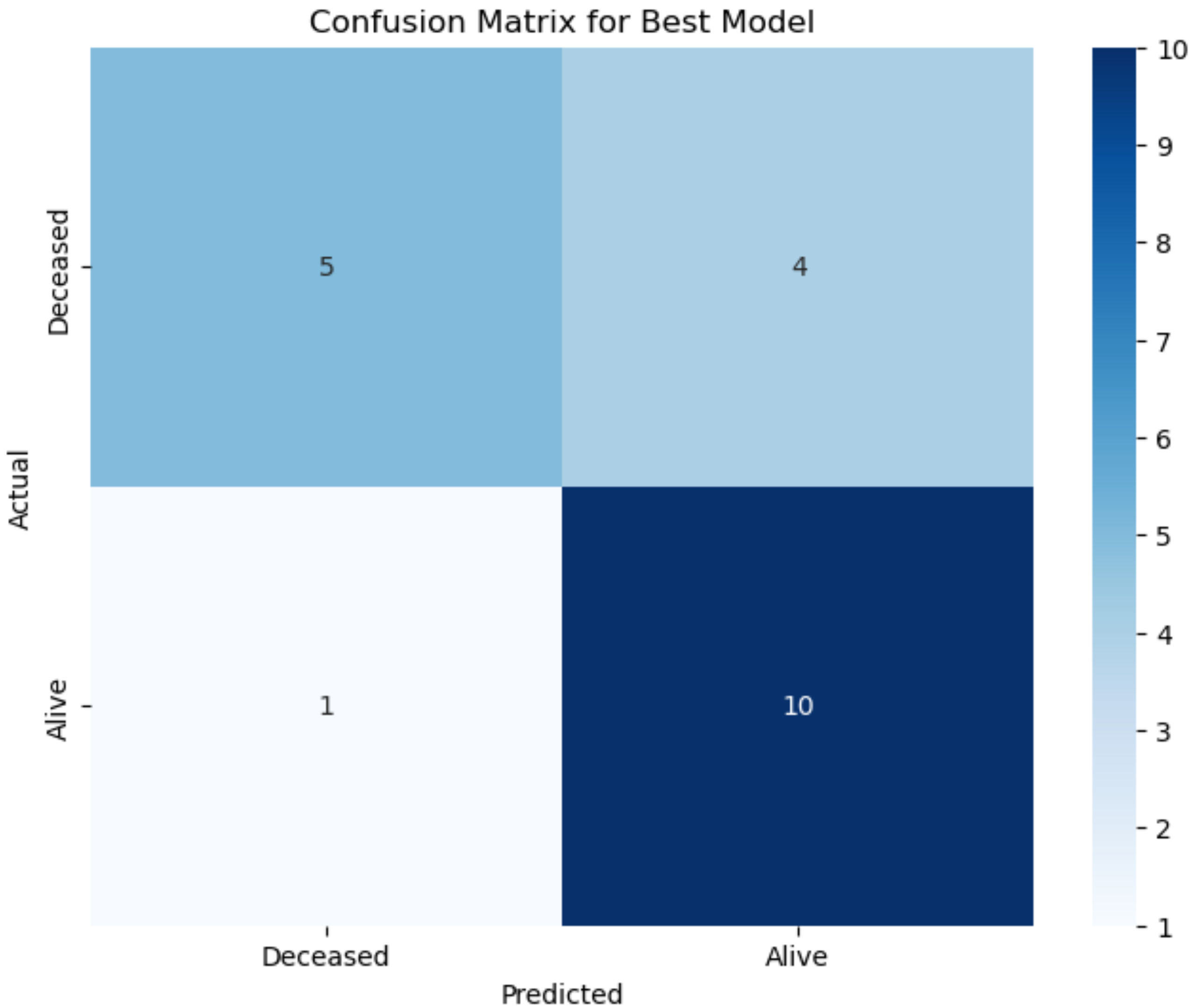
In [11]:
```
# Define the parameter grid
param_grid = {
    'max_depth': [3, 5, 7, 10, None],
    'min_samples_split': [2, 5, 10, 20],
    'min_samples_leaf': [1, 2, 4, 6],
    'criterion': ['gini', 'entropy']
}

grid_search = GridSearchCV(estimator=DecisionTreeClassifier(random_state=42)
grid_search.fit(X_train, y_train)

best_model = grid_search.best_estimator_
best_predictions = best_model.predict(X_test)
```

```
print("Best Parameters:", grid_search.best_params_)
print("Best Model ROC AUC:", roc_auc_score(y_test, best_predictions))
print("Best Model Classification Report:")
print(classification_report(y_test, best_predictions))
print("Confusion Matrix for Best Model:")
print(confusion_matrix(y_test, best_predictions))
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 3, 'min_samples_lea
f': 4, 'min_samples_split': 20}
Best Model ROC AUC: 0.7323232323232324
Best Model Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.56      0.67         9
           1       0.71      0.91      0.80        11

    accuracy                           0.75        20
   macro avg       0.77      0.73      0.73        20
weighted avg       0.77      0.75      0.74        20

Confusion Matrix for Best Model:
[[ 5  4]
 [ 1 10]]
```

In [12]:

```
# Plot the confusion matrix
conf_matrix = confusion_matrix(y_test, best_predictions)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['De
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Best Model')
plt.show()
```


Confusion Matrix for Best Model
Actual
Deceased
Alive
Predicted
Deceased
Alive
5
4
1
10
10
9
8
7
6
5
4
3
2
1