IMPORT LIBRARIES

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import joblib
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay, roc_auc_score
import warnings
warnings.filterwarnings("ignore")
```

IMPORT DATA

In [2]:
```
data = pd.read_csv("loan_data.csv")
```

DISPLAY DATA

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

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_A
0	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	
1	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	
2	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	
3	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	
4	LP001013	Male	Yes	0	Not Graduate	No	2333	1516.0	95.0	

In [4]:
```
data.tail()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan
376	LP002953	Male	Yes	3+	Graduate	No	5703	0.0	128.0	
377	LP002974	Male	Yes	0	Graduate	No	3232	1950.0	108.0	
378	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	
379	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	
380	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	

In [5]:
```
print(' Num of rows :',data.shape[0],'\n','Num of columns :',data.shape[1])
```

```
Num of rows : 381
Num of columns : 13
```

In [6]:
```
data.describe()
```

Out[6]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	381.000000	381.000000	381.000000	370.000000	351.000000
mean	3579.845144	1277.275381	104.986877	340.864865	0.837607
std	1419.813818	2340.818114	28.358464	68.549257	0.369338
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2600.000000	0.000000	90.000000	360.000000	1.000000
50%	3333.000000	983.000000	110.000000	360.000000	1.000000
75%	4288.000000	2016.000000	127.000000	360.000000	1.000000
max	9703.000000	33837.000000	150.000000	480.000000	1.000000

In [7]:
```
data.describe(include='object')
```

Out[7]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
count	381	376	381	373	381	360	381	381
unique	381	2	2	4	2	2	3	2
top	LP001003	Male	Yes	0	Graduate	No	Semiurban	Y
freq	1	291	228	234	278	325	149	271

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381 entries, 0 to 380
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            381 non-null    object 
 1   Gender             376 non-null    object 
 2   Married            381 non-null    object 
 3   Dependents         373 non-null    object 
 4   Education          381 non-null    object 
 5   Self_Employed      360 non-null    object 
 6   ApplicantIncome    381 non-null    int64  
 7   CoapplicantIncome  381 non-null    float64
 8   LoanAmount         381 non-null    float64
 9   Loan_Amount_Term   370 non-null    float64
 10  Credit_History     351 non-null    float64
 11  Property_Area      381 non-null    object 
 12  Loan_Status        381 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 38.8+ KB
```

In [9]:
```
data.duplicated().sum()
```

Out[9]: 0

CHECKING NULL VALUES

In [10]:
```
print("\nNull Values Before Imputation:\n", data.isnull().sum())
```

```
Null Values Before Imputation:
 Loan_ID               0
Gender               5
Married              0
Dependents           8
Education            0
Self_Employed       21
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term    11
Credit_History      30
Property_Area        0
Loan_Status          0
dtype: int64
```

In [11]:
```
for col in ['Gender', 'Married', 'Dependents', 'Self_Employed']:
    data[col].fillna(data[col].mode()[0], inplace=True)
data['Credit_History'].fillna(data['Credit_History'].mean(), inplace=True)
data['Loan_Amount_Term'].fillna(data['Loan_Amount_Term'].mean(), inplace=True)
data['LoanAmount'].fillna(data['LoanAmount'].median(), inplace=True)

print("\nNull Values After Imputation:\n", data.isnull().sum())
```

```
Null Values After Imputation:
 Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

In [12]:
```
data['Dependents'].value_counts()
```

Out[12]:
```
Dependents
0     242
2      59
1      52
3+     28
Name: count, dtype: int64
```

Encode categorical features

In [13]:
```
label_encoder = LabelEncoder()
categorical_cols = data.select_dtypes(include=['object']).columns
for col in categorical_cols:
    data[col] = label_encoder.fit_transform(data[col].astype(str))
```

In [14]:
```
data['Loan_Status_encoded'] = label_encoder.fit_transform(data['Loan_Status'])
```

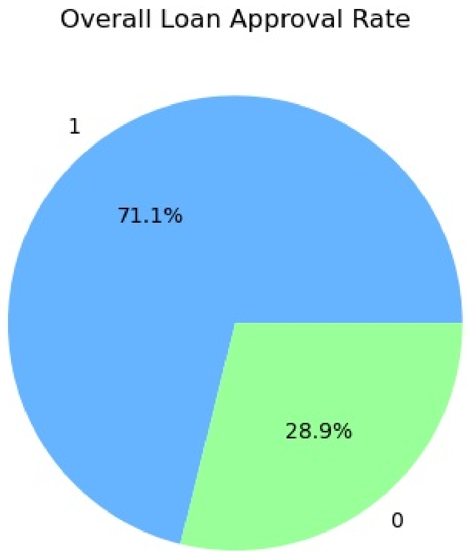
In [15]:
```
data.head()
```

Out[15]:

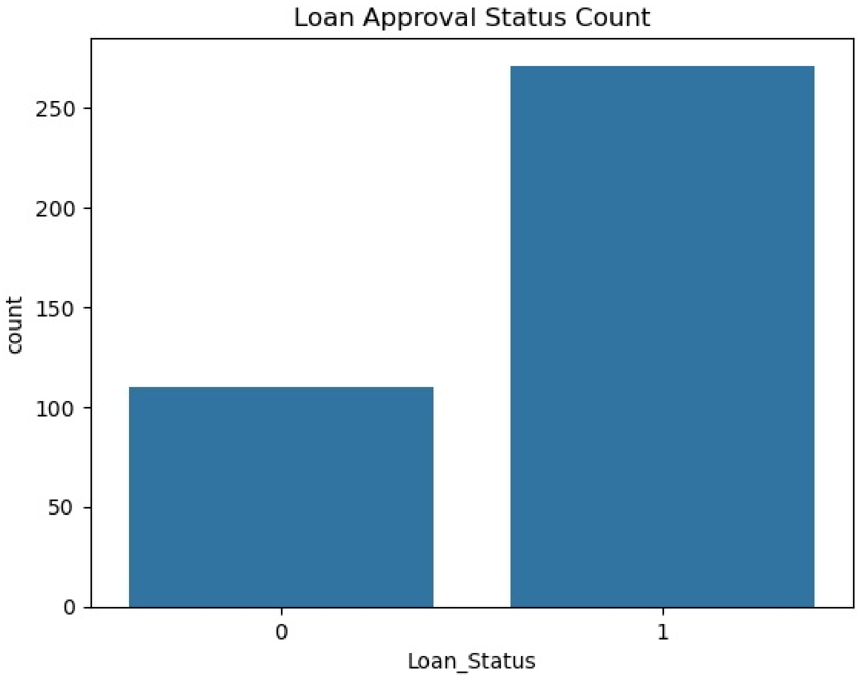
	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_An
0	0	1	1	1	0	0	4583	1508.0	128.0	
1	1	1	1	0	0	1	3000	0.0	66.0	
2	2	1	1	0	1	0	2583	2358.0	120.0	
3	3	1	0	0	0	0	6000	0.0	141.0	
4	4	1	1	0	1	0	2333	1516.0	95.0	

PERFORMING EDA

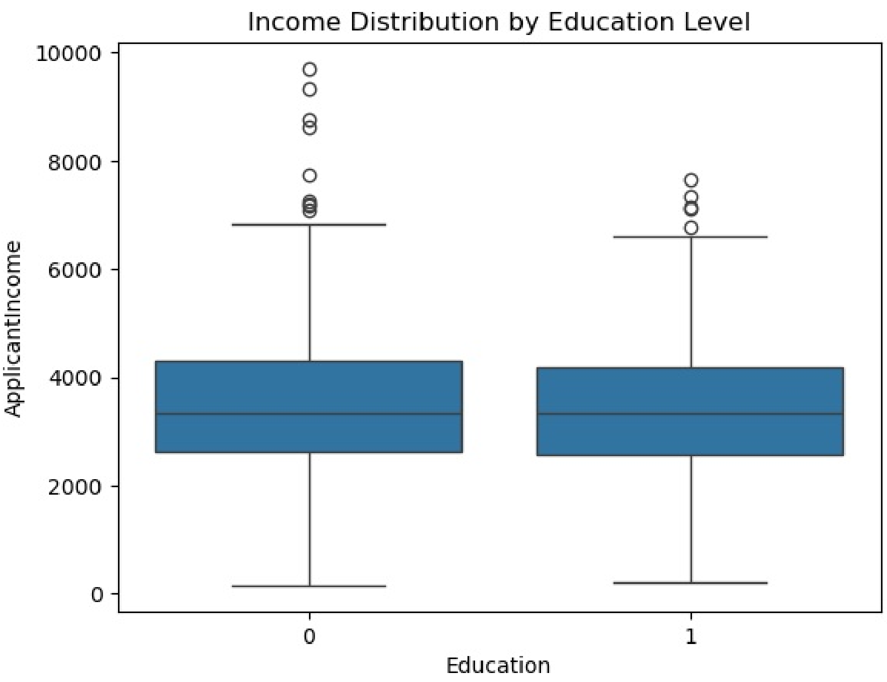
In [16]:
```
# Overall approval rate
approval_counts = data['Loan_Status'].value_counts()
plt.pie(approval_counts, labels=approval_counts.index, autopct='%1.1f%%', colors=['#66b3ff','#99ff99'])
plt.title('Overall Loan Approval Rate')
plt.show()
```



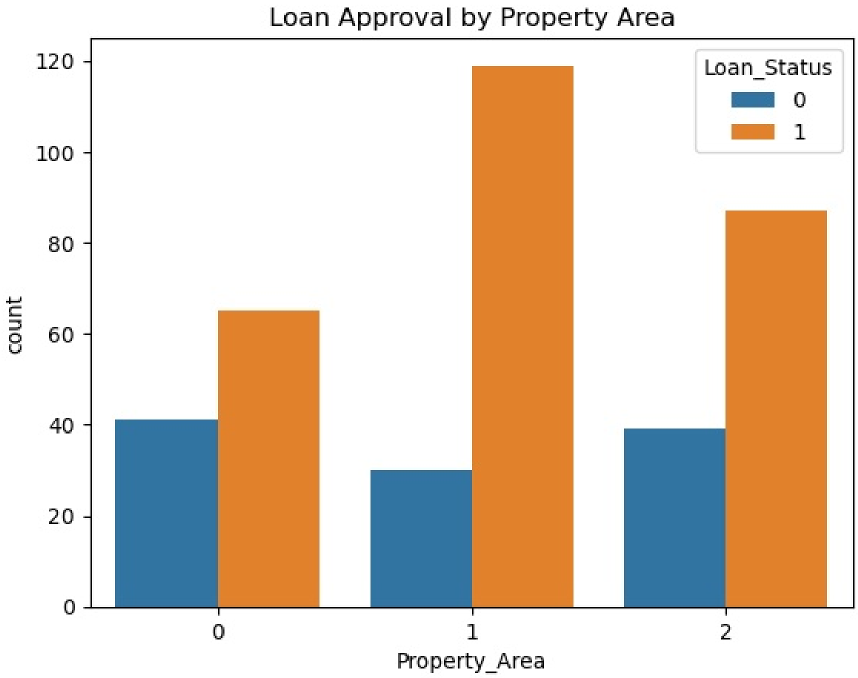
In [17]:
```
#Loan Status Count
sns.countplot(data=data, x='Loan_Status')
plt.title('Loan Approval Status Count')
plt.show()
```



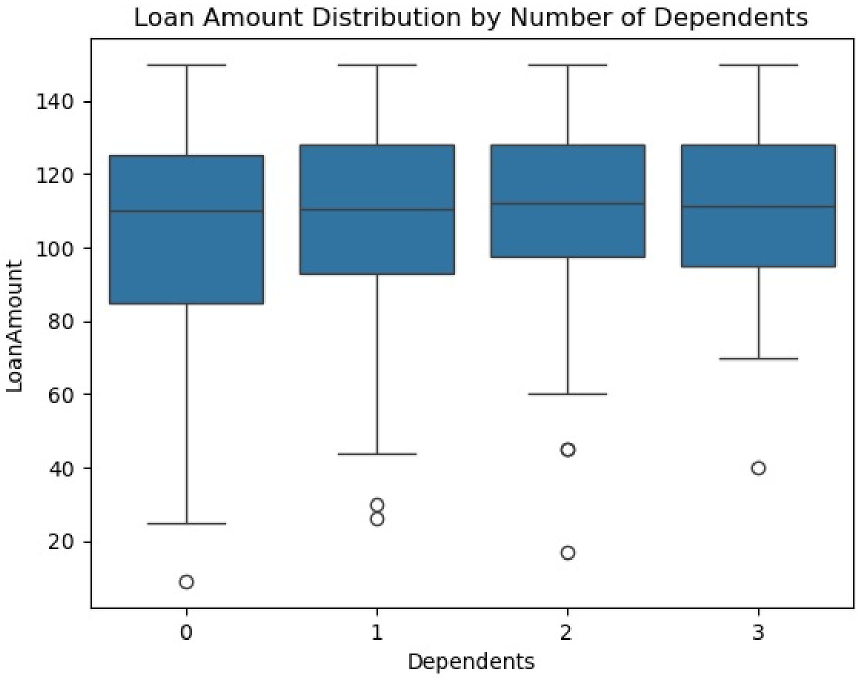
In [18]:
```
#  Income Distribution by Education
sns.boxplot(data=data, x='Education', y='ApplicantIncome')
plt.title('Income Distribution by Education Level')
plt.show()
```



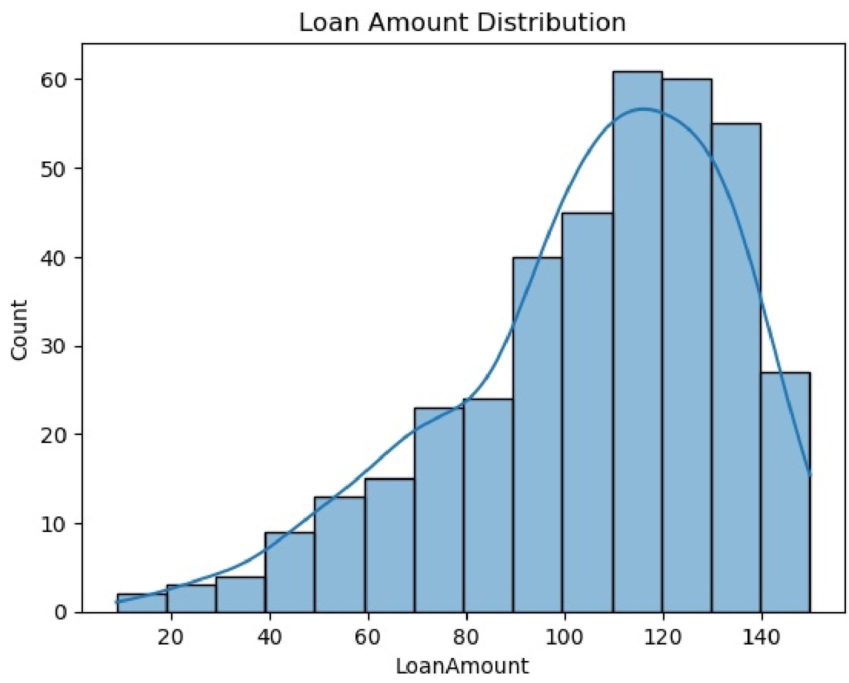
In [19]:
```
#  Loan Status by Property Area
sns.countplot(data=data, x='Property_Area', hue='Loan_Status')
plt.title('Loan Approval by Property Area')
plt.show()
```



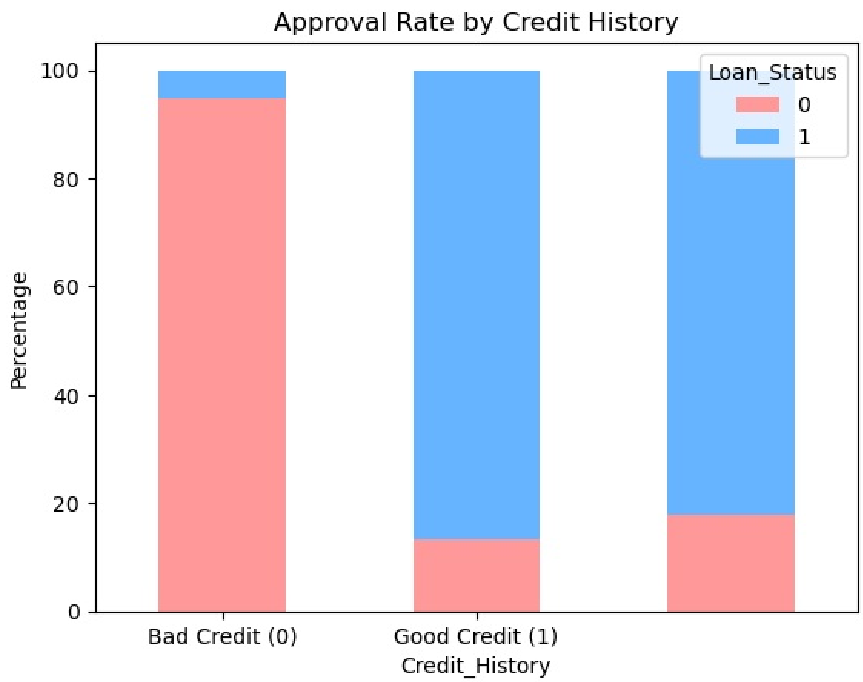
In [20]:
```
#  Loan Amount by Dependents
sns.boxplot(data=data, x='Dependents', y='LoanAmount')
plt.title('Loan Amount Distribution by Number of Dependents')
plt.show()
```



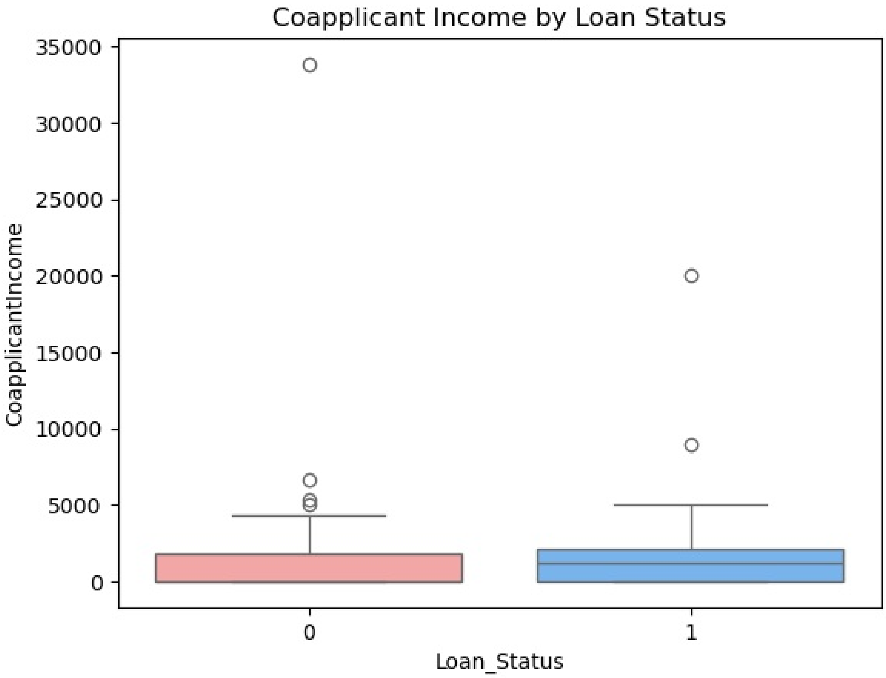
In [21]:
```
# Loan Amount Distribution
sns.histplot(data=data, x='LoanAmount', kde=True)
plt.title('Loan Amount Distribution')
plt.show()
```



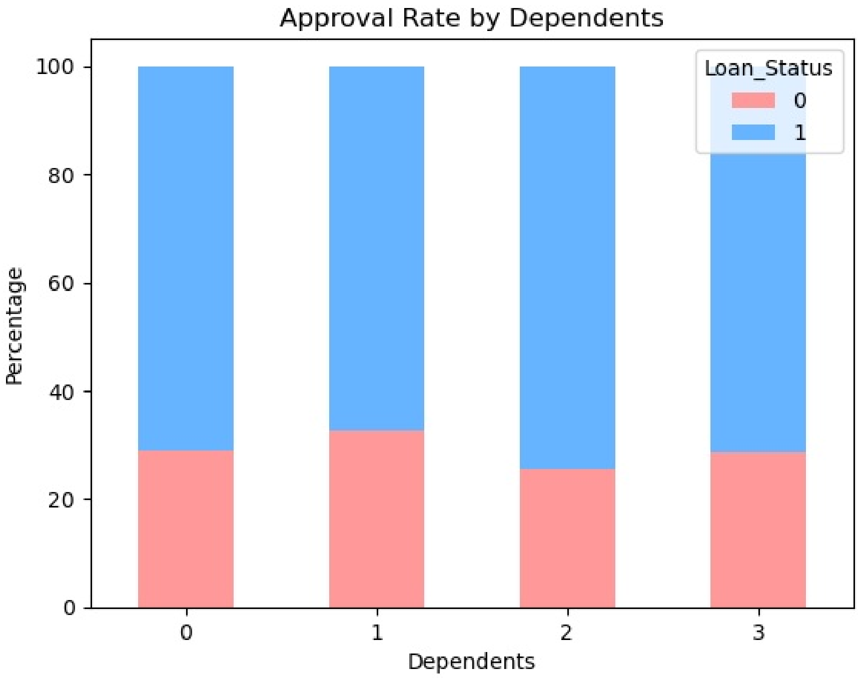
In [22]:
```
# Credit History vs Loan Status
credit_approval = pd.crosstab(data['Credit_History'], data['Loan_Status'], normalize='index') * 100
credit_approval.plot(kind='bar', stacked=True, color=['#ff9999','#66b3ff'])
plt.title('Approval Rate by Credit History')
plt.ylabel('Percentage')
plt.xticks([0, 1], ['Bad Credit (0)', 'Good Credit (1)'], rotation=0)
plt.show()
```



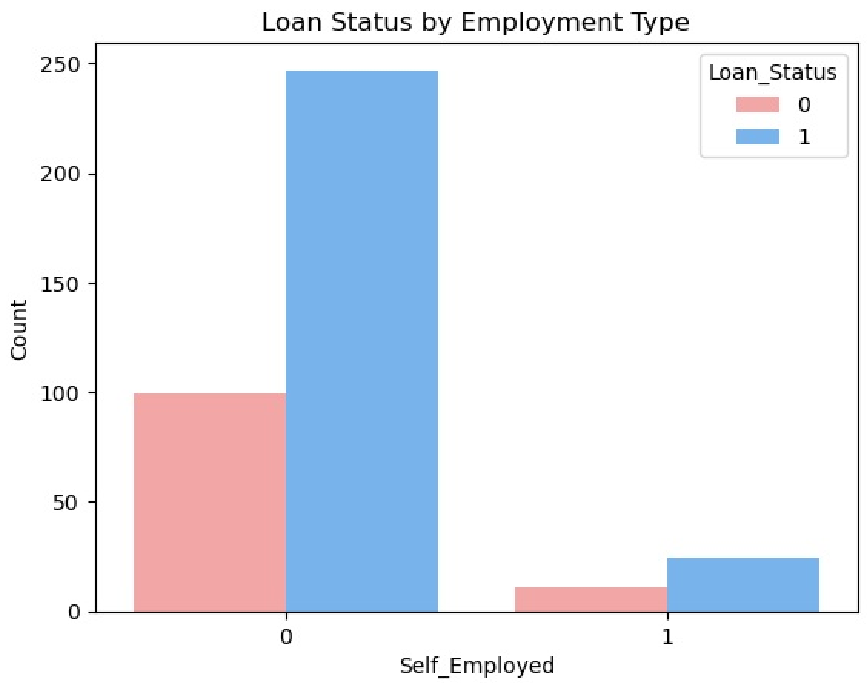
In [23]:
```
# Coapplicant Income by Loan Status
sns.boxplot(x='Loan_Status', y='CoapplicantIncome', data=data, palette=['#ff9999','#66b3ff'])
plt.title('Coapplicant Income by Loan Status')
plt.show()
```



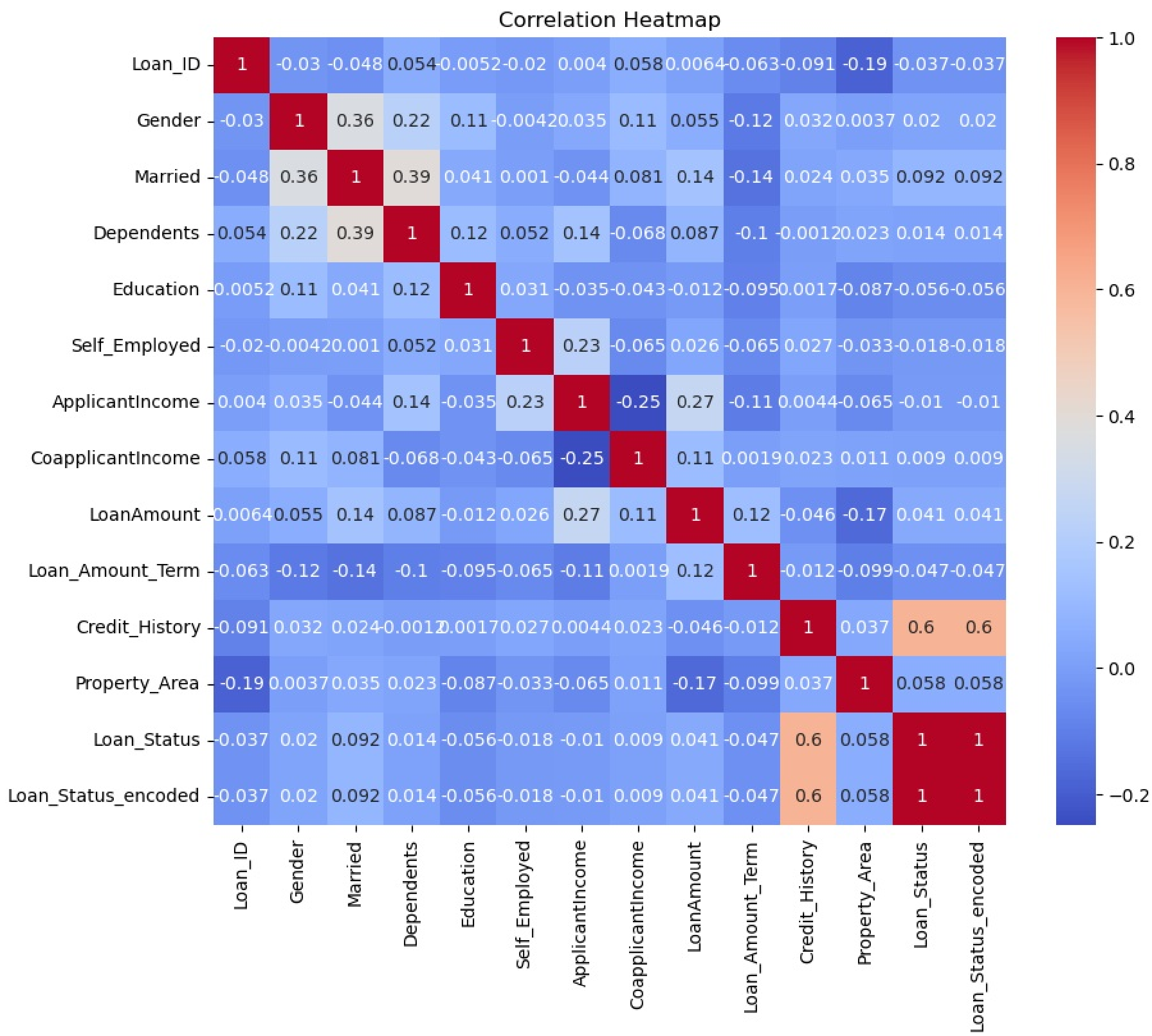
In [24]:
```
# APPROVAL RATE BY DEPENDENTS
dependents_approval = pd.crosstab(data['Dependents'], data['Loan_Status'], normalize='index') * 100
dependents_approval.plot(kind='bar', stacked=True, color=['#ff9999','#66b3ff'])
plt.title('Approval Rate by Dependents')
plt.ylabel('Percentage')
plt.xticks(rotation=0)
plt.show()
```



In [25]:
```
# Employment vs Loan Status
sns.countplot(x='Self_Employed', hue='Loan_Status', data=data, palette=['#ff9999','#66b3ff'])
plt.title('Loan Status by Employment Type')
plt.ylabel('Count')
plt.show()
```



In [26]:
```
#  Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



MODEL TRAINING

In [27]:
```python
# Prepare features and target
X = data.drop(['Loan_Status', 'Loan_Status_encoded', 'Loan_ID'], axis=1)
y = data['Loan_Status_encoded']
```

In [28]:
```python
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [29]:
```python
# Create model with class weight balanced
rf_model = RandomForestClassifier(class_weight='balanced')
rf_model.fit(X_train, y_train)
```

Out[29]:
```
▾ RandomForestClassifier
RandomForestClassifier(class_weight='balanced')
```

In [30]:
```python
# Evaluate Accuracy
print("\n\u2705 Training Accuracy:", round(rf_model.score(X_train, y_train), 2))
print("\u2705 Test Accuracy:", round(rf_model.score(X_test, y_test), 2))
```

```
✅ Training Accuracy: 1.0
✅ Test Accuracy: 0.81
```

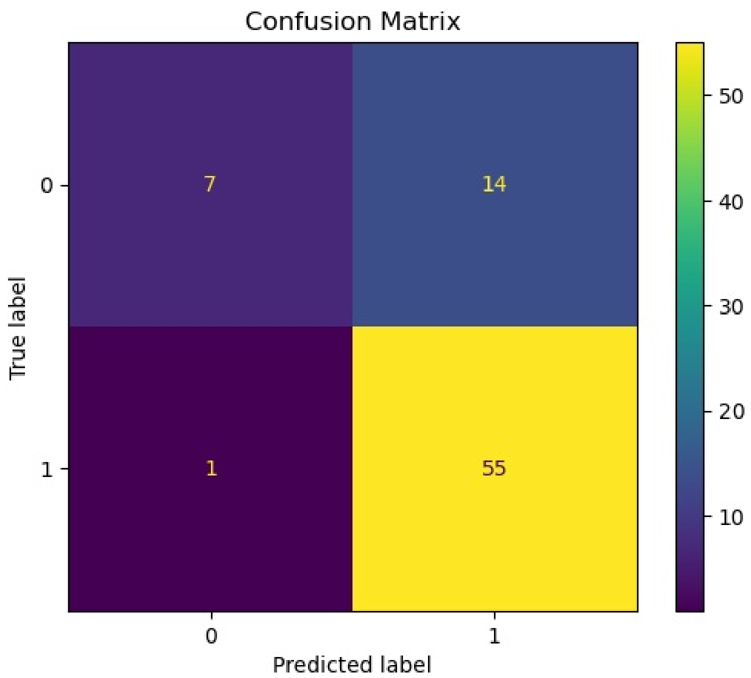
In [31]:
```python
# Classification report
y_pred = rf_model.predict(X_test)
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.33      0.48        21
           1       0.80      0.98      0.88        56

    accuracy                           0.81        77
   macro avg       0.84      0.66      0.68        77
weighted avg       0.82      0.81      0.77        77
```

In [32]:
```python
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(cm).plot()
plt.title("Confusion Matrix")
plt.show()
```

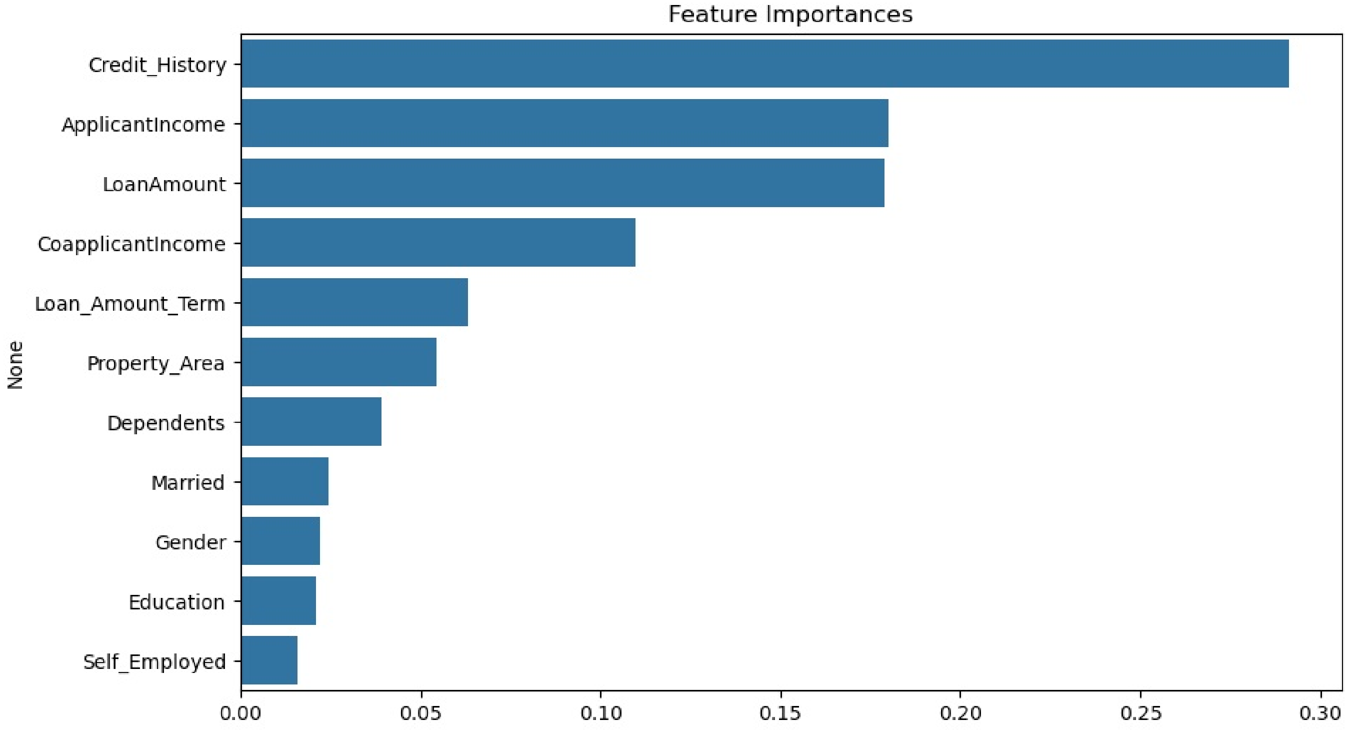


In [33]:
```python
# ROC-AUC
y_pred_prob = rf_model.predict_proba(X_test)[:, 1]
print("\nROC-AUC Score:", round(roc_auc_score(y_test, y_pred_prob), 2))
```

```
ROC-AUC Score: 0.78
```

In [34]:
```python
# Feature Importance
plt.figure(figsize=(10, 6))
importances = rf_model.feature_importances_
indices = np.argsort(importances)[::-1]
plt.title("Feature Importances")
sns.barplot(x=importances[indices], y=X.columns[indices])
```

```
plt.show()
```



In [35]:
```
joblib.dump(rf_model, "loan_model.joblib")
print("✅ Model saved as loan_model.joblib")
```

```
✅ Model saved as loan_model.joblib
```

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