In [4]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
```

In [5]:
```
df = pd.read_csv("loan_data.csv")
print(df.head())
print(df.info())
```

```
                                                Text  Income  Credit_Score  \
0  I need a loan to pay for an international vaca...   26556           581
1  I want to make home improvements like installi...  197392           389
2  I need a loan for home renovation, including a...   44561           523
3  I need funds to buy new furniture and applianc...  190363           729
4           I need a loan to start a small business.   61853           732

   Loan_Amount  DTI_Ratio Employment_Status  Approval
0         8314      79.26          employed  Rejected
1       111604      22.14          employed  Rejected
2        34118      45.44          employed  Rejected
3       118757      10.22        unemployed  Rejected
4        19210      44.13          employed  Approved
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24000 entries, 0 to 23999
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Text               24000 non-null  object
 1   Income             24000 non-null  int64
 2   Credit_Score       24000 non-null  int64
 3   Loan_Amount        24000 non-null  int64
 4   DTI_Ratio          24000 non-null  float64
 5   Employment_Status  24000 non-null  object
 6   Approval           24000 non-null  object
dtypes: float64(1), int64(3), object(3)
memory usage: 1.3+ MB
None
```

In [6]:
```
print(df.isnull().sum())
df = df.dropna()   # simple option
```

```
Text               0
Income             0
Credit_Score       0
Loan_Amount        0
DTI_Ratio          0
Employment_Status  0
Approval           0
dtype: int64
```

In [7]:
```
encoder = LabelEncoder()
for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = encoder.fit_transform(df[col])
```

In [11]:
```
X = df.drop('Approval', axis=1)  # Features
y = df['Approval']               # Target (Approved/Not Approved)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [9]:
```
print(df.columns)
```

```
Index(['Text', 'Income', 'Credit_Score', 'Loan_Amount', 'DTI_Ratio',
       'Employment_Status', 'Approval'],
      dtype='object')
```

In [12]:
```
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
print("Before SMOTE:", y_train.value_counts())
print("After SMOTE:", y_train_res.value_counts())
```

```
Before SMOTE: Approval
1    16020
0     3180
Name: count, dtype: int64
After SMOTE: Approval
1    16020
0    16020
Name: count, dtype: int64
```

In [13]:
```
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train_res, y_train_res)
y_pred_log = log_reg.predict(X_test)
```

In [14]:
```
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train_res, y_train_res)
y_pred_dt = dt.predict(X_test)
```

In [15]:
```
print("Logistic Regression Report:\n", classification_report(y_test, y_pred_log))
print("Decision Tree Report:\n", classification_report(y_test, y_pred_dt))
```

```
Logistic Regression Report:
              precision    recall  f1-score   support

           0       0.65      0.94      0.77       753
           1       0.99      0.91      0.95      4047

    accuracy                           0.91      4800
   macro avg       0.82      0.92      0.86      4800
weighted avg       0.93      0.91      0.92      4800

Decision Tree Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       753
           1       1.00      1.00      1.00      4047

    accuracy                           1.00      4800
   macro avg       0.99      0.99      0.99      4800
weighted avg       1.00      1.00      1.00      4800
```

In [16]:
```
print("Logistic Regression Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lo
print("Decision Tree Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
```

```
Logistic Regression Confusion Matrix:
 [[ 707   46]
 [ 379 3668]]
Decision Tree Confusion Matrix:
 [[ 744    9]
 [  11 4036]]
```

In [17]:
```
df.head()
```

Out[17]:

	Text	Income	Credit_Score	Loan_Amount	DTI_Ratio	Employment_Status	Approval
0	14	26556	581	8314	79.26	0	1
1	64	197392	389	111604	22.14	0	1
2	0	44561	523	34118	45.44	0	1
3	35	190363	729	118757	10.22	1	1
4	20	61853	732	19210	44.13	0	0

In [21]:
```
# Example with Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Define the model
model = LogisticRegression(max_iter=1000)

# Train the model
```

```
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
```

In [22]:
```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(random_state=42)
```

In [23]:
```
from sklearn.metrics import classification_report, confusion_matrix

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[ 585  168]
 [ 173 3874]]

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.78      0.77       753
           1       0.96      0.96      0.96      4047

    accuracy                           0.93      4800
   macro avg       0.87      0.87      0.87      4800
weighted avg       0.93      0.93      0.93      4800
```

In [24]:
```
from sklearn.metrics import accuracy_score

print("Accuracy:", accuracy_score(y_test, y_pred))
```

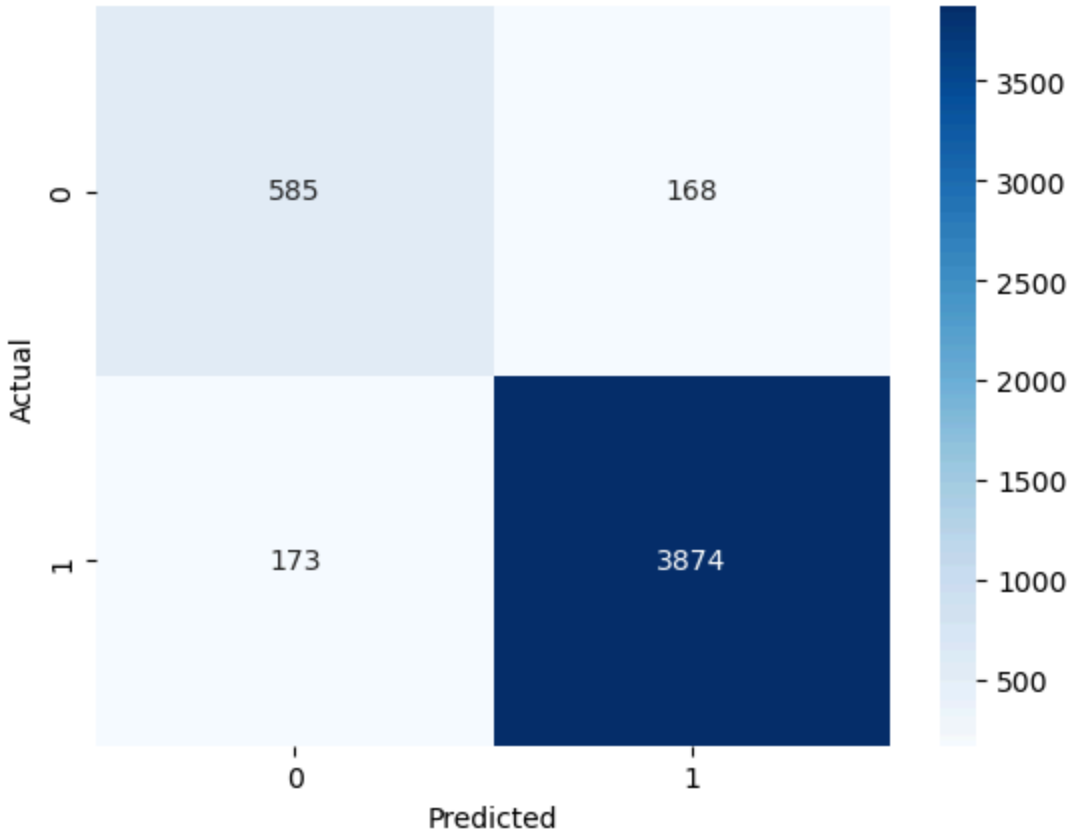
```
Accuracy: 0.9289583333333333
```

In [25]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.78      0.77       753
           1       0.96      0.96      0.96      4047

    accuracy                           0.93      4800
   macro avg       0.87      0.87      0.87      4800
weighted avg       0.93      0.93      0.93      4800
```

In [26]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
plt.show()
```



In [27]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

# Logistic Regression
log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train, y_train)
log_pred = log_model.predict(X_test)

print("Logistic Regression Report:")
print(classification_report(y_test, log_pred))

# Decision Tree
tree_model = DecisionTreeClassifier()
tree_model.fit(X_train, y_train)
tree_pred = tree_model.predict(X_test)

print("Decision Tree Report:")
print(classification_report(y_test, tree_pred))
```

```
Logistic Regression Report:
              precision    recall  f1-score   support

           0       0.77      0.78      0.77       753
           1       0.96      0.96      0.96      4047

    accuracy                           0.93      4800
   macro avg       0.87      0.87      0.87      4800
weighted avg       0.93      0.93      0.93      4800

Decision Tree Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       753
           1       1.00      1.00      1.00      4047

    accuracy                           1.00      4800
   macro avg       0.99      0.99      0.99      4800
weighted avg       1.00      1.00      1.00      4800
```

In [32]:
```
print(X.dtypes)
```

```
Text                 object
Income                int64
Credit_Score          int64
Loan_Amount           int64
DTI_Ratio           float64
Employment_Status    object
dtype: object
```

In [34]:
```
# Separate features and target
X = df.drop("Approval", axis=1)
y = df["Approval"]                # Target variable

# One-hot encode all categorical variables automatically
X = pd.get_dummies(X, drop_first=True)

print("Shape after encoding:", X.shape)
```

```
Shape after encoding: (24000, 6)
```

In [35]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

model = DecisionTreeClassifier()
model.fit(X_train, y_train)

print("Training done ✅")
```

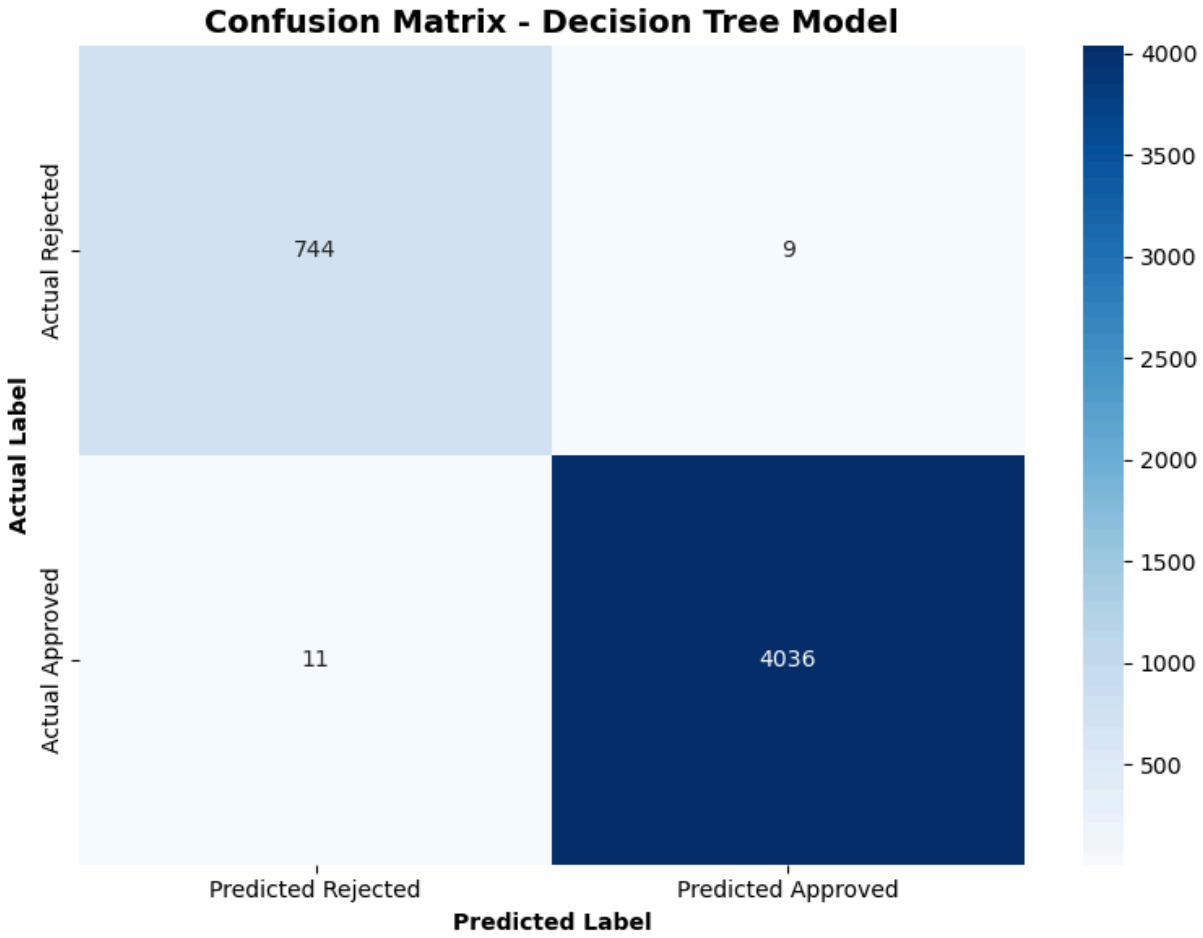
```
Training done ✅
```

In [36]:
```
sample = X.iloc[0].values.reshape(1, -1)
print("Prediction:", model.predict(sample))
```

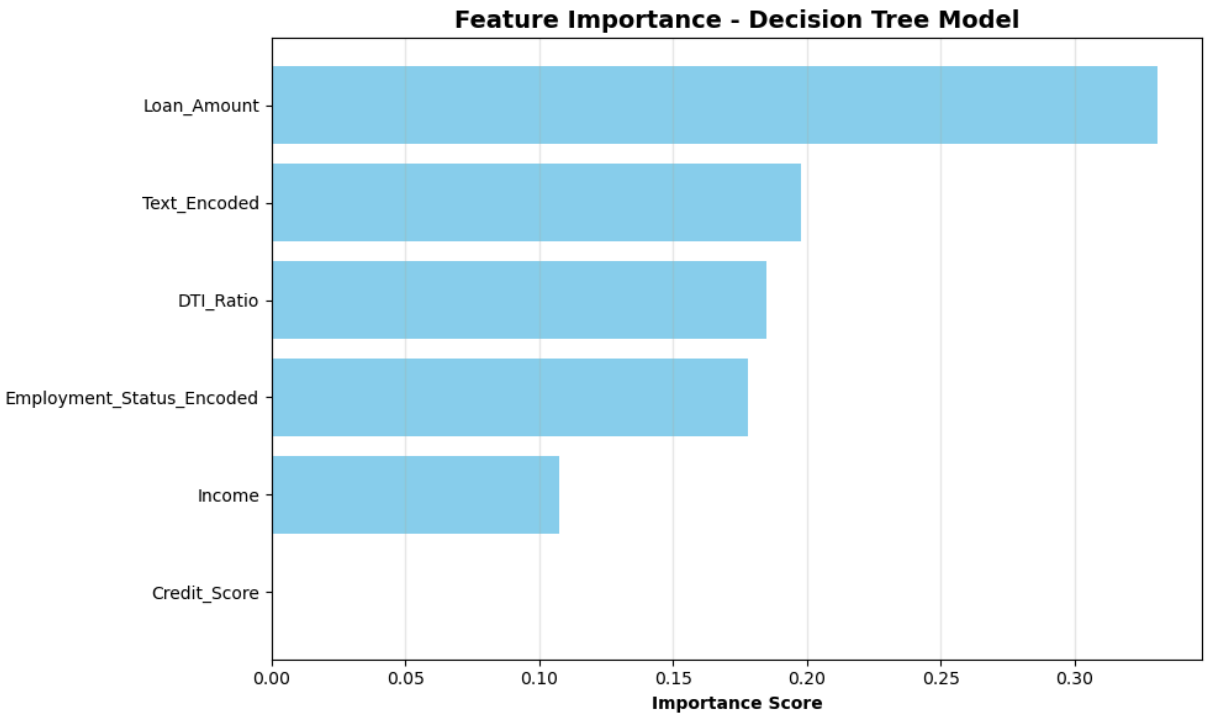
```
Prediction: [1]
```

```
C:\Users\aaa\anaconda3\Lib\site-packages\sklearn\utils\validation.py:2739: UserWarni
ng: X does not have valid feature names, but DecisionTreeClassifier was fitted with
feature names
  warnings.warn(
```

In [37]:
```python
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Your model's results
y_true = [0]*753 + [1]*4047 # Actual values: 753 Rejected, 4047 Approved
y_pred = [0]*744 + [1]*9 + [0]*11 + [1]*4036 # Predictions from the confusion matri

# Calculate the confusion matrix
cm = confusion_matrix(y_true, y_pred)

# Create a beautiful visual plot
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Rejected', 'Predicted Approved'],
            yticklabels=['Actual Rejected', 'Actual Approved'])
plt.title('Confusion Matrix - Decision Tree Model', fontsize=14, fontweight='bold')
plt.ylabel('Actual Label', fontweight='bold')
plt.xlabel('Predicted Label', fontweight='bold')
plt.tight_layout()
plt.savefig('confusion_matrix.png', dpi=300, bbox_inches='tight') # Save as high-re
plt.show()
```



In [38]:
```
# Get feature importances from your trained model
feature_importance = model.feature_importances_

# Create feature names (adjust based on your actual feature names after encoding)
# These should match the order of features in your training data
feature_names = ['Credit_Score', 'Income', 'Loan_Amount', 'DTI_Ratio',
                 'Employment_Status_Encoded', 'Text_Encoded']  # Update with your a

# Create a DataFrame for easy plotting
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
}).sort_values('Importance', ascending=True)

# Create the plot
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'], importance_df['Importance'], color='skyblue')
plt.xlabel('Importance Score', fontweight='bold')
plt.title('Feature Importance - Decision Tree Model', fontsize=14, fontweight='bold
plt.grid(axis='x', alpha=0.3)
plt.tight_layout()
plt.savefig('feature_importance.png', dpi=300, bbox_inches='tight') # Save as high-
plt.show()
```


Feature Importance - Decision Tree Model
Loan_Amount
Text_Encoded
DTI_Ratio
Employment_Status_Encoded
Income
Credit_Score
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Importance Score

In [ ]: