Loan Approval Prediction System

In [1]:
```
# Import Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import accuracy_score,f1_score, confusion_matrix, roc_auc_score,roc_curve,classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import RandomOverSampler
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline
```

In [2]:
```
trn_data = pd.read_csv("loan-train.csv")
tst_data = pd.read_csv("loan-test.csv")
```

In [3]:
```
df = pd.concat([trn_data, tst_data], axis=0)
df
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0
...	...	...	...	...	...	...	...	...	...	...
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777.0	113.0	360.0
363	LP002975	Male	Yes	0	Graduate	No	4158	709.0	115.0	360.0
364	LP002980	Male	No	0	Graduate	No	3250	1993.0	126.0	360.0
365	LP002986	Male	Yes	0	Graduate	No	5000	2393.0	158.0	360.0
366	LP002989	Male	No	0	Graduate	Yes	9200	0.0	98.0	180.0

981 rows × 13 columns

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Loan_ID                0
Gender                24
Married                3
Dependents            25
Education              0
Self_Employed         55
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount            27
Loan_Amount_Term      20
Credit_History        79
Property_Area          0
Loan_Status          367
dtype: int64
```

In [5]:
```
df.dropna(subset=["Loan_Status"], inplace=True)
```

In [6]:
```
df
```

Out[6]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0
...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0

614 rows × 13 columns

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [8]:
```
df = df.bfill()
```

In [9]:
```
df.describe()
```

Out[9]:

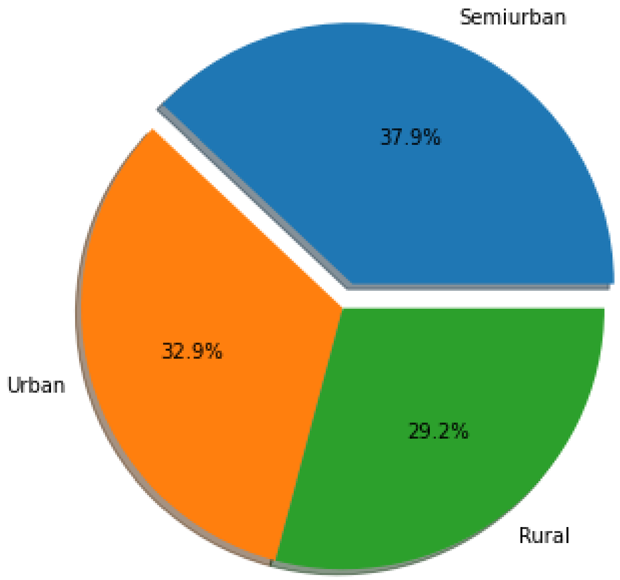
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.00000
mean	5403.459283	1621.245798	146.416938	342.410423	0.84202
std	6109.041673	2926.248369	84.917398	64.428629	0.36502
min	150.000000	0.000000	9.000000	12.000000	0.00000
25%	2877.500000	0.000000	100.000000	360.000000	1.00000
50%	3812.500000	1188.500000	128.000000	360.000000	1.00000
75%	5795.000000	2297.250000	166.750000	360.000000	1.00000
max	81000.000000	41667.000000	700.000000	480.000000	1.00000

In [10]:
```
df.info()
```

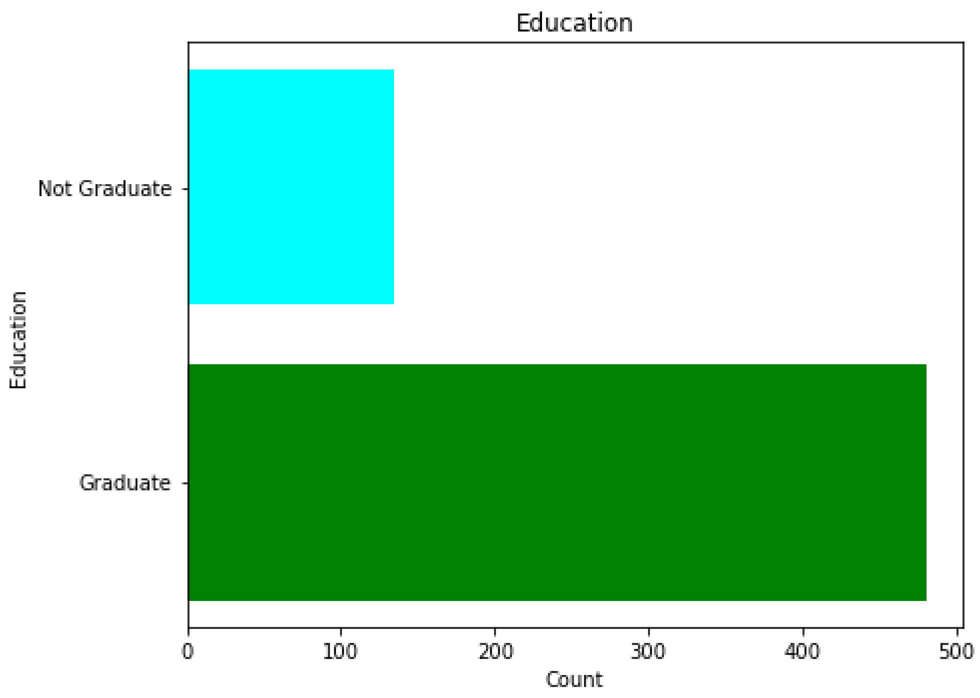
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             614 non-null    object 
 2   Married            614 non-null    object 
 3   Dependents         614 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      614 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    float64
 9   Loan_Amount_Term   614 non-null    float64
 10  Credit_History     614 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 67.2+ KB
```

EDA

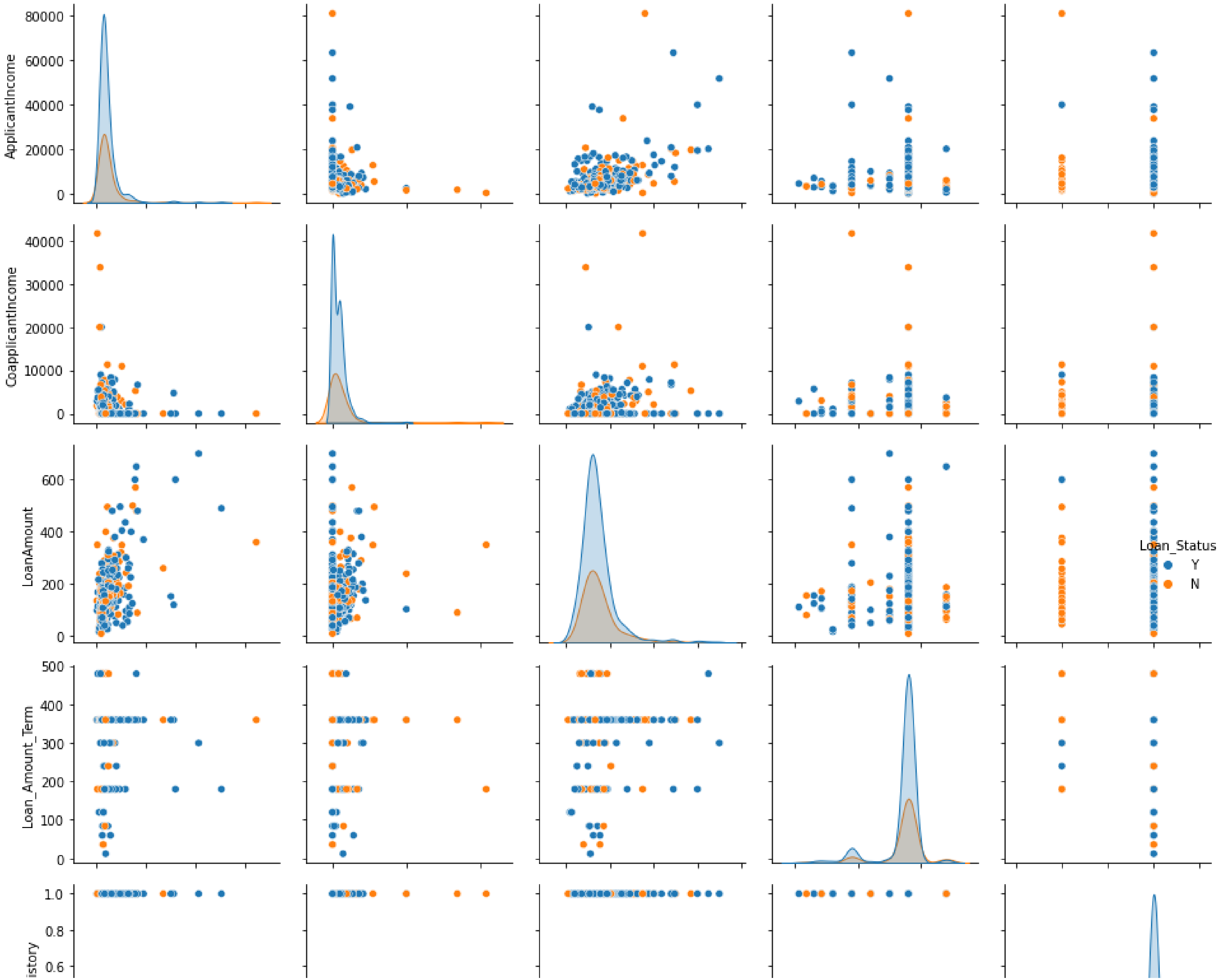
In [11]:
```
# PLot a Pie Chart
plt.figure(figsize=(6,6))
explode = (0.1, 0, 0)
plt.pie(list(df['Property_Area'].value_counts()), labels=list(df['Property_Area'].value_counts().keys()),
        shadow=True, autopct ='%0.1f%%', explode=explode)
plt.show()
```

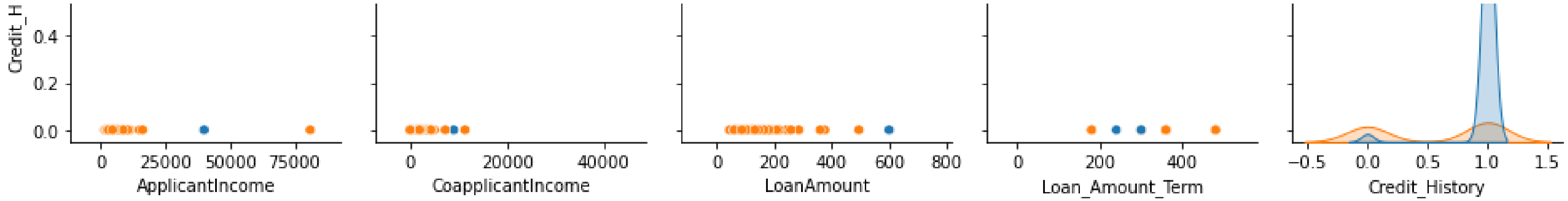


In [12]:
```
# Plot bar graph.
plt.figure(figsize=(7, 5))
plt.barh(y=df['Education'].value_counts().index, width=df['Education'].value_counts(), color=['Green','Cyan'])
plt.xlabel('Count')
plt.ylabel('Education')
plt.title('Education')
plt.tight_layout()
plt.show()
```



In [13]:
```
sns.pairplot(data = df, hue="Loan_Status" )
plt.tight_layout()
plt.show()
```


ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
istory
Loan_Status
Y
N
80000
60000
40000
20000
0
40000
30000
20000
10000
0
600
400
200
0
500
400
300
200
100
0
1.0
0.8
0.6



In [14]:
```
# perform lable encoding.
for col in df.columns:
    le=LabelEncoder()
    df[col]= le.fit_transform(df[col])
```

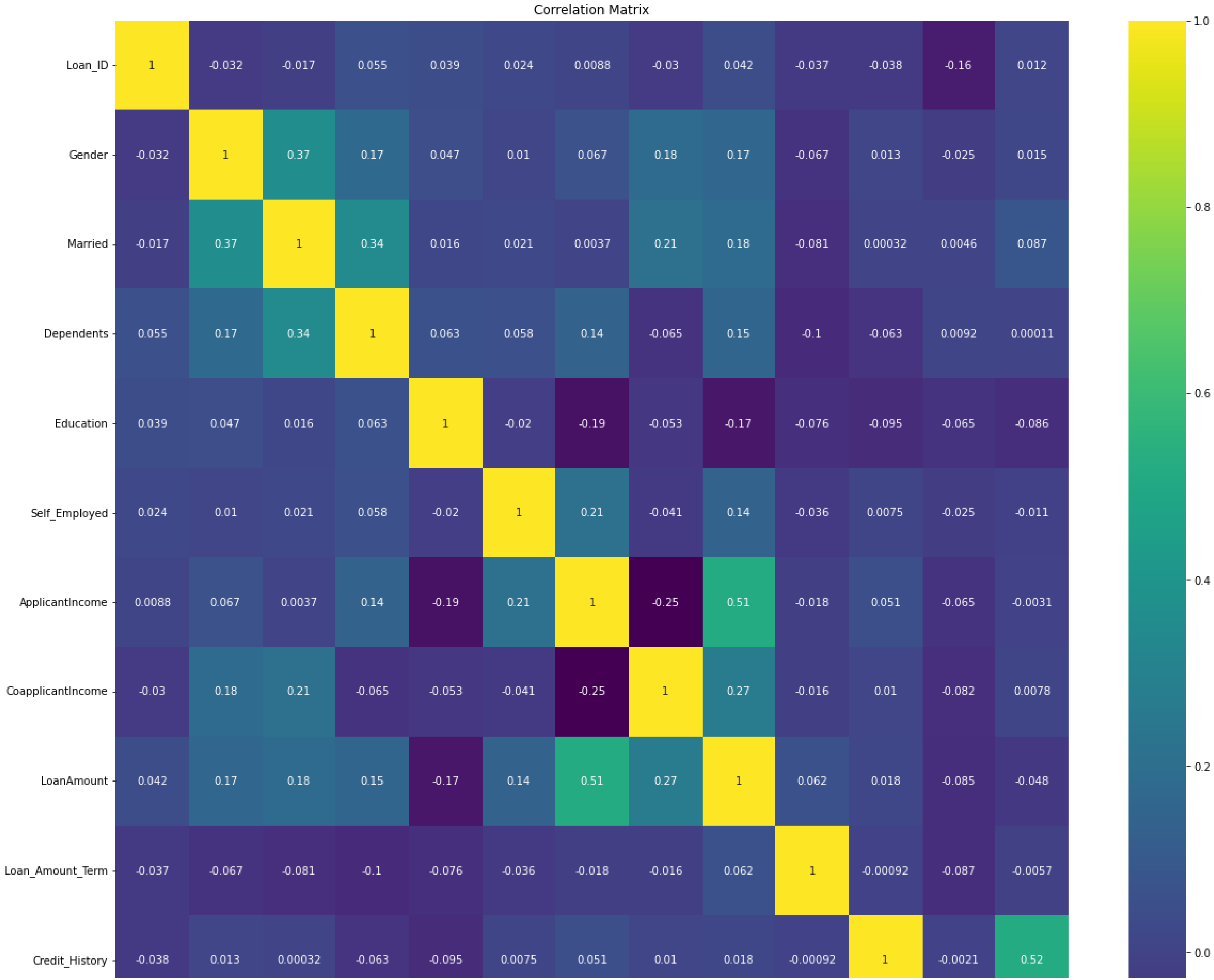
In [15]:
```
df.head()
```

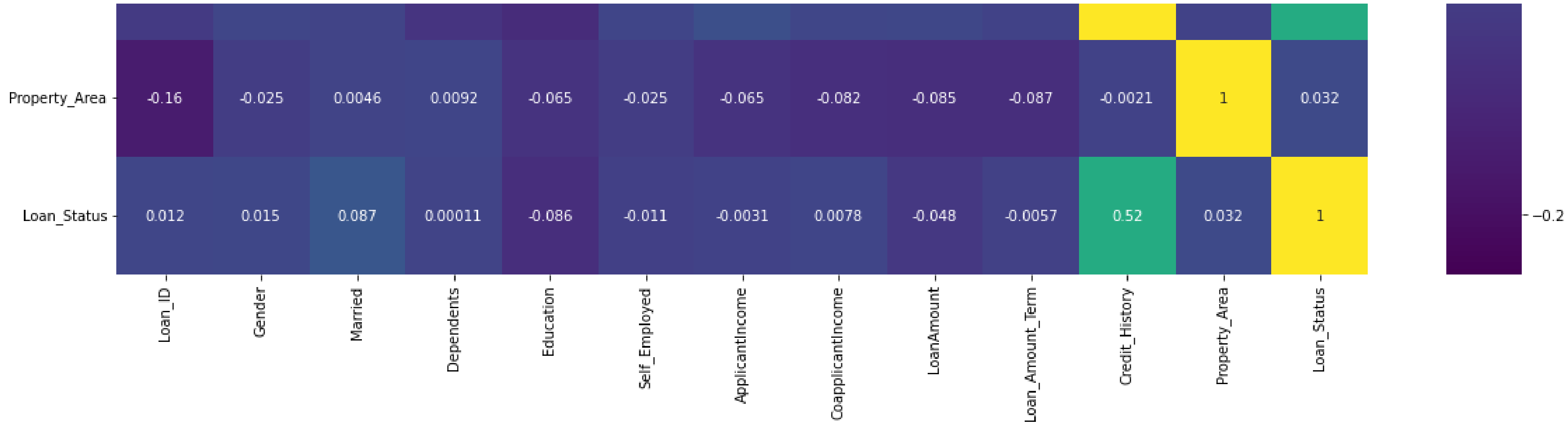
Out[15]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cre
0	0	1	0	0	0	0	376	0	81	8	
1	1	1	1	1	0	0	306	60	81	8	
2	2	1	1	0	0	1	139	0	26	8	
3	3	1	1	0	1	0	90	160	73	8	
4	4	1	0	0	0	0	381	0	94	8	

In [16]:

```
plt.figure(figsize=(20,20))
sns.heatmap(df.corr(), cmap='viridis', annot=True)
plt.title("Correlation Matrix")
plt.show()
```


Correlation Matrix
Loan_ID 1 -0.032 -0.017 0.055 0.039 0.024 0.0088 -0.03 0.042 -0.037 -0.038 -0.16 0.012
Gender -0.032 1 0.37 0.17 0.047 0.01 0.067 0.18 0.17 -0.067 0.013 -0.025 0.015
Married -0.017 0.37 1 0.34 0.016 0.021 0.0037 0.21 0.18 -0.081 0.00032 0.0046 0.087
Dependents 0.055 0.17 0.34 1 0.063 0.058 0.14 -0.065 0.15 -0.1 -0.063 0.0092 0.00011
Education 0.039 0.047 0.016 0.063 1 -0.02 -0.19 -0.053 -0.17 -0.076 -0.095 -0.065 -0.086
Self_Employed 0.024 0.01 0.021 0.058 -0.02 1 0.21 -0.041 0.14 -0.036 0.0075 -0.025 -0.011
ApplicantIncome 0.0088 0.067 0.0037 0.14 -0.19 0.21 1 -0.25 0.51 -0.018 0.051 -0.065 -0.0031
CoapplicantIncome -0.03 0.18 0.21 -0.065 -0.053 -0.041 -0.25 1 0.27 -0.016 0.01 -0.082 0.0078
LoanAmount 0.042 0.17 0.18 0.15 -0.17 0.14 0.51 0.27 1 0.062 0.018 -0.085 -0.048
Loan_Amount_Term -0.037 -0.067 -0.081 -0.1 -0.076 -0.036 -0.018 -0.016 0.062 1 -0.00092 -0.087 -0.0057
Credit_History -0.038 0.013 0.00032 -0.063 -0.095 0.0075 0.051 0.01 0.018 -0.00092 1 -0.0021 0.52
1.0
0.8
0.6
0.4
0.2
0.0

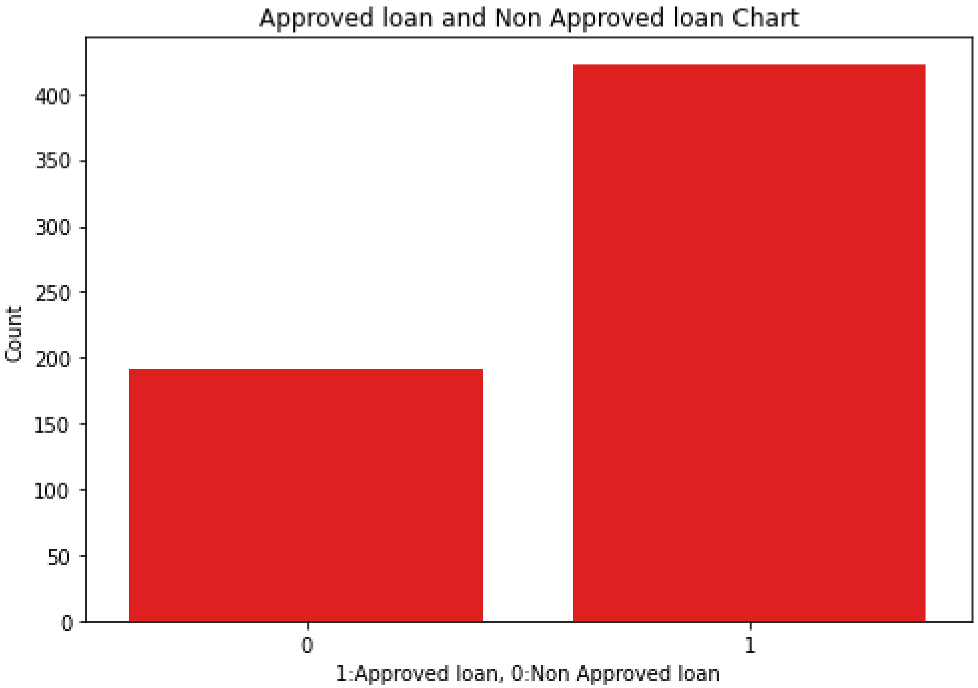


In [17]:

```
# Get the count for Approved and Non Approved Loan.
approved = df["Loan_Status"].value_counts()[1]
non_approved =  df["Loan_Status"].value_counts()[0]
print("Approved loan {1}: ",approved,"Non Approved loan {0}: ",non_approved )
```

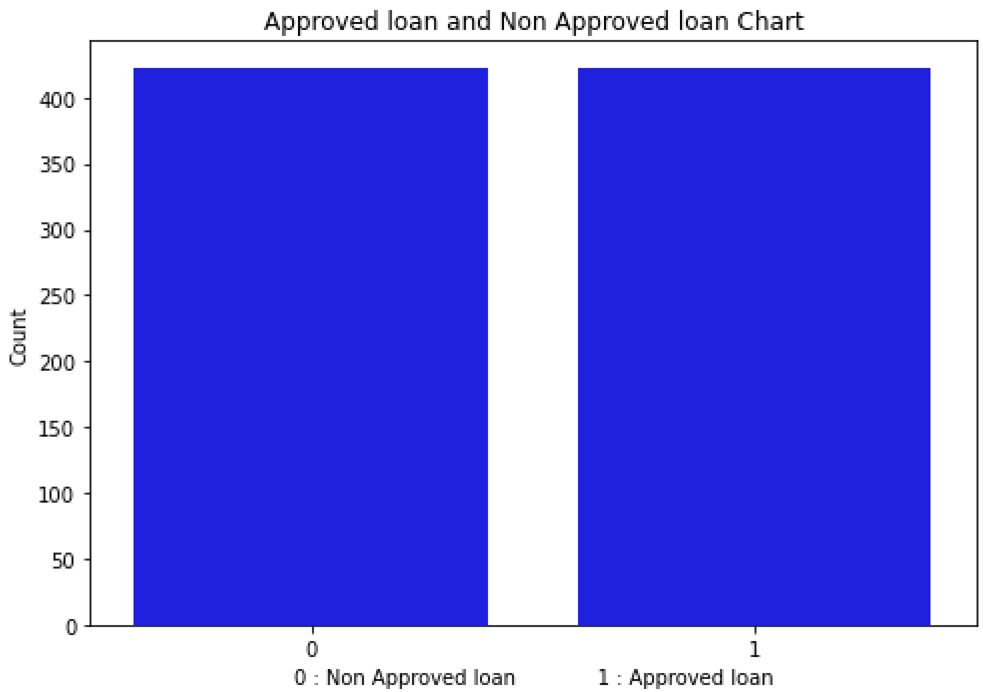
```
Approved loan {1}:  422 Non Approved loan {0}:  192
```

In [18]:
```
# Plot Bar Ghraph
plt.figure(figsize=(7,5))
sns.barplot(x= df['Loan_Status'].value_counts().index, y= df['Loan_Status'].value_counts() , color='red')
plt.xlabel('1:Approved loan, 0:Non Approved loan')
plt.ylabel('Count')
plt.title("Approved loan and Non Approved loan Chart")
plt.tight_layout()
plt.show()
```



In [19]:
```
# Use oversampling technique as our output feature is imbalanced.
X = df.drop("Loan_Status", axis =1)
y = df["Loan_Status"]

over_sampler = RandomOverSampler(random_state=42)
X_oversampled, y_oversampled = over_sampler.fit_resample(X, y)
df_oversampled = pd.concat([X_oversampled, y_oversampled], axis=1)
```

In [20]:
```
# Plot Bar Ghraph to check our output feature is balanced after oversampling.
plt.figure(figsize=(7,5))
sns.barplot(x= df_oversampled['Loan_Status'].value_counts().index, y= df_oversampled['Loan_Status'].value_counts() , c
plt.xlabel('0 : Non Approved loan             1 : Approved loan')
plt.ylabel('Count')
plt.title("Approved loan and Non Approved loan Chart")
plt.tight_layout()
plt.show()
```



In [21]:
```python
df_oversampled
```

Out[21]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
0	0	1	0	0	0	0	376	0	81	8
1	1	1	1	1	0	0	306	60	81	8
2	2	1	1	0	0	1	139	0	26	8
3	3	1	1	0	1	0	90	160	73	8
4	4	1	0	0	0	0	381	0	94	8
...	...	...	...	...	...	...	...	...	...	...
839	202	1	1	3	1	0	266	0	88	5
840	583	1	1	1	0	0	27	0	22	8
841	584	1	1	1	0	0	115	111	99	8
842	400	1	1	2	1	0	122	0	10	5
843	464	1	0	0	0	0	279	0	51	8

844 rows × 13 columns

In [38]:
```python
# Define dependant & independant variables for oversampled df.
X = df_oversampled.drop("Loan_Status", axis =1)
y = df_oversampled["Loan_Status"]
```

In [39]:
```python
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [40]:
```
# Apply differnt ML models
log = LogisticRegression()
svc = SVC()
knn = KNeighborsClassifier()
dt = DecisionTreeClassifier()
rf  = RandomForestClassifier()
```

In [41]:
```
# fit the model on train & test data set.
log_model = log.fit(X_train, y_train)
svc_model = svc.fit(X_train, y_train)
knn_odel = knn.fit(X_train, y_train)
dt_model  = dt.fit(X_train, y_train)
rf_model  = rf.fit(X_train, y_train)
```

In [42]:
```
# Calculate predicted values
log_pred = log.predict(X_test)
svc_pred = svc.predict(X_test)
knn_pred = knn.predict(X_test)
dt_pred  = dt.predict(X_test)
rf_pred  = rf.predict(X_test)
```

In [43]:
```
# Calculate Accuracy score
log_score = accuracy_score(y_test, log_pred)
svc_score = accuracy_score(y_test, svc_pred)
knn_score = accuracy_score(y_test, knn_pred)
dt_score  = accuracy_score(y_test, dt_pred)
rf_score  = accuracy_score(y_test, rf_pred)

print("Accuracy score of Logistic Regression is : ",round(log_score,2))
print("Accuracy score of Support Vector Classifier is : ", round(svc_score,2))
print("Accuracy score of K Neighbors Classifier is : ", round(knn_score,2))
print("Accuracy score of Decision Tree Classifier is : ", round(dt_score,2))
print("Accuracy score of Random Forest Classifier is : ", round(rf_score,2))
```

```
Accuracy score of Logistic Regression is :  0.72
Accuracy score of Support Vector Classifier is :  0.46
Accuracy score of K Neighbors Classifier is :  0.6
Accuracy score of Decision Tree Classifier is :  0.86
Accuracy score of Random Forest Classifier is :  0.9
```

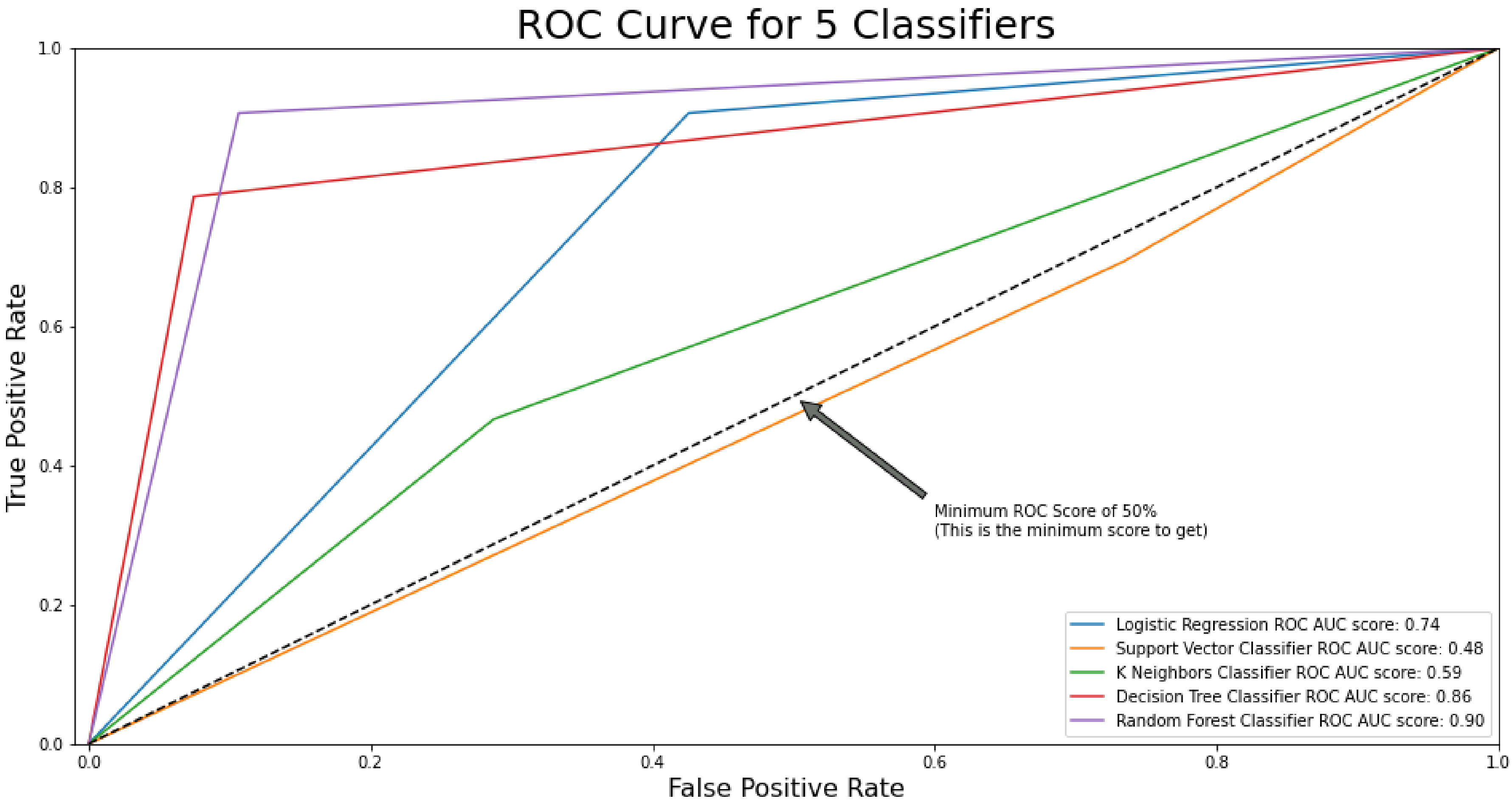
In [44]:
```
# Calculating cross-validation scores for different classifiers
log_cv_score = cross_val_score(log, X_train, y_train, cv=5)
svc_cv_score = cross_val_score(svc, X_train, y_train, cv=5)
knn_cv_score = cross_val_score(knn, X_train, y_train, cv=5)
dt_cv_score  = cross_val_score(dt, X_train, y_train, cv=5)
rf_cv_score  = cross_val_score(rf, X_train, y_train, cv=5)

print("Cross-Validation score of Logistic Regression is : ", round(log_cv_score.mean(),2))
print("Cross-Validation score of Support Vector Classifier is : ", round(svc_cv_score.mean(),2))
print("Cross-Validation score of K Neighbors Classifier is : ", round(knn_cv_score.mean(),2))
print("Cross-Validation score of Decision Tree Classifier is : ", round(dt_cv_score.mean(),2))
print("Cross-Validation score of Random Forest Classifier is : ", round(rf_cv_score.mean(),2))
```

```
Cross-Validation score of Logistic Regression is :  0.74
Cross-Validation score of Support Vector Classifier is :  0.54
Cross-Validation score of K Neighbors Classifier is :  0.63
Cross-Validation score of Decision Tree Classifier is :  0.79
Cross-Validation score of Random Forest Classifier is :  0.86
```

In [45]:
```
# Calculate ROC AUC score
print("Logistic Regression ROC AUC score :", round(roc_auc_score(y_test,log_pred),2))
print("Support Vector Classifier ROC AUC score :", round(roc_auc_score(y_test,svc_pred),2))
print("K Nearest Neighbors ROC AUC score :", round(roc_auc_score(y_test,knn_pred),2))
print("Decision Tree Classifier ROC AUC score :", round(roc_auc_score(y_test,dt_pred),2))
print("Random Forest Classifier ROC AUC score :", round(roc_auc_score(y_test,rf_pred),2))
```

```
Logistic Regression ROC AUC score : 0.74
Support Vector Classifier ROC AUC score : 0.48
K Nearest Neighbors ROC AUC score : 0.59
Decision Tree Classifier ROC AUC score : 0.86
Random Forest Classifier ROC AUC score : 0.9
```

In [46]:
```python
# Plot ROC curve
log_fpr, log_tpr, log_threshold = roc_curve(y_test, log_pred)
svc_fpr, svc_tpr, svc_threshold = roc_curve(y_test, svc_pred)
knn_fpr, knn_tpr, knn_threshold = roc_curve(y_test, knn_pred)
dt_fpr,  dt_tpr,  dt_threshold  = roc_curve(y_test, dt_pred)
rf_fpr,  rf_tpr,  rf_threshold  = roc_curve(y_test, rf_pred)

plt.figure(figsize=(16, 8))
plt.title('ROC Curve for 5 Classifiers', fontsize=25)
plt.plot(log_fpr, log_tpr, label="Logistic Regression ROC AUC score: {:.2f}".format(roc_auc_score(y_test, log_pred)))
plt.plot(svc_fpr, svc_tpr, label="Support Vector Classifier ROC AUC score: {:.2f}".format(roc_auc_score(y_test, svc_pr
plt.plot(knn_fpr, knn_tpr, label="K Neighbors Classifier ROC AUC score: {:.2f}".format(roc_auc_score(y_test, knn_pred)
plt.plot(dt_fpr,  dt_tpr, label="Decision Tree Classifier ROC AUC score: {:.2f}".format(roc_auc_score(y_test, dt_pred)
plt.plot(rf_fpr,  rf_tpr, label="Random Forest Classifier ROC AUC score: {:.2f}".format(roc_auc_score(y_test, rf_pred)
plt.plot([0, 1], [0, 1], 'k--')
plt.axis([-0.01, 1, 0, 1])
plt.xlabel('False Positive Rate', fontsize=16)
plt.ylabel('True Positive Rate', fontsize=16)
plt.annotate('Minimum ROC Score of 50%\n(This is the minimum score to get)', xy=(0.5, 0.5), xytext=(0.6, 0.3),
                 arrowprops=dict(facecolor='#6E726D', shrink=0.05))
plt.legend()
plt.show()
```



ROC Curve for 5 Classifiers
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Minimum ROC Score of 50%
(This is the minimum score to get)
Logistic Regression ROC AUC score: 0.74
Support Vector Classifier ROC AUC score: 0.48
K Neighbors Classifier ROC AUC score: 0.59
Decision Tree Classifier ROC AUC score: 0.86
Random Forest Classifier ROC AUC score: 0.90

In [47]:

```
# Define the models and their hyperparameter grids
models = {'Logistic Regression': LogisticRegression(),'Support Vector Classifier': SVC(),
    'K Nearest Neighbors': KNeighborsClassifier(),'Decision Tree Classifier': DecisionTreeClassifier(),
    'Random Forest Classifier': RandomForestClassifier()}

param_grids = {'Logistic Regression': {'model__C': [0.1, 1, 10]},'Support Vector Classifier': {'model__C': [0.1, 1, 10
    'model__kernel': ['linear', 'rbf']},'K Nearest Neighbors': {'model__n_neighbors': [3, 5, 7]},
    'Decision Tree Classifier': {'model__max_depth': [3, 5, 7]},
    'Random Forest Classifier': {'model__n_estimators': [50, 100, 150]}}

# Data preprocessing pipeline
preprocessor = Pipeline([('scaler', MinMaxScaler()), ('model', None)])
```

In [48]:
```
# Hyperparameter Tuning
for model_name, model in models.items():
    preprocessor.steps[1] = ('model', model)
    param_grid = param_grids[model_name]

    grid_search = GridSearchCV(preprocessor, param_grid, cv=5)
    grid_search.fit(X_train, y_train)

    print(f"Best parameters for {model_name}: {grid_search.best_params_}")
    print(f"Training score for {model_name}: {grid_search.best_score_:.2f}")
    print()
```

```
Best parameters for Logistic Regression: {'model__C': 10}
Training score for Logistic Regression: 0.74

Best parameters for Support Vector Classifier: {'model__C': 10, 'model__kernel': 'rbf'}
Training score for Support Vector Classifier: 0.79

Best parameters for K Nearest Neighbors: {'model__n_neighbors': 3}
Training score for K Nearest Neighbors: 0.75

Best parameters for Decision Tree Classifier: {'model__max_depth': 7}
Training score for Decision Tree Classifier: 0.75

Best parameters for Random Forest Classifier: {'model__n_estimators': 100}
Training score for Random Forest Classifier: 0.86
```

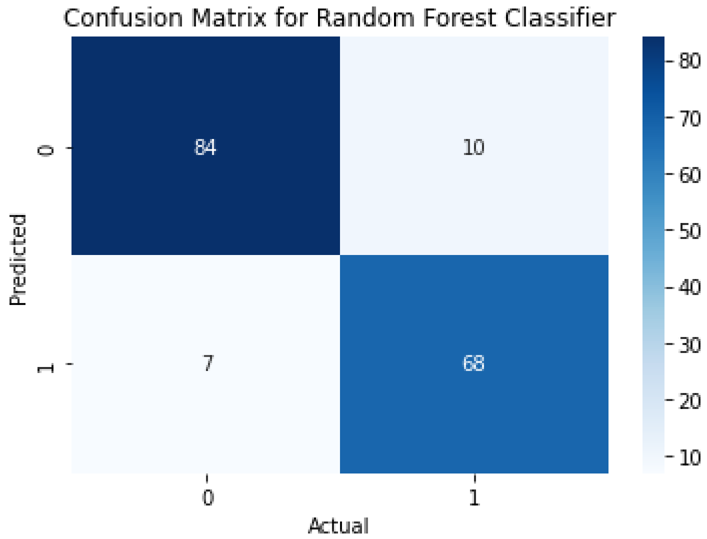
In [52]:
```
# Classification Report for Random Forest Classifier
print(classification_report(y_test, rf_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.89      0.91        94
           1       0.87      0.91      0.89        75

    accuracy                           0.90       169
   macro avg       0.90      0.90      0.90       169
weighted avg       0.90      0.90      0.90       169
```

In [53]:
```
# Confusion Matrix Random Forest Classifier.
matrics = confusion_matrix(y_test, rf_pred)
print(matrics)
```

```
[[84 10]
 [ 7 68]]
```

In [54]:
```
# Create a heatmap for the confusion matrix
sns.heatmap(matrics, annot=True,  cmap='Blues')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Confusion Matrix for Random Forest Classifier')
plt.show()
```



Conclusion:

Loan Approval Prediction using Machine Learning offers financial institutions a reliable tool to assess loan applications, optimize loan portfolios, and make informed decisions while ensuring compliance with regulatory guidelines. The proposed solution leverages machine learning algorithms and applicant data analysis to accurately predict the likelihood of loan approval, enabling lenders to streamline their operations, reduce risk, and provide better customer experiences. From the above obervations we can conclude that Random Forest Classifier is best suited ML Model for Loan Approval Prediction System.