Nilakshi_043_AIML_lab 7

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

df = pd.read_csv('loan_train.csv');
df.head()
```

Out[1]:

	Unnamed: 0.1	Unnamed: 0	loan_status	Principal	terms	effective_date	due_date	age	edu
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	Sc
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	B
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	

In [4]:
```
# Display basic info about the data
print("\nDataset Info:")
print(df.info())

# Shape of the dataset
print("\nShape of dataset", df.shape)

# Check for missing values
print("\nMissing values: no missing values found")
print(df.isnull().sum())

# Summary statistics of numerical columns
print("\nstatistics:")
print(df.describe())
```

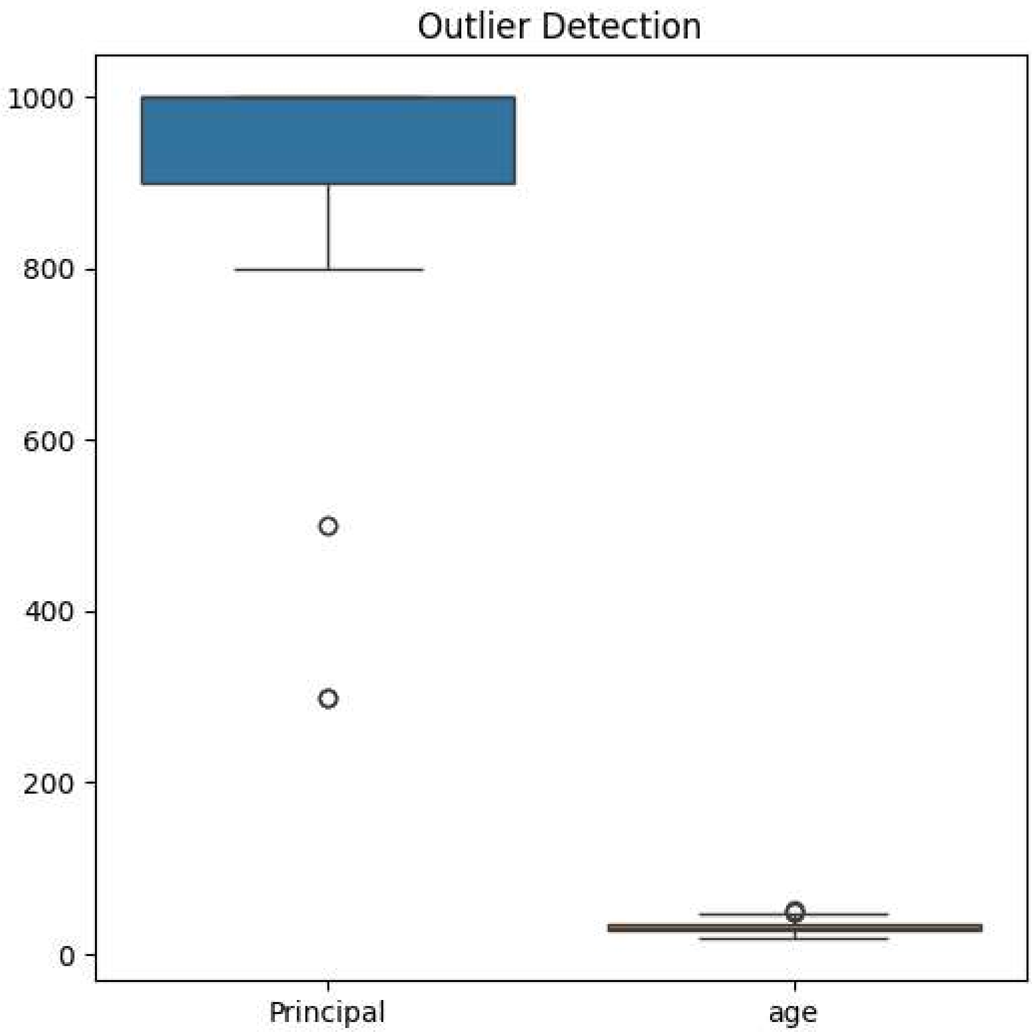
```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 346 entries, 0 to 345
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Unnamed: 0.1    346 non-null    int64 
 1   Unnamed: 0      346 non-null    int64 
 2   loan_status     346 non-null    object
 3   Principal       346 non-null    int64 
 4   terms           346 non-null    int64 
 5   effective_date  346 non-null    object
 6   due_date        346 non-null    object
 7   age             346 non-null    int64 
 8   education       346 non-null    object
 9   Gender          346 non-null    object
dtypes: int64(5), object(5)
memory usage: 27.2+ KB
None

Shape of dataset (346, 10)

Missing values: no missing values found
Unnamed: 0.1      0
Unnamed: 0        0
loan_status       0
Principal         0
terms             0
effective_date    0
due_date          0
age               0
education         0
Gender            0
dtype: int64

statistics:
       Unnamed: 0.1  Unnamed: 0    Principal       terms         age
count    346.000000  346.000000   346.000000  346.000000  346.000000
mean     202.167630  202.167630   943.641618   22.653179   30.939306
std      115.459715  115.459715   109.425530    7.991006    6.039418
min        0.000000    0.000000   300.000000    7.000000   18.000000
25%      107.250000  107.250000   900.000000   15.000000   27.000000
50%      204.500000  204.500000  1000.000000   30.000000   30.000000
75%      298.750000  298.750000  1000.000000   30.000000   35.000000
max      399.000000  399.000000  1000.000000   30.000000   51.000000
```

In [6]:
```
# counting unique values in categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    print(f"\nUnique values in '{col}':\n", df[col].value_counts())
```

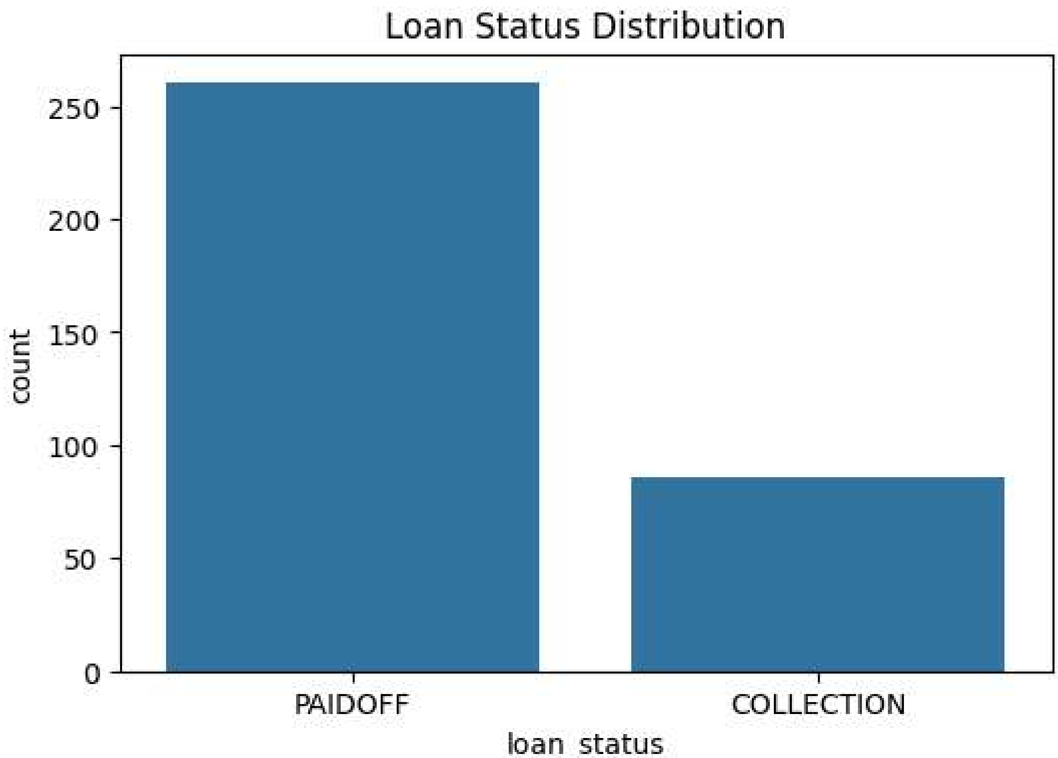
```
Unique values in 'loan_status':
 loan_status
PAIDOFF       260
COLLECTION     86
Name: count, dtype: int64

Unique values in 'effective_date':
 effective_date
9/11/2016    166
9/12/2016     87
9/10/2016     31
9/14/2016     31
9/13/2016     20
9/9/2016       8
9/8/2016       3
Name: count, dtype: int64

Unique values in 'due_date':
 due_date
10/10/2016    90
9/25/2016     63
9/26/2016     42
10/11/2016    36
10/13/2016    19
10/9/2016     18
9/24/2016     12
9/27/2016     11
9/28/2016     10
11/9/2016      6
10/12/2016     6
10/8/2016      5
10/25/2016     4
11/10/2016     4
9/19/2016      3
9/23/2016      3
9/18/2016      3
9/16/2016      3
9/17/2016      2
11/12/2016     2
10/7/2016      2
10/26/2016     1
9/22/2016      1
Name: count, dtype: int64

Unique values in 'education':
 education
High School or Below    151
college                 149
Bechalor                 44
Master or Above           2
Name: count, dtype: int64

Unique values in 'Gender':
 Gender
male      294
```

```
female     52
Name: count, dtype: int64
```

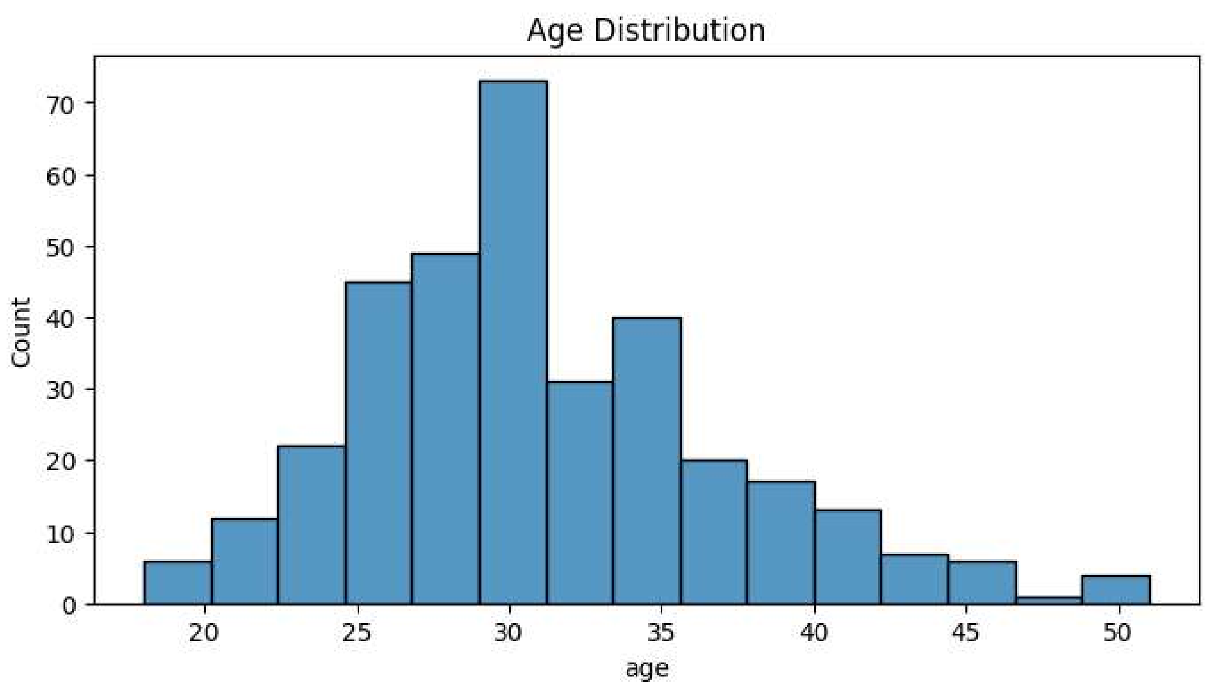
In [10]:
```
# Outliers detection
plt.figure(figsize=(6, 6))
sns.boxplot(data=df[['Principal', 'age']])
plt.title('Outlier Detection')
plt.show()
```



In [15]:
```
# Distribution of Loan Status
plt.figure(figsize=(6, 4))
sns.countplot(x='loan_status', data=df)
plt.title('Loan Status Distribution')
plt.show()

# Heatmap of correlation between numerical features
# plt.figure(figsize=(10, 6))
# sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
# plt.title('Correlation Heatmap')
# plt.show()
```

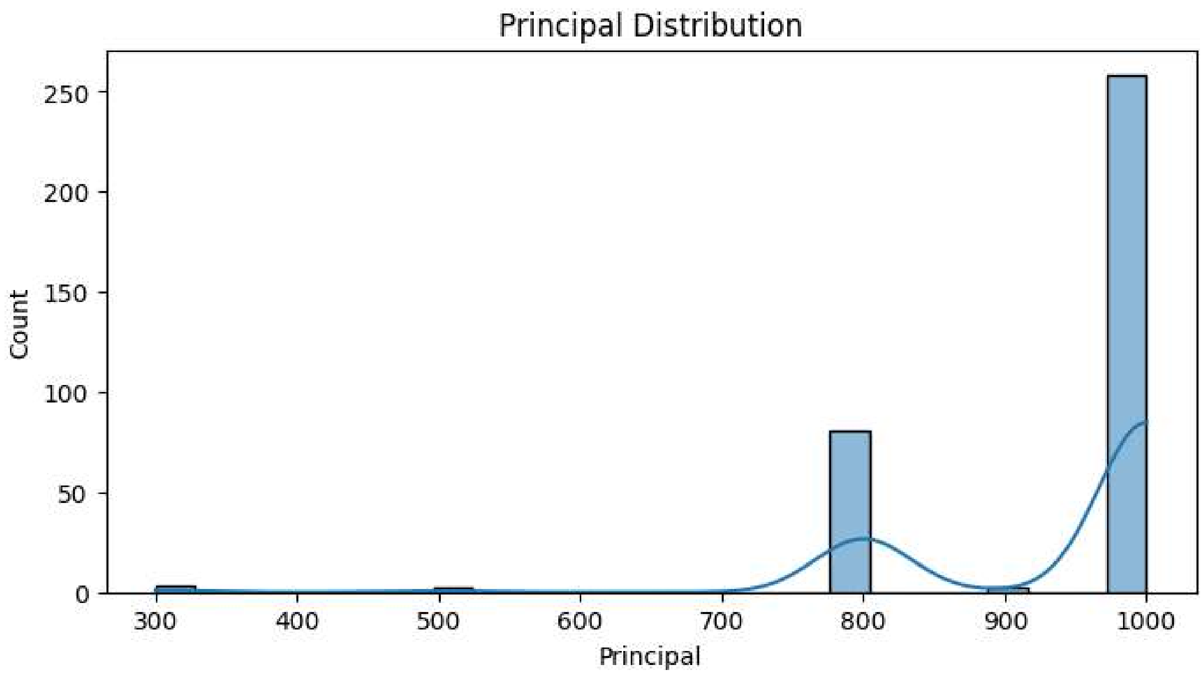


In [12]:
```
# Distribution of Age
plt.figure(figsize=(8, 4))
sns.histplot(df['age'])
plt.title('Age Distribution')
plt.show()
```



In [17]:
```
# Distribution of Principal Amount
plt.figure(figsize=(8, 4))
# kde=> Kernal Density Estimate for smoothed estimate of the underlying probability
sns.histplot(df['Principal'], kde=True)
```

```
plt.title('Principal Distribution')
plt.show()
```



In [36]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Preprocessing
le = LabelEncoder()
df['loan_status'] = le.fit_transform(df['loan_status'])  # Encode target variable
df['education'] = le.fit_transform(df['education'])
df['Gender'] = le.fit_transform(df['Gender'])

# Split data into features and target
X = df.drop('loan_status', axis=1)
y = df['loan_status']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, ran
```

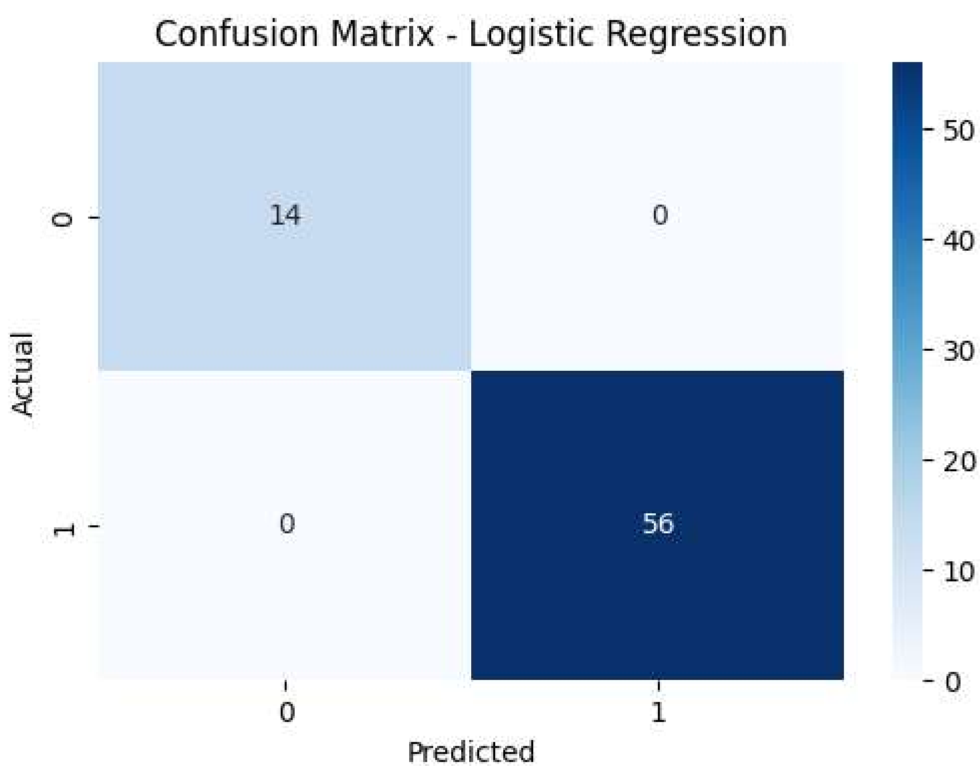
In [34]:

```
# Function to evaluate models
def evaluate_model(model, model_name):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    print(f"\nModel: {model_name}")
```

```
    print(f"Accuracy: {accuracy_score(y_test, y_pred):.4f}")
    print("\nClassification Report:\n", classification_report(y_test, y_pred))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=le.classes_, yti
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```

In [33]:
```
# Logistic Regression
log_reg = LogisticRegression()
evaluate_model(log_reg, "Logistic Regression")
```

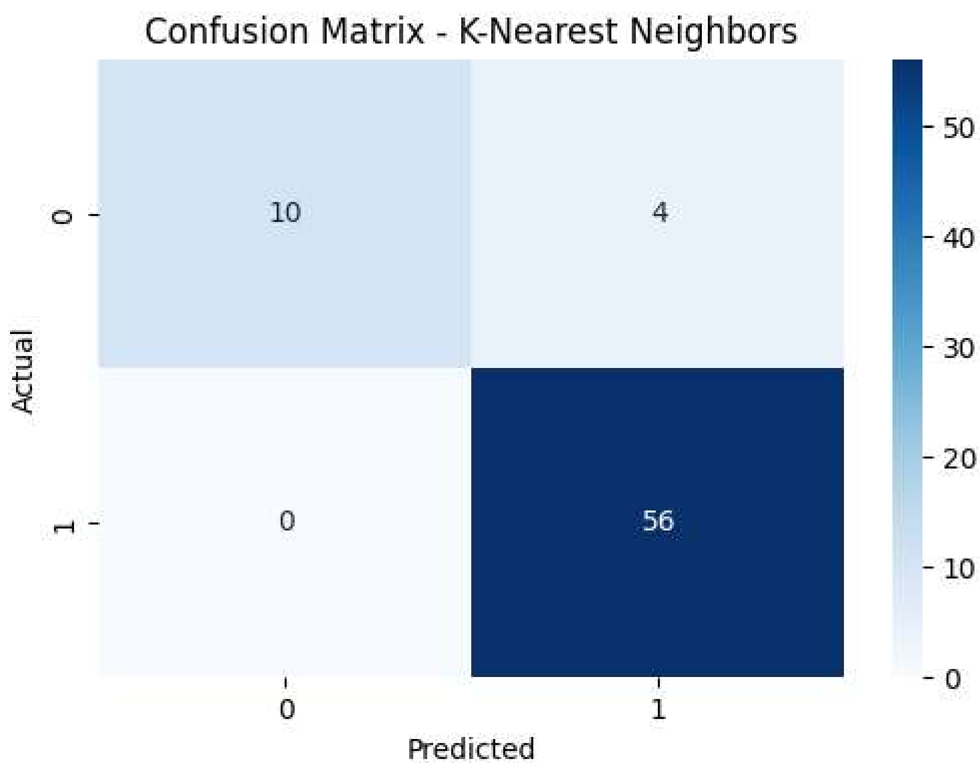
```
Model: Logistic Regression
Accuracy: 1.0000

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      1.00      1.00        56

    accuracy                           1.00        70
   macro avg       1.00      1.00      1.00        70
weighted avg       1.00      1.00      1.00        70
```



In [32]:
```
# KNN Classifier
knn = KNeighborsClassifier(n_neighbors=5)
```

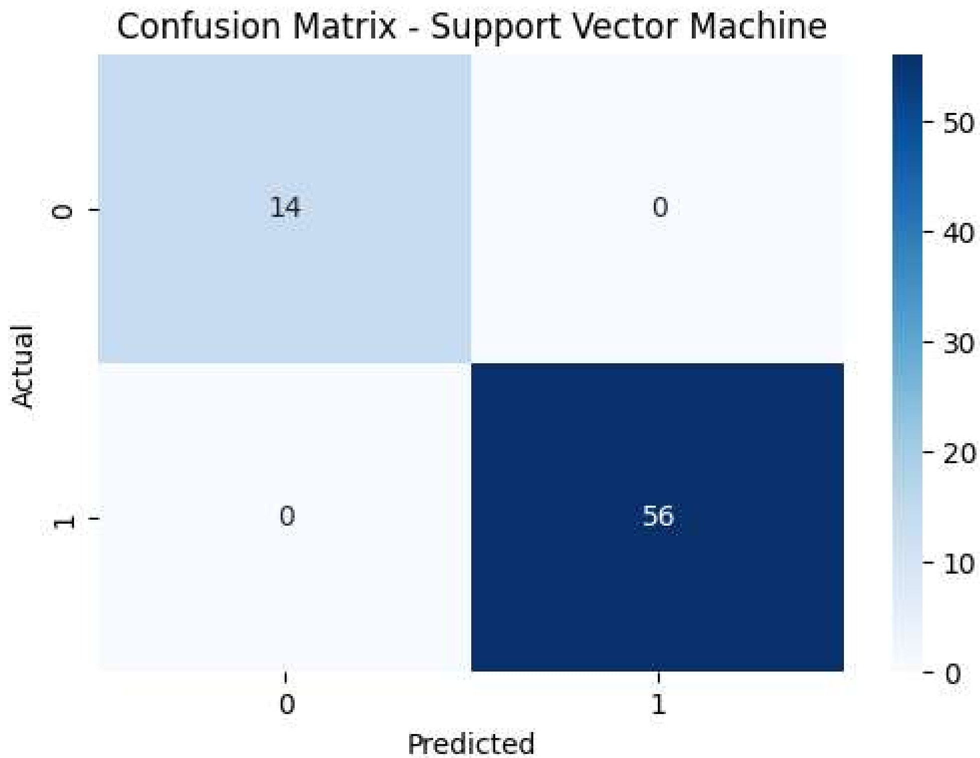
```
evaluate_model(knn, "K-Nearest Neighbors")
```

```
Model: K-Nearest Neighbors
Accuracy: 0.9429

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.71      0.83        14
           1       0.93      1.00      0.97        56

    accuracy                           0.94        70
   macro avg       0.97      0.86      0.90        70
weighted avg       0.95      0.94      0.94        70
```



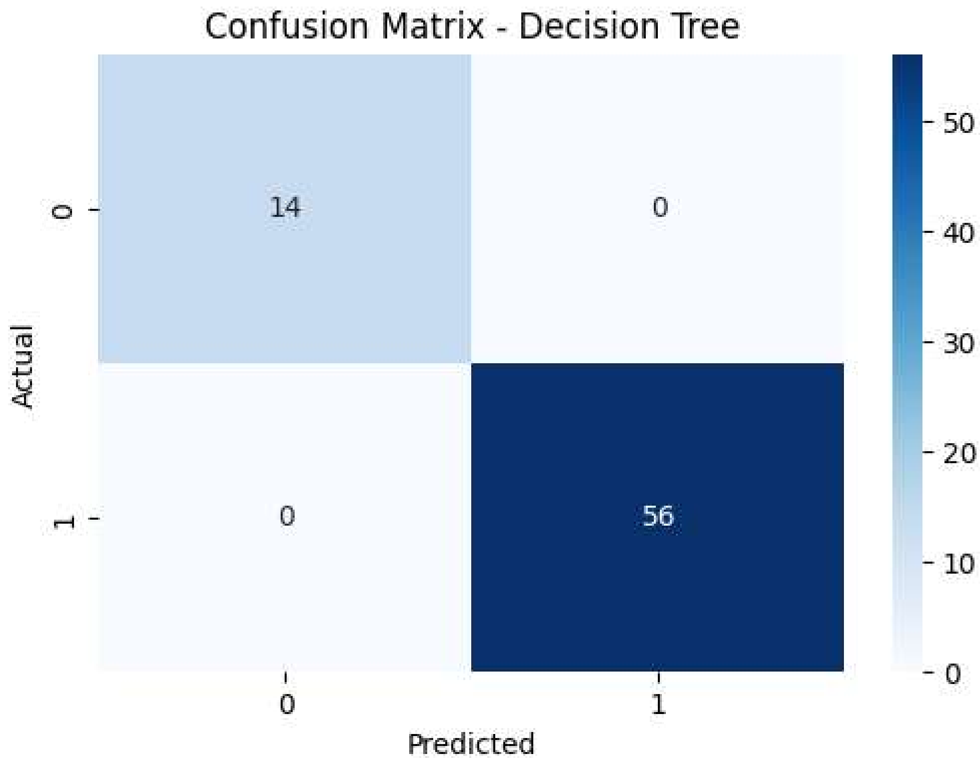
In [31]:
```
# SVM Classifier
svm = SVC(kernel='linear')
evaluate_model(svm, "Support Vector Machine")
```

```
Model: Support Vector Machine
Accuracy: 1.0000

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      1.00      1.00        56

    accuracy                           1.00        70
   macro avg       1.00      1.00      1.00        70
weighted avg       1.00      1.00      1.00        70
```



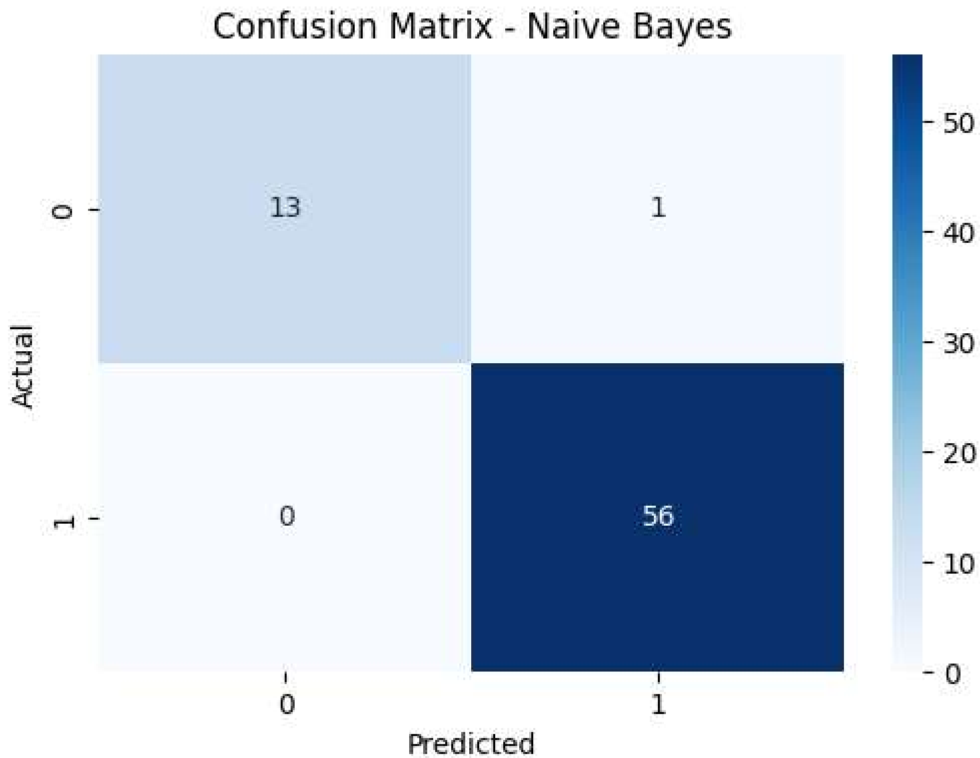
In [30]:
```python
# Decision Tree Classifier
dt = DecisionTreeClassifier()
evaluate_model(dt, "Decision Tree")
```

```
Model: Decision Tree
Accuracy: 1.0000

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      1.00      1.00        56

    accuracy                           1.00        70
   macro avg       1.00      1.00      1.00        70
weighted avg       1.00      1.00      1.00        70
```



In [29]:
```python
# Naive Bayes Classifier
nb = GaussianNB()
evaluate_model(nb, "Naive Bayes")
```

```
Model: Naive Bayes
Accuracy: 0.9857

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.93      0.96        14
           1       0.98      1.00      0.99        56

    accuracy                           0.99        70
   macro avg       0.99      0.96      0.98        70
weighted avg       0.99      0.99      0.99        70
```



In [45]:

```
#Summary of Accuracy of Models
data = {
    'Model': ['Logistic Regression', 'Naive Bayes', 'Decision Tree', 'SVM', 'KNN'],
    'Accuracy': [1.0000, 0.9857, 1.0000, 1.0000, 0.9429]
}

df = pd.DataFrame(data)
print(df)

print('\nFinal Models: Logistic Regression, Decision Tree, SVM')
```

```
                 Model  Accuracy
0  Logistic Regression    1.0000
1          Naive Bayes    0.9857
2        Decision Tree    1.0000
3                  SVM    1.0000
4                  KNN    0.9429

Final Models: Logistic Regression, Decision Tree, SVM
```