Loan Status Prediction

Importing the Model Library

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Reading the Dataset

In [2]:

```
df = pd.read_csv("C:/Users/user/Desktop/Loan_Status_Prediction_Case_Study-main/Loan_Status_Predictior
```

In [3]:

```
df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849	0.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0

Understanding the dataset

In [4]:

```
df.shape
```

Out[4]:

```
(614, 13)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 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: 62.5+ KB
```

In [6]:

```
df.describe()
```

Out[6]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [7]:

```
df.describe(include= object)
```

Out[7]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
count	614	601	611	599	614	582	614	614
unique	614	2	2	4	2	2	3	2
top	LP001002	Male	Yes	0	Graduate	No	Semiurban	Y
freq	1	489	398	345	480	500	233	422

Checking the missing values

In [8]:

```
df.isnull().sum()
```

Out[8]:

```
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
```

Checking Percentage of the missing value

In [9]:

```
df.isnull().sum() * 100 / df.shape[0]
```

Out[9]:

```
Loan_ID              0.000000
Gender               2.117264
Married              0.488599
Dependents           2.442997
Education            0.000000
Self_Employed        5.211726
ApplicantIncome      0.000000
CoapplicantIncome    0.000000
LoanAmount           3.583062
Loan_Amount_Term     2.280130
Credit_History       8.143322
Property_Area        0.000000
Loan_Status          0.000000
dtype: float64
```

Replacing null values with mode for object data type (i.e. Caterorical Data)

In [10]:

```
df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])
df['Married'] = df['Married'].fillna(df['Married'].mode()[0])
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
```

In [11]:

```
df.isnull().sum()
```

Out[11]:

```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

Replacing null values with median for numberic data type

In [12]:

```
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].median())
df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].median())
```

In [13]:

```
df.isnull().sum()
```

Out[13]:

```
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 [14]:

```
df.shape
```

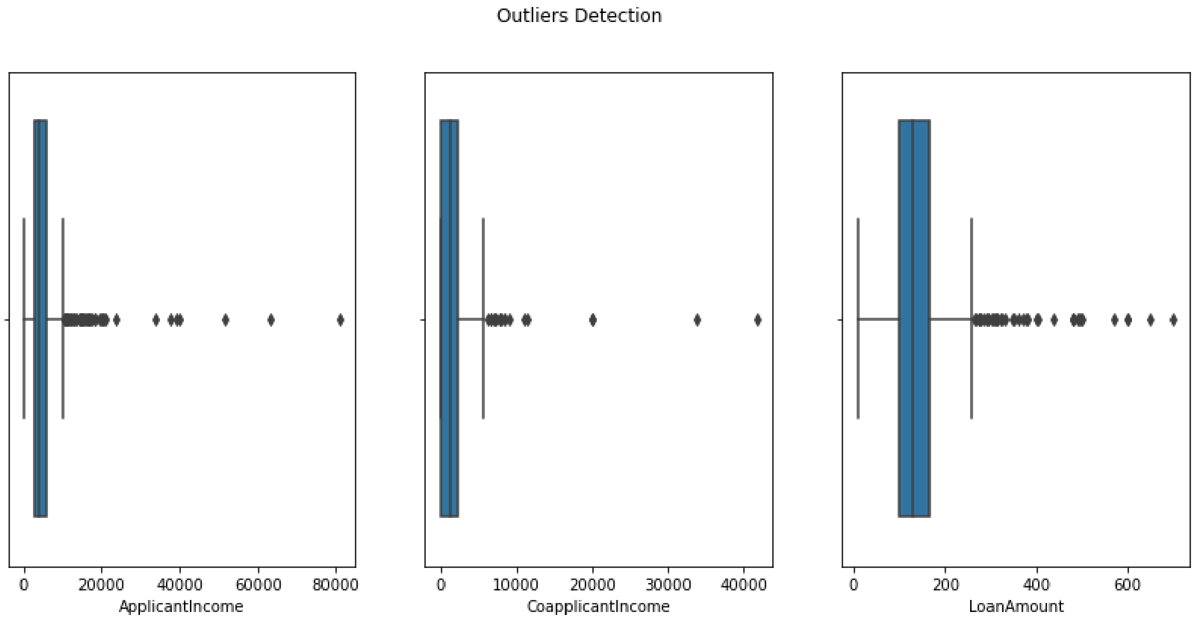
Out[14]:

```
(614, 13)
```

Checking the outliers detection and its treatments

In [15]:

```
plt.figure(figsize = (14,6))

plt.subplot(1,3,1)
sns.boxplot(df['ApplicantIncome'])

plt.subplot(1,3,2)
sns.boxplot(df['CoapplicantIncome'])

plt.subplot(1,3,3)
sns.boxplot(df['LoanAmount'])

plt.suptitle('Outliers Detection')
plt.show()
```



In [16]:

```
print("Before Removing the outliers", df.shape)

df = df[df['ApplicantIncome']<25000]

print("After Removing the outliers", df.shape)
```

```
Before Removing the outliers (614, 13)
After Removing the outliers (607, 13)
```

In [17]:

```
print("Before Removing the outliers", df.shape)

df = df[df['CoapplicantIncome']<12000]

print("After Removing the outliers", df.shape)
```

```
Before Removing the outliers (607, 13)
After Removing the outliers (603, 13)
```

In [18]:

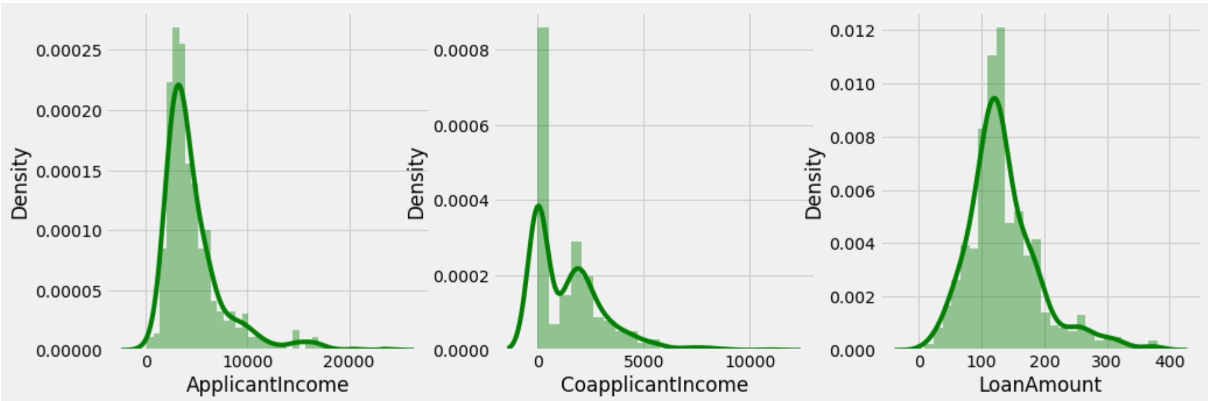
```
print("Before Removing the outliers", df.shape)

df = df[df['LoanAmount']<400]

print("After Removing the outliers", df.shape)
```

```
Before Removing the outliers (603, 13)
After Removing the outliers (591, 13)
```

Analysis

In [19]:

```
plt.style.use('fivethirtyeight')
plt.rcParams['figure.figsize'] = (15,5)


plt.subplot(1,3,1)
sns.distplot(df['ApplicantIncome'], color='green')

plt.subplot(1,3,2)
sns.distplot(df['CoapplicantIncome'], color='green')

plt.subplot(1,3,3)
sns.distplot(df['LoanAmount'], color='green')

plt.show()
```



Univariate Analysis

Target Variable

In [20]:

```
df['Loan_Status'].value_counts()
```

Out[20]:

```
Y    408
N    183
Name: Loan_Status, dtype: int64
```

In [21]:

```
df['Loan_Status'].value_counts(normalize = True)
```

Out[21]:

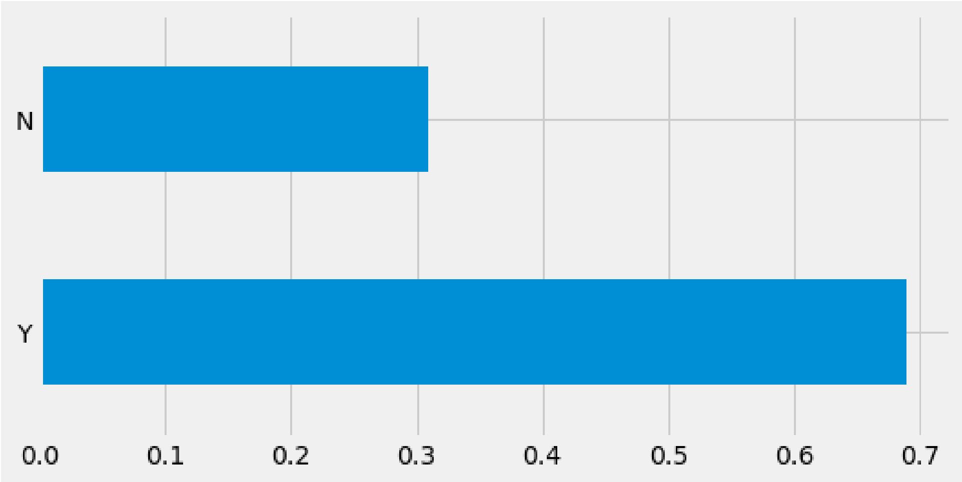
```
Y    0.690355
N    0.309645
Name: Loan_Status, dtype: float64
```

In [22]:

```
df['Loan_Status'].value_counts(normalize = True).plot.barh(figsize = (8,4))
```

Out[22]:

```
<AxesSubplot:>
```



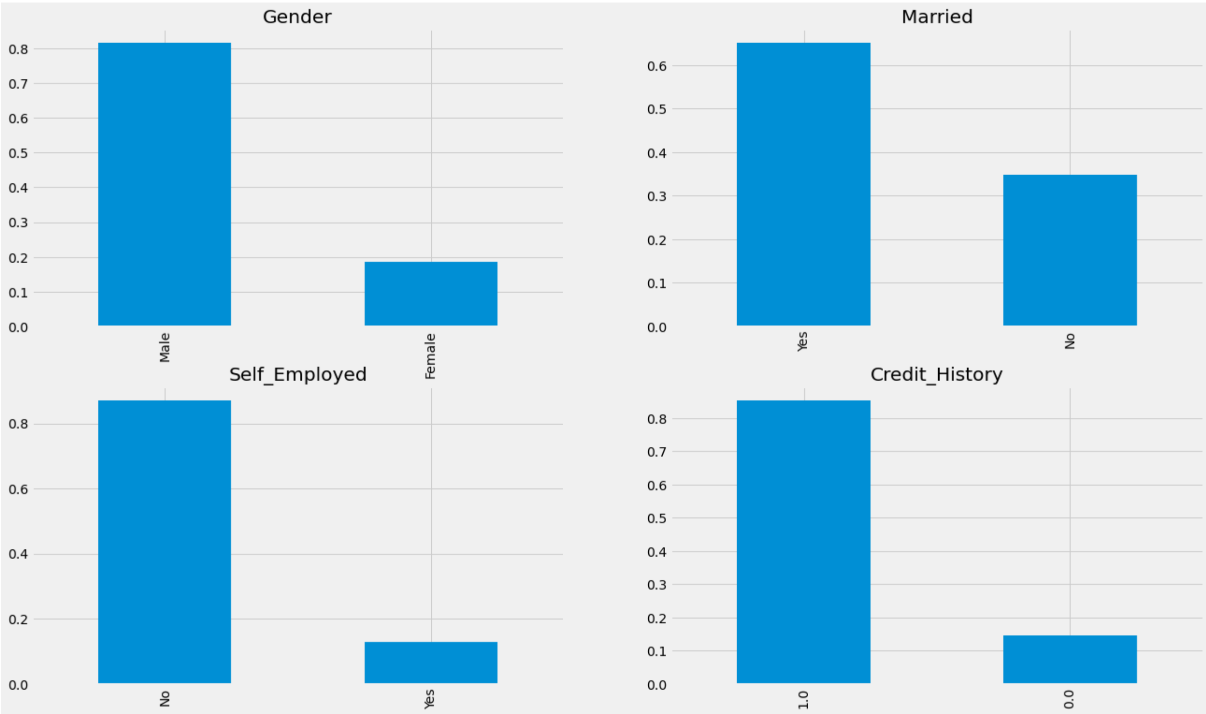
Conclusions

- 408(around 69%) people out of 591 got the approval.

Independent Variable (Categorical)

In [23]:

```
plt.figure(1)

plt.subplot(221)
df['Gender'].value_counts(normalize=True).plot.bar(figsize=(20,12), title= 'Gender')

plt.subplot(222)
df['Married'].value_counts(normalize=True).plot.bar(title= 'Married')

plt.subplot(223)
df['Self_Employed'].value_counts(normalize=True).plot.bar(title= 'Self_Employed')

plt.subplot(224)
df['Credit_History'].value_counts(normalize=True).plot.bar(title= 'Credit_History')

plt.show()
```



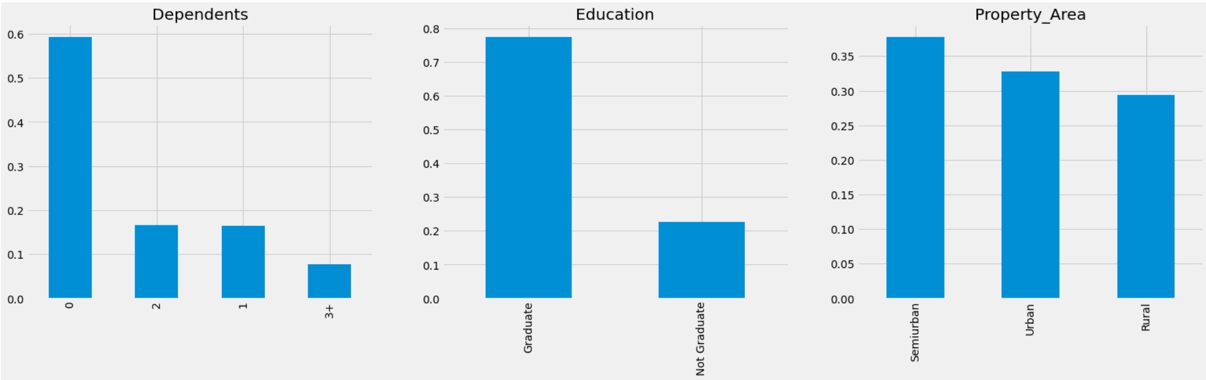
Conclusions

- 80% of applicants in the dataset are male.
- Around 65% of the applicants in the dataset are married.
- About 15% of applicants in the dataset are self-employed.
- About 85% of applicants have repaid their debts.

Independent Variable (Ordinal)

In [24]:

```
plt.figure(1)

plt.subplot(131)
df['Dependents'].value_counts(normalize=True).plot.bar(figsize=(24,6),title='Dependents')

plt.subplot(132)
df['Education'].value_counts(normalize=True).plot.bar(title= 'Education')

plt.subplot(133)
df['Property_Area'].value_counts(normalize=True).plot.bar(title= 'Property_Area')

plt.show()
```



Conclusions

- Most of the applicants don't have dependents.
- About 78% of the applicants are graduates.
- Most of the applicants are from semi-urban areas.

Bivariate Analysis

Analysis on Categorical with target

In [25]:

```
categorical_col = df.select_dtypes(include='object').columns
categorical_col
```

Out[25]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [26]:

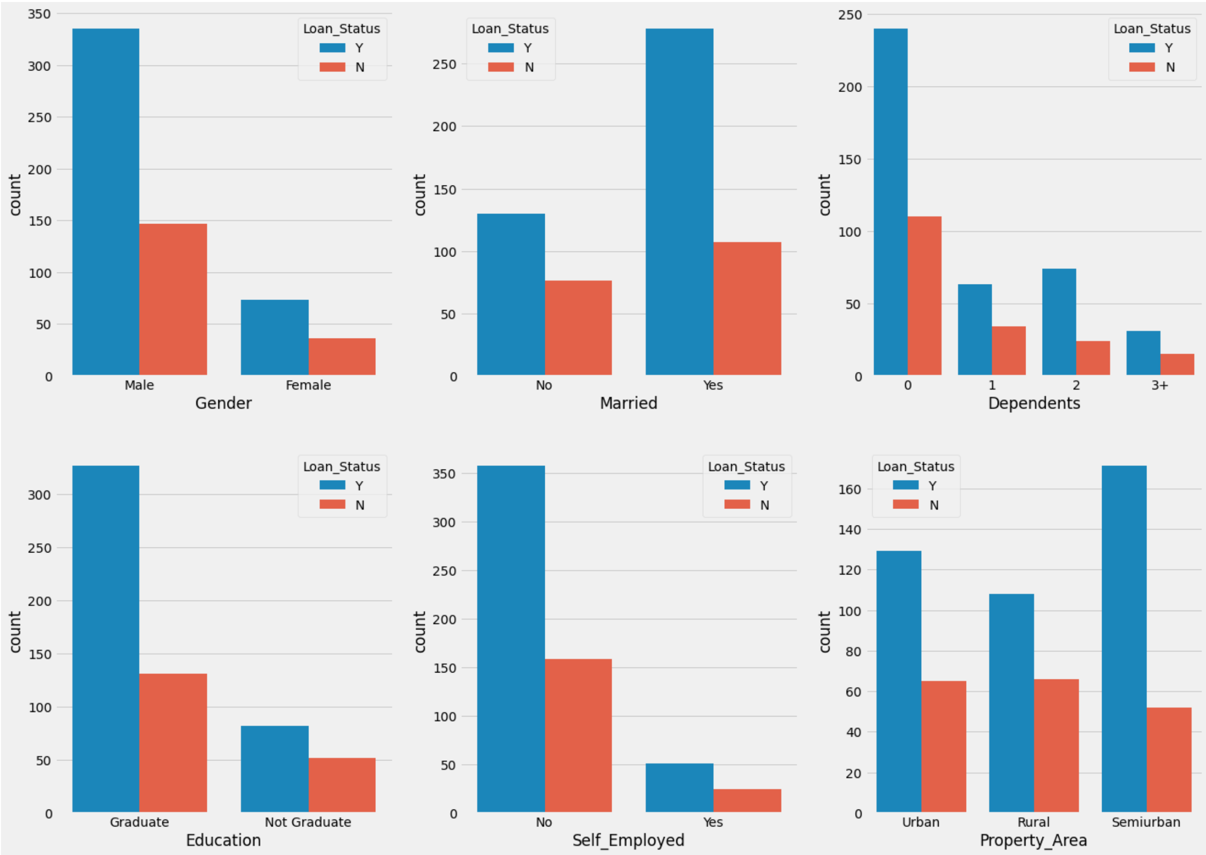
```
cat = categorical_col[1:-1]
cat
```

Out[26]:

```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'Property_Area'],
      dtype='object')
```

In [27]:

```
fig , axes = plt.subplots(figsize=(20,15),nrows=2, ncols=3)

for ax, column in zip(axes.flatten(),cat):
    sns.countplot(df[column],ax=ax, hue=df['Loan_Status'])
```

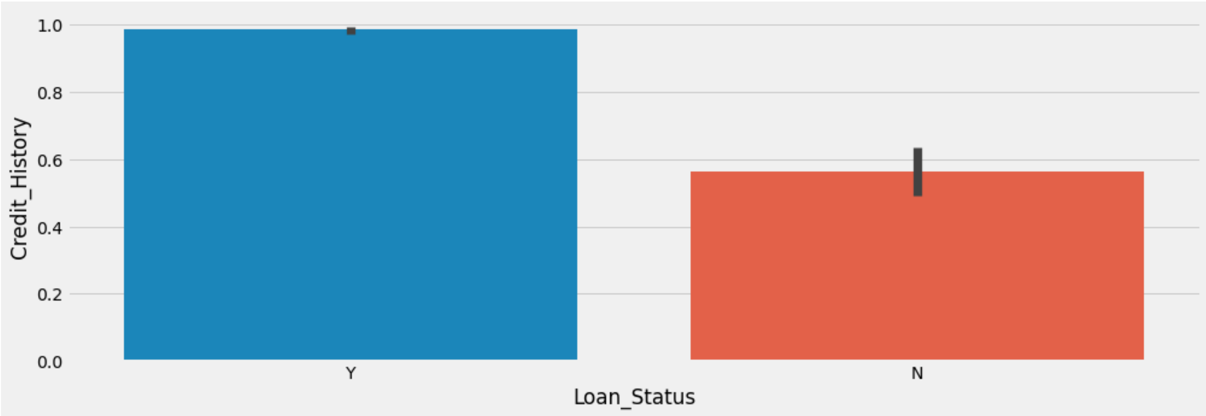


In [28]:

```
sns.barplot(df.Loan_Status, df.Credit_History, data = df)
```

Out[28]:

```
<AxesSubplot:xlabel='Loan_Status', ylabel='Credit_History'>
```



Conclusions

- The proportion of male and female applicants is more or less the same for both approved and unapproved loans.
- The proportion of married applicants is higher for the approved loans.
- The proportion of loans getting approved with 0 dependents is more as pompared to the 1 or 2 or 3+ dependents.
- The loan is getting approved much higher for graduate than Not graduate.
- The self employed is getting less loan approved as compared to non self employed.
- The proportion of loans getting approved in semi-urban areas is higher as compared to that in rural or urban areas.
- The people with a credit history of 1 are more likely to get their loans approved.

Categorical with Target

In [29]:

```
df.columns
```

Out[29]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [30]:

```
pd.crosstab(df['Loan_Status'],df['Gender'])
```

Out[30]:

Gender	Female	Male
Loan_Status		
N	36	147
Y	73	335

In [31]:

```
pd.crosstab(df['Loan_Status'],df['Married'])
```

Out[31]:

Married	No	Yes
Loan_Status		
N	76	107
Y	130	278

In [32]:

```
pd.crosstab(df['Loan_Status'],df['Dependents'])
```

Out[32]:

Dependents	0	1	2	3+
Loan_Status				
N	110	34	24	15
Y	240	63	74	31

In [33]:

```
pd.crosstab(df['Loan_Status'],df['Education'])
```

Out[33]:

Education	Graduate	Not Graduate
Loan_Status		
N	131	52
Y	326	82

In [34]:

```
pd.crosstab(df['Loan_Status'],df['Self_Employed'])
```

Out[34]:

Self_Employed	No	Yes
Loan_Status		
N	158	25
Y	357	51

In [35]:

```
pd.crosstab(df['Loan_Status'],df['Property_Area'])
```

Out[35]:

Property_Area	Rural	Semiurban	Urban
Loan_Status			
N	66	52	65
Y	108	171	129

In [36]:

```
pd.crosstab(df['Loan_Status'],df['Credit_History'])
```

Out[36]:

Credit_History	0.0	1.0
Loan_Status		
N	80	103
Y	6	402

Data Preparation

In [37]:

```
df.select_dtypes('object').head()
```

Out[37]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	Urban	Y
4	LP001008	Male	No	0	Graduate	No	Urban	Y

Drop the Loan_id column, doesn't make any impact on the target

In [38]:

```
df.head()
```

Out[38]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849	0.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0

In [39]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 591 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            591 non-null    object 
 1   Gender             591 non-null    object 
 2   Married            591 non-null    object 
 3   Dependents         591 non-null    object 
 4   Education          591 non-null    object 
 5   Self_Employed      591 non-null    object 
 6   ApplicantIncome    591 non-null    int64  
 7   CoapplicantIncome  591 non-null    float64
 8   LoanAmount         591 non-null    float64
 9   Loan_Amount_Term   591 non-null    float64
 10  Credit_History     591 non-null    float64
 11  Property_Area      591 non-null    object 
 12  Loan_Status        591 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 80.8+ KB
```

In [40]:

```
df = df.drop(['Loan_ID'], axis = 1)
```

In [41]:

```
df.select_dtypes(include = 'object').head()
```

Out[41]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
0	Male	No	0	Graduate	No	Urban	Y
1	Male	Yes	1	Graduate	No	Rural	N
2	Male	Yes	0	Graduate	Yes	Urban	Y
3	Male	Yes	0	Not Graduate	No	Urban	Y
4	Male	No	0	Graduate	No	Urban	Y

Label Encoding for Object datatype

In [42]:

```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

```
Gender: ['Male' 'Female']
Married: ['No' 'Yes']
Dependents: ['0' '1' '2' '3+']
Education: ['Graduate' 'Not Graduate']
Self_Employed: ['No' 'Yes']
Property_Area: ['Urban' 'Rural' 'Semiurban']
Loan_Status: ['Y' 'N']
```

In [43]:

```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
Gender: [1 0]
Married: [0 1]
Dependents: [0 1 2 3]
Education: [0 1]
Self_Employed: [0 1]
Property_Area: [2 0 1]
Loan_Status: [1 0]
```

In [44]:

```
df.head()
```

Out[44]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmo
0	1	0	0	0	0	5849	0.0	12
1	1	1	1	0	0	4583	1508.0	12
2	1	1	0	0	1	3000	0.0	6
3	1	1	0	1	0	2583	2358.0	12
4	1	0	0	0	0	6000	0.0	14

In [45]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 591 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             591 non-null    int32  
 1   Married            591 non-null    int32  
 2   Dependents         591 non-null    int32  
 3   Education          591 non-null    int32  
 4   Self_Employed      591 non-null    int32  
 5   ApplicantIncome    591 non-null    int64  
 6   CoapplicantIncome  591 non-null    float64
 7   LoanAmount         591 non-null    float64
 8   Loan_Amount_Term   591 non-null    float64
 9   Credit_History     591 non-null    float64
 10  Property_Area      591 non-null    int32  
 11  Loan_Status        591 non-null    int32  
dtypes: float64(4), int32(7), int64(1)
memory usage: 60.0 KB
```

Checking unique values in our dataset for better understanding

In [46]:

```
df.nunique()
```

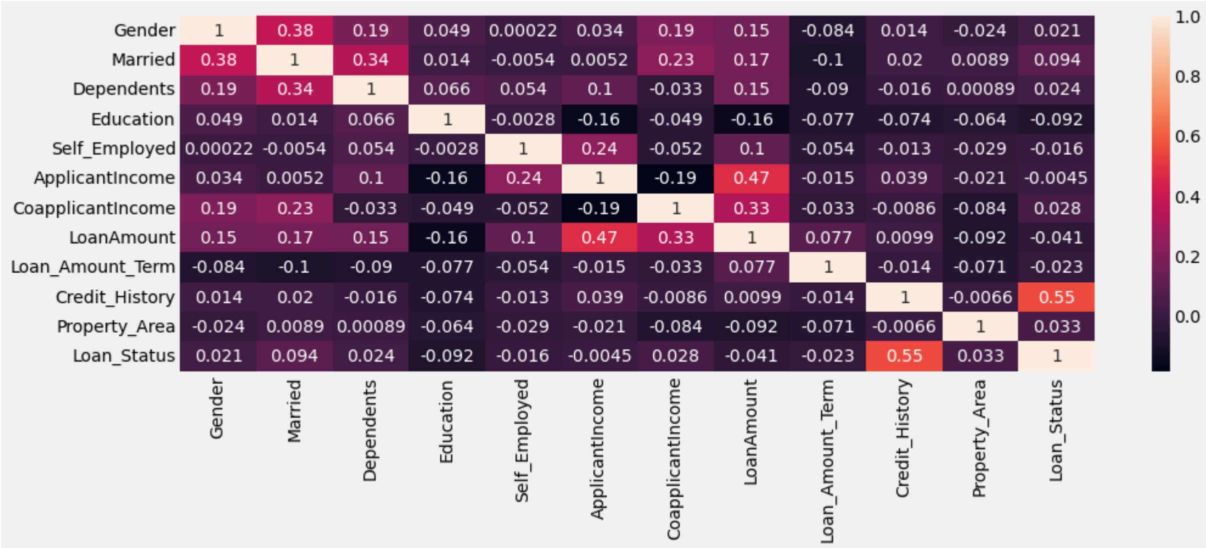
Out[46]:

```
Gender                 2
Married                2
Dependents             4
Education              2
Self_Employed          2
ApplicantIncome      485
CoapplicantIncome    280
LoanAmount           188
Loan_Amount_Term      10
Credit_History         2
Property_Area          3
Loan_Status            2
dtype: int64
```

Correlation of data

In [47]:

```
sns.heatmap(df.corr(),annot=True)
plt.show()
```



Conclusions

- Credit History is Highly correlated to our target.
- Education, Self Employed, Applicant Income, Loan Amount, Loan Amount Term has Negative correlation.
- Gender, Married, Dependents, Coapplicant Income and Property Area are correlated.

Splitting dataset

In [48]:

```
X = df.drop(['Loan_Status'], axis = 1)
y = df['Loan_Status']
```

In [49]:

```
print(X.shape, y.shape)
```

```
(591, 11) (591,)
```

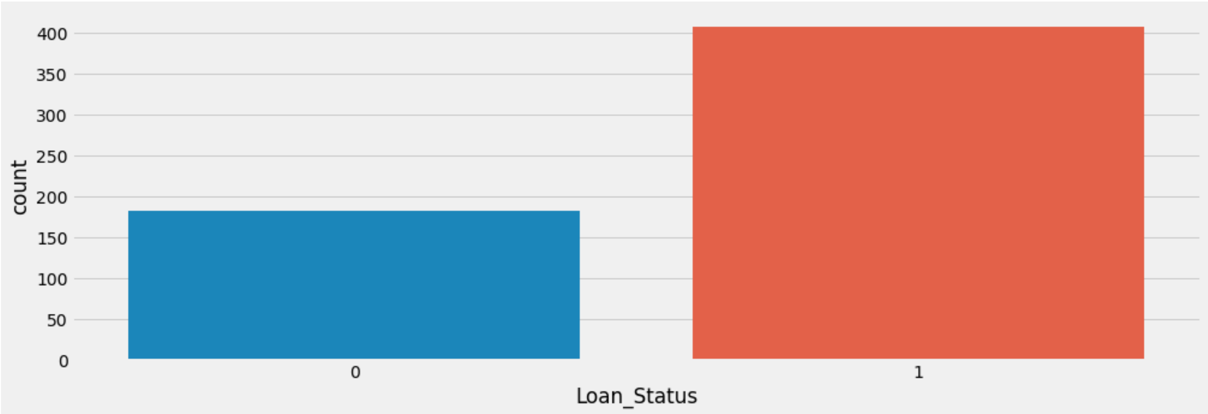
Check if the Label 'Loan_Status' is balanced or not

In [50]:

```
sns.countplot(df['Loan_Status'])
df['Loan_Status'].value_counts()
```

Out[50]:

```
1    408
0    183
Name: Loan_Status, dtype: int64
```



Handling Imbalance Data

In [51]:

```
from imblearn import under_sampling, over_sampling
from imblearn.over_sampling import SMOTE
```

In [52]:

```
X_resample, y_resample = SMOTE().fit_resample(X, y)
```

In [53]:

```
print(X_resample.shape)
print(y_resample.shape)
```

```
(816, 11)
(816,)
```

Train Test Split

In [54]:

```
from sklearn.model_selection import train_test_split
```

In [55]:

```
X_train, X_test, y_train, y_test = train_test_split(X_resample, y_resample, test_size = 0.20, random_
```

In [56]:

```
X_train.shape, X_test.shape
```

Out[56]:

```
((652, 11), (164, 11))
```

In [57]:

```
y_train.shape, y_test.shape
```

Out[57]:

```
((652,), (164,))
```

Models we will use:

- Decision Tree
- Random Forest
- XGBoost
- Logistic Regression
- SVC

The Process of Modeling the Data:

- Importing the model
- Fitting the model
- Classification report by Loan Status
- Overall accuracy
- Predicting Loan Status

Decision Tree

In [100]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
dtree = DecisionTreeClassifier()
param_grid = {
    'max_depth': [3, 4, 5, 6, 7, 8],
    'min_samples_split': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3, 4]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(dtree, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 7, 'min_samples_leaf': 1, 'min_samples_split': 4}
```

In [101]:

```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(random_state = 0, max_depth=7, min_samples_leaf=1, min_samples_split=4
dtree.fit(X_train, y_train)
```

Out[101]:

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=7, min_samples_split=4, random_state=0)
```

In [102]:

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
y_pred = dtree.predict(X_test)
DT_SC = accuracy_score(y_test, y_pred)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

```
Accuracy Score : 76.83 %
```

In [103]:

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [104]:

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

```
              precision    recall  f1-score   support

           0       0.80      0.72      0.76        82
           1       0.74      0.82      0.78        82

    accuracy                           0.77       164
   macro avg       0.77      0.77      0.77       164
weighted avg       0.77      0.77      0.77       164
```

Checking Training and Testing Accuracy

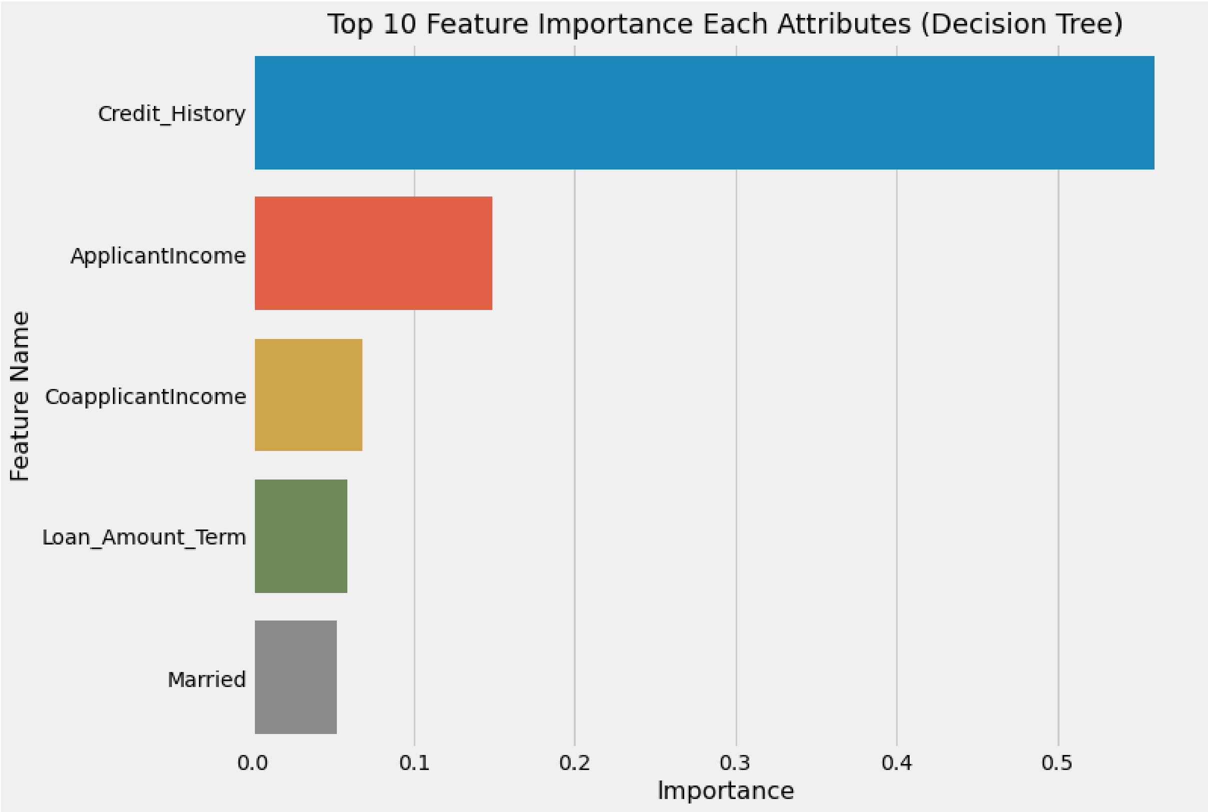
In [105]:

```
print("Training Accuracy",dtree.score(X_train,y_train))
print("Testing Accuracy",dtree.score(X_test,y_test))
```

```
Training Accuracy 0.8941717791411042
Testing Accuracy 0.7682926829268293
```

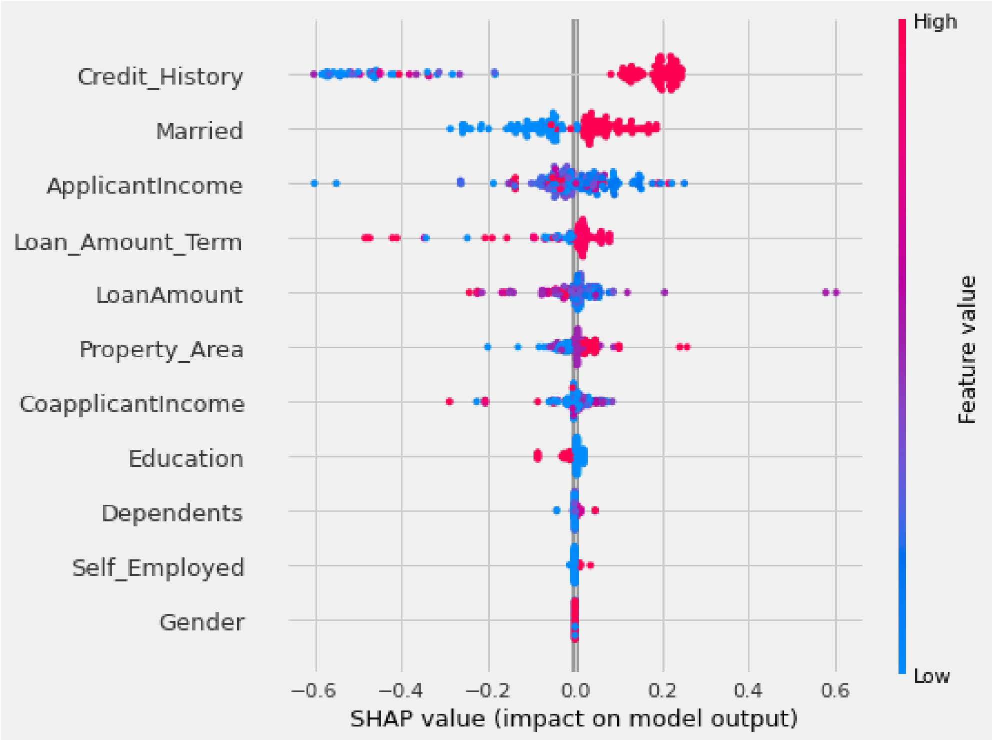
In [106]:

```
# Checking the important features

imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(5)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Decision Tree)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



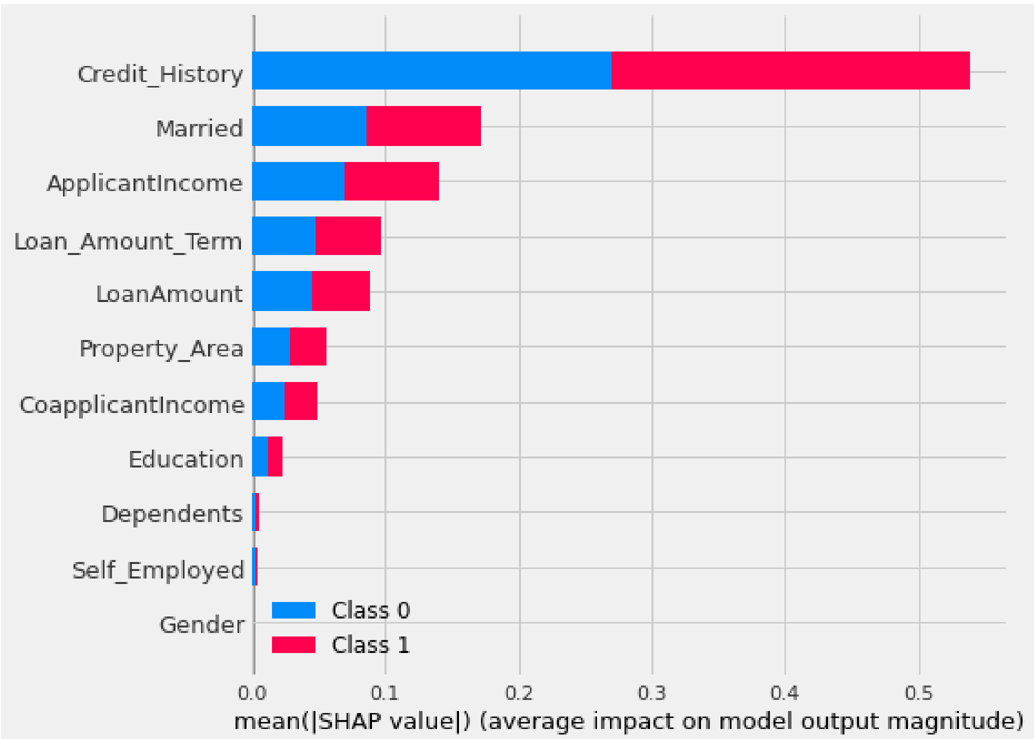
In [107]:

```
import shap
# compute SHAP values
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```



In [108]:

```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```

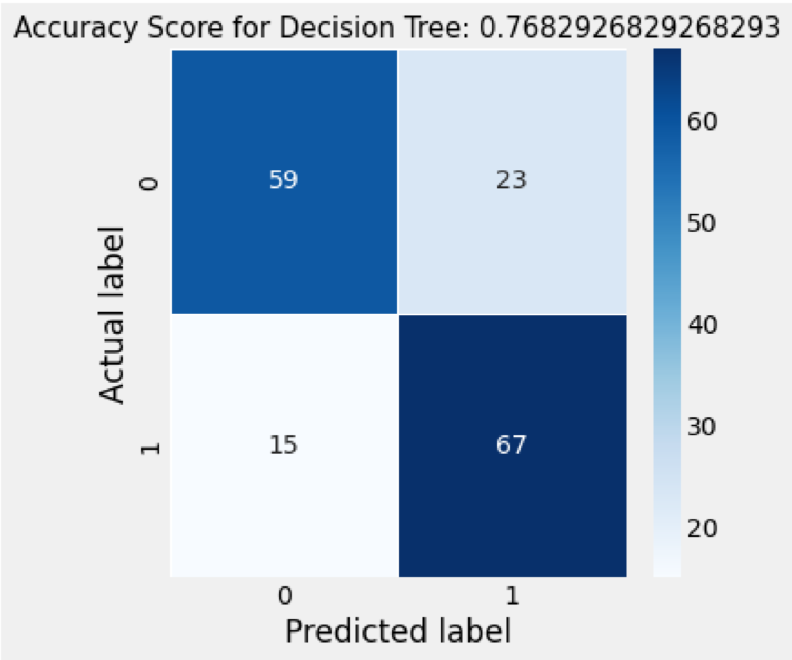


In [109]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Decision Tree: {0}'.format(dtree.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[109]:

```
Text(0.5, 1.0, 'Accuracy Score for Decision Tree: 0.7682926829268293')
```

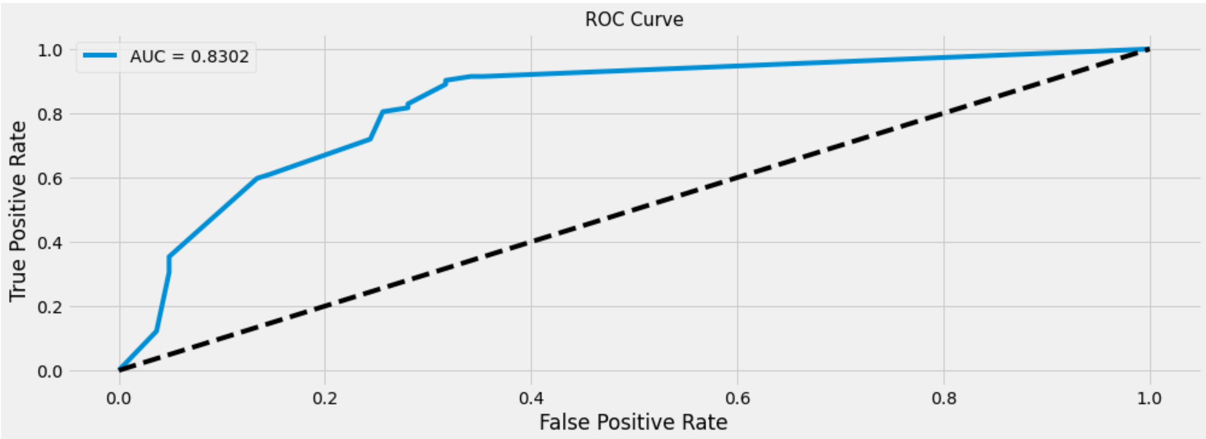


In [112]:

```
# Plotting ROC Curve and Calculating AUC

from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = dtree.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc1 = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc1)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[112]:

```
<matplotlib.legend.Legend at 0x26e37c50820>
```



Random Forest

In [114]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
rfc = RandomForestClassifier()
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 5, 10],
    'max_features': ['sqrt', 'log2', None]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(rfc, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 10, 'max_features': None, 'n_estimators': 100}
```

In [115]:

```
rfc = RandomForestClassifier(max_depth = 10, random_state=0, max_features=None, n_estimators=100)
rfc.fit(X_train, y_train)
```

Out[115]:

```
RandomForestClassifier

RandomForestClassifier(max_depth=10, max_features=None, random_state=0)
```

In [116]:

```
y_pred = rfc.predict(X_test)
RF_SC = accuracy_score(y_test, y_pred)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

```
Accuracy Score : 78.05 %
```

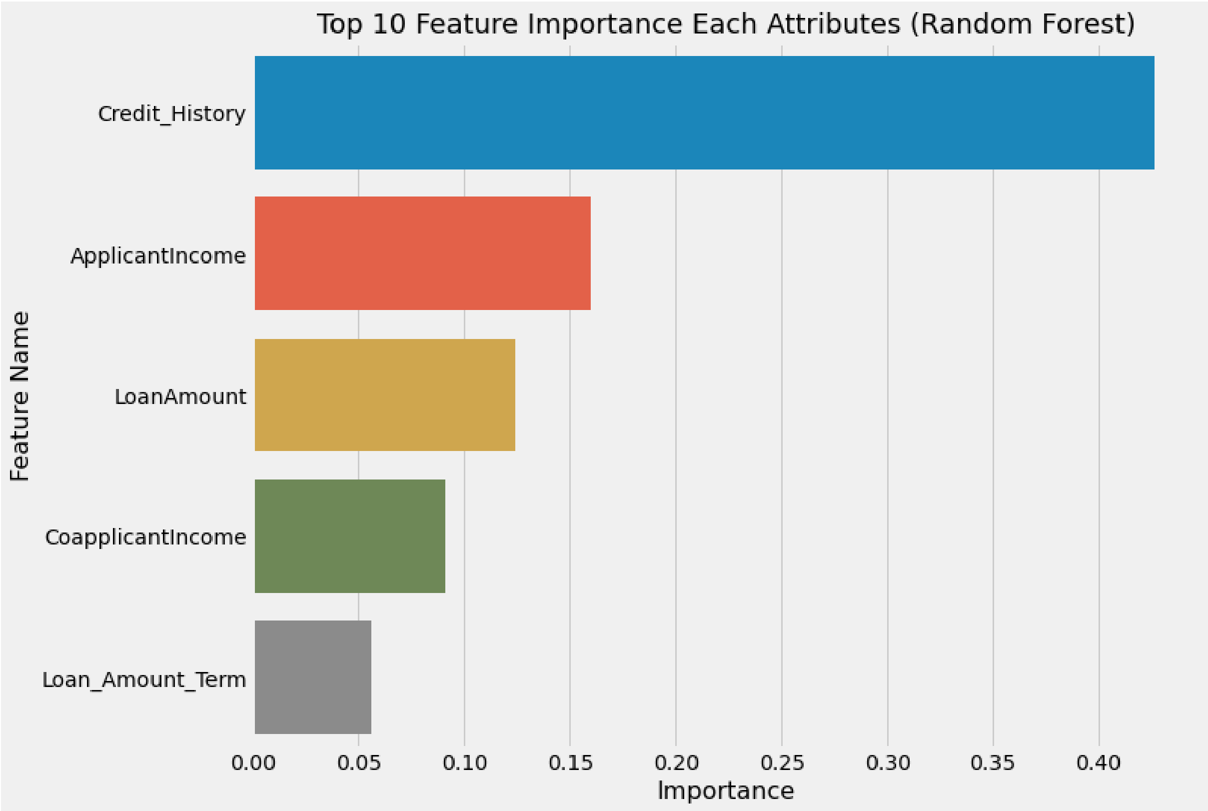
In [117]:

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.73      0.77        82
           1       0.76      0.83      0.79        82

    accuracy                           0.78       164
   macro avg       0.78      0.78      0.78       164
weighted avg       0.78      0.78      0.78       164
```

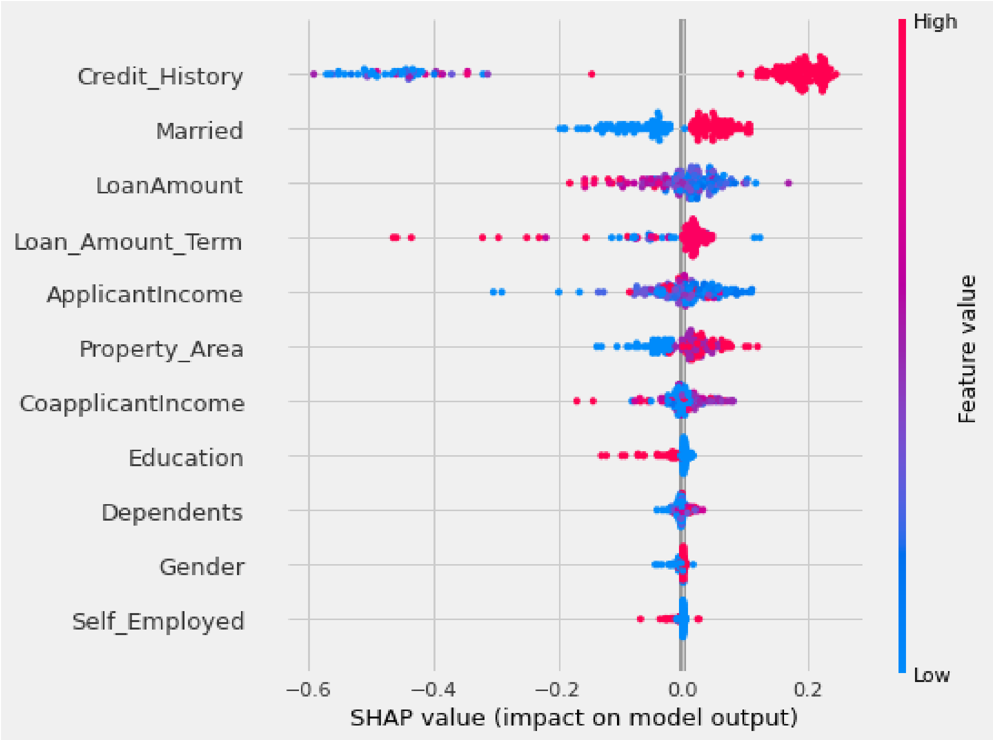
In [118]:

```
# Checking the important features

imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": rfc.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(5)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Random Forest)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



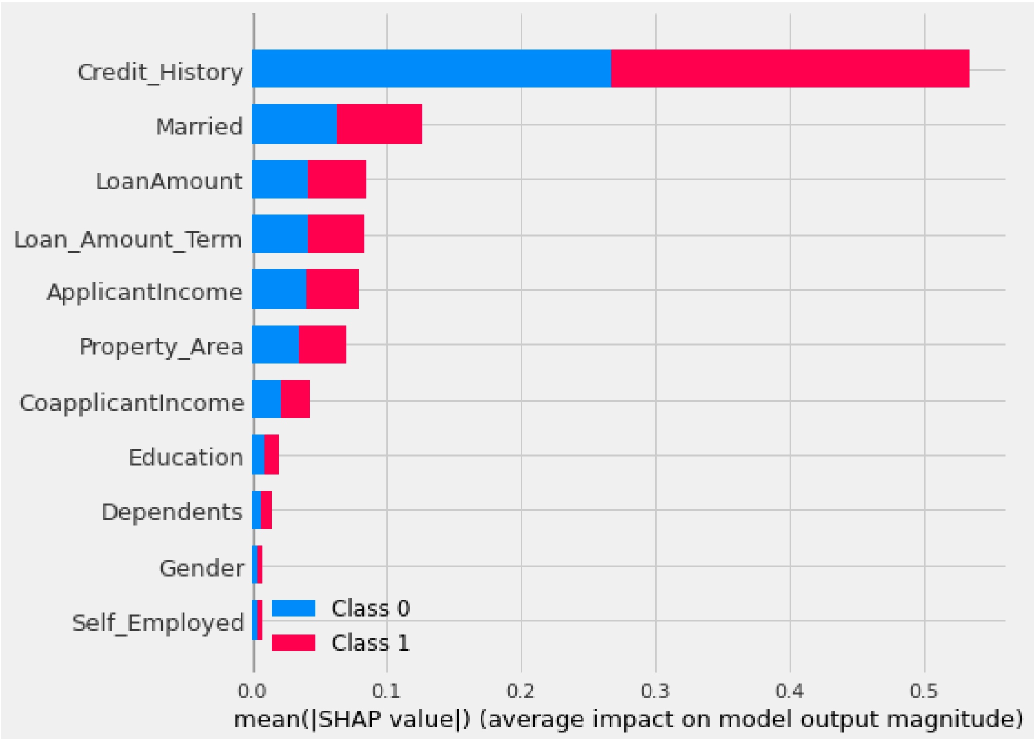
In [119]:

```
import shap
# compute SHAP values
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```



In [120]:

```
import shap
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```

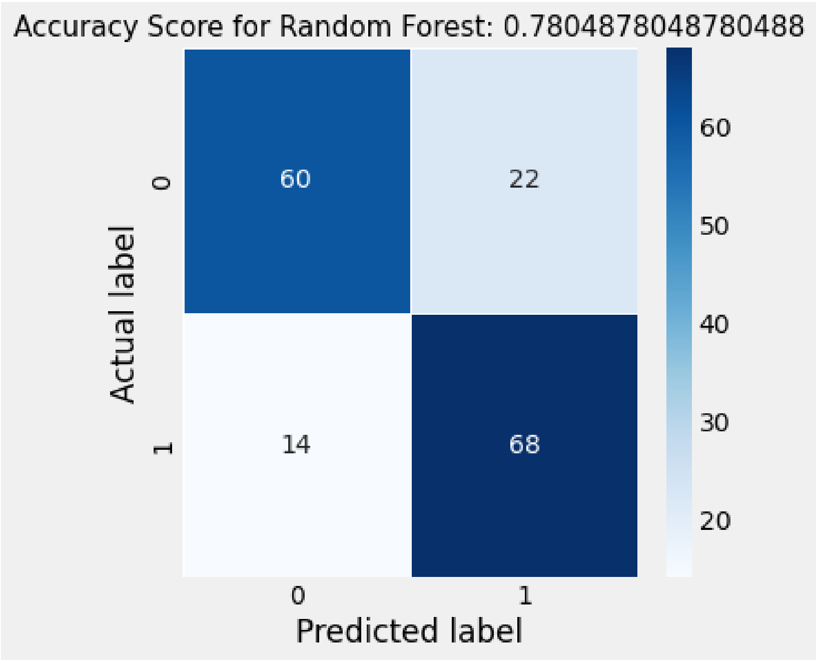


In [121]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Random Forest: {0}'.format(rfc.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[121]:

```
Text(0.5, 1.0, 'Accuracy Score for Random Forest: 0.7804878048780488')
```

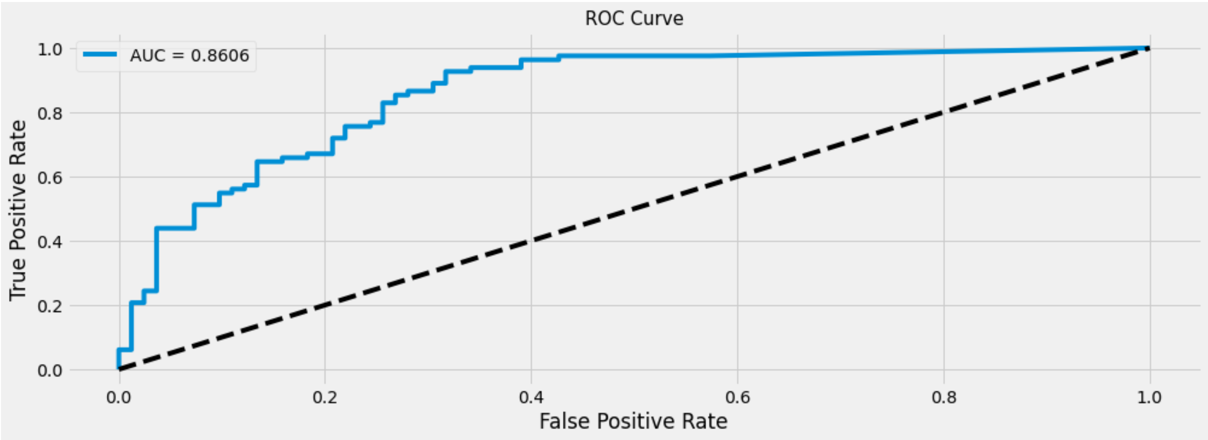


In [122]:

```
# Plotting ROC Curve and Calculating AUC

from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = rfc.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc2 = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc2)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[122]:

```
<matplotlib.legend.Legend at 0x26e3f7fd4c0>
```



XGBoost

In [123]:

```
from xgboost import XGBClassifier
```

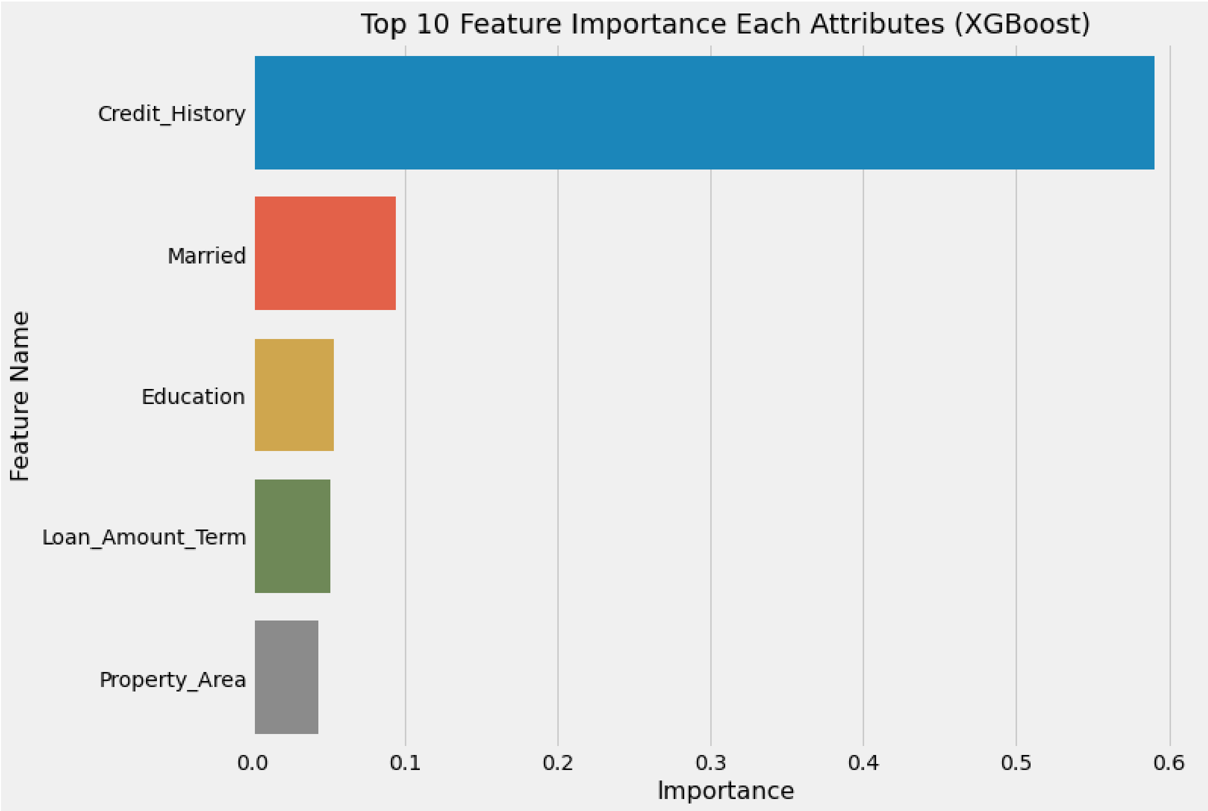
In [124]:

```
XGB = XGBClassifier()
XGB.fit(X_train, y_train)

y_predict = XGB.predict(X_test)

# Accuracy score
XGB_SC = accuracy_score(y_test, y_pred)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")

#  prediction Summary by species
print(classification_report(y_test, y_predict))
```

```
Accuracy Score : 78.05 %
              precision    recall  f1-score   support

           0       0.80      0.79      0.80        82
           1       0.80      0.80      0.80        82

    accuracy                           0.80       164
   macro avg       0.80      0.80      0.80       164
weighted avg       0.80      0.80      0.80       164
```

In [125]:

```
# Checking the important features

imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": XGB.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(5)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (XGBoost)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```

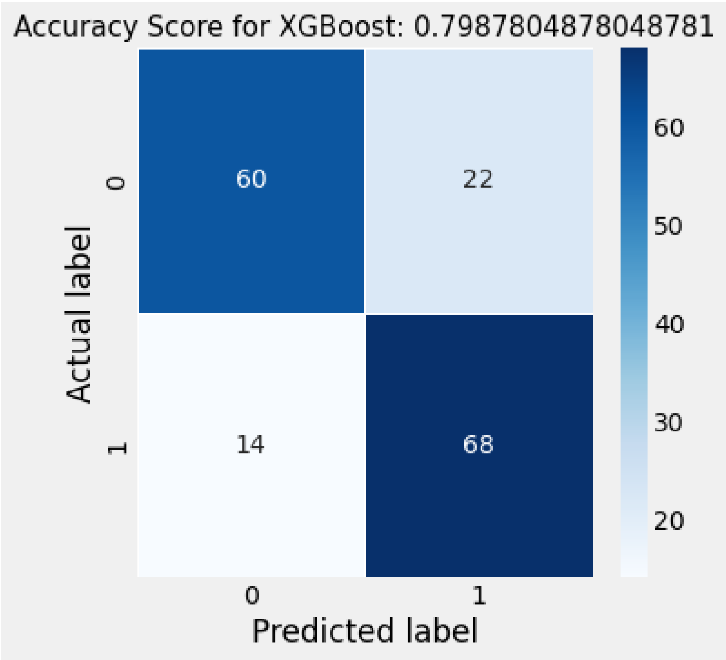


In [126]:

```
from sklearn.metrics import confusion_matrix
cm1 = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm1,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for XGBoost: {0}'.format(XGB.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[126]:

```
Text(0.5, 1.0, 'Accuracy Score for XGBoost: 0.7987804878048781')
```

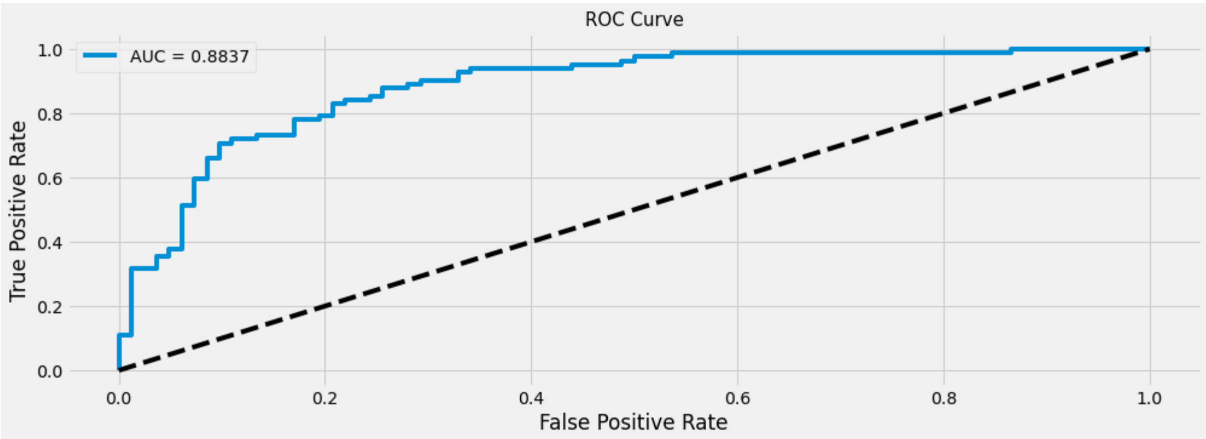


In [127]:

```
# Plotting ROC Curve and Calculating AUC

from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = XGB.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc3 = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc3)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[127]:

```
<matplotlib.legend.Legend at 0x26e406bcfa0>
```



Logistic Regression

In [128]:

```
from sklearn.linear_model import LogisticRegression
```

In [129]:

```
lr = LogisticRegression()
lr.fit(X_train,y_train)

y_pred = lr.predict(X_test)

# Accuracy score
LR_SC = accuracy_score(y_test, y_pred)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")

#  prediction Summary by species
print(classification_report(y_test, y_predict))
```

```
Accuracy Score : 74.39 %
              precision    recall  f1-score   support

           0       0.80      0.79      0.80        82
           1       0.80      0.80      0.80        82

    accuracy                           0.80       164
   macro avg       0.80      0.80      0.80       164
weighted avg       0.80      0.80      0.80       164
```

Checking Training and Testing Accuracy

In [130]:

```
print("Training Accuracy",lr.score(X_train,y_train))
print("Testing Accuracy",lr.score(X_test,y_test))
```

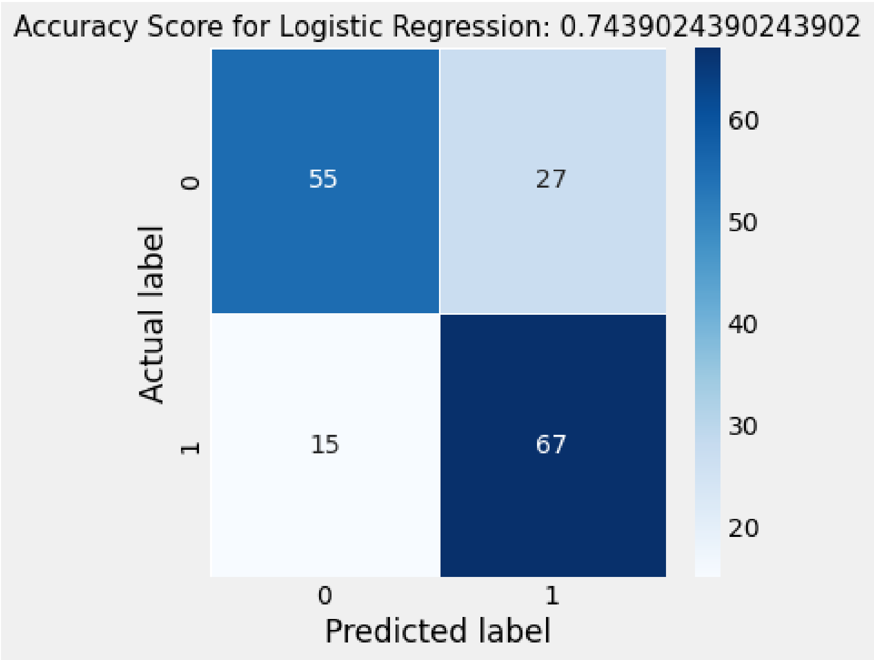
```
Training Accuracy 0.7576687116564417
Testing Accuracy 0.7439024390243902
```

In [131]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Logistic Regression: {0}'.format(lr.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[131]:

```
Text(0.5, 1.0, 'Accuracy Score for Logistic Regression: 0.7439024390243902')
```

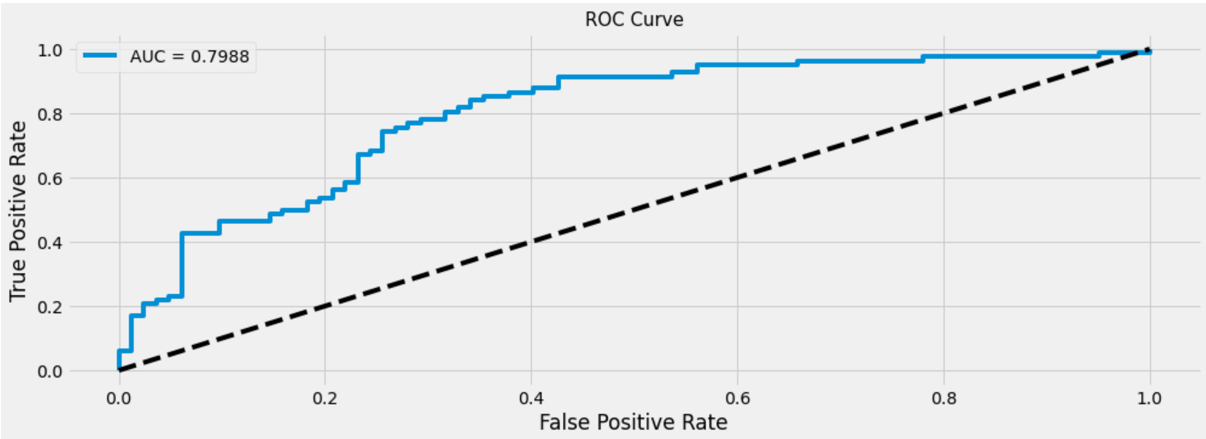


In [132]:

```
# Plotting ROC Curve and Calculating AUC

from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = lr.predict_proba(X_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(y
df_actual_predicted.index = y_test.index

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc4 = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc4)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[132]:

```
<matplotlib.legend.Legend at 0x26e4070b850>
```



SVC Algorithm

In [133]:

```
from sklearn.svm import SVC
```

In [134]:

```
classifier = SVC(kernel='linear', gamma = 'auto', probability = True)
classifier.fit(X_train,y_train)

y_pred = classifier.predict(X_test)

# Accuracy score
SVC_SC = accuracy_score(y_test, y_pred)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")

#  prediction Summary by species
print(classification_report(y_test, y_predict))
```

```
Accuracy Score : 74.39 %
              precision    recall  f1-score   support

           0       0.80      0.79      0.80        82
           1       0.80      0.80      0.80        82

    accuracy                           0.80       164
   macro avg       0.80      0.80      0.80       164
weighted avg       0.80      0.80      0.80       164
```

Checking Training and Testing Accuracy

In [135]:

```
print("Training Accuracy",classifier.score(X_train,y_train))
print("Testing Accuracy",classifier.score(X_test,y_test))
```

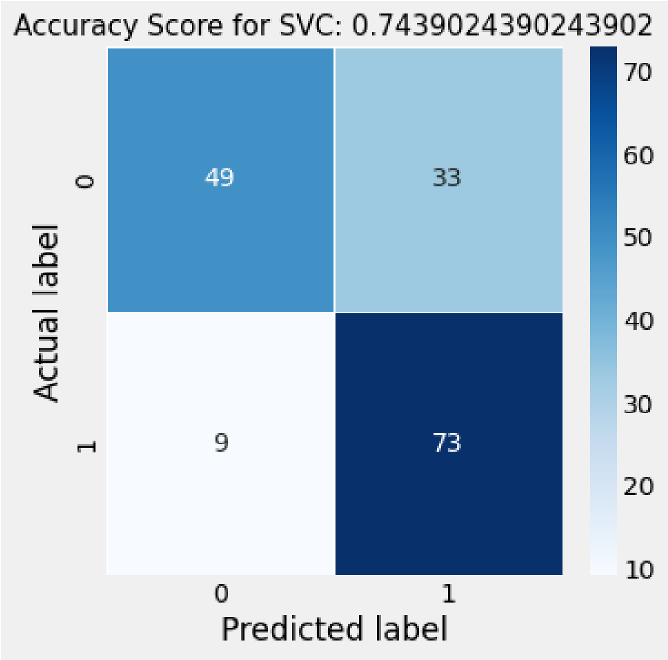
```
Training Accuracy 0.7668711656441718
Testing Accuracy 0.7439024390243902
```

In [136]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for SVC: {0}'.format(classifier.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

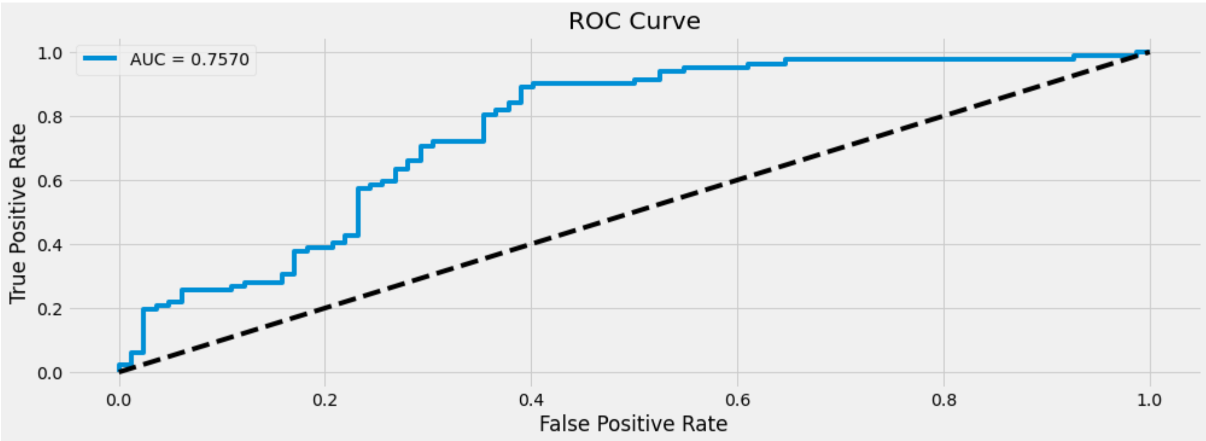
Out[136]:

```
Text(0.5, 1.0, 'Accuracy Score for SVC: 0.7439024390243902')
```



In [137]:

```
# Plotting ROC Curve and Calculating AUC

# Predict the probabilities of the positive class for the test data
y_pred_proba = classifier.predict_proba(X_test)[:, 1]

# Compute the false positive rate (FPR) and true positive rate (TPR) for differe
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

# Compute the area under the ROC curve (AUC)
auc5 = roc_auc_score(y_test, y_pred_proba)

# Plot thr ROC Curve
plt.plot(fpr, tpr, label='AUC = %0.4f' %auc5)
plt.plot([0,1],[0,1], linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```



Comparison of Accuracy for Different Methods

In [138]:

```
Score = [DT_SC,RF_SC,XGB_SC,LR_SC,SVC_SC]
Models = pd.DataFrame({
    'n_neighbors': ["Decision Tree","Random Forest","XGBoost", "Logistic Regression","SVC"],
    'Score': Score})
Models.sort_values(by='Score', ascending=False)
```

Out[138]:

	n_neighbors	Score
1	Random Forest	0.780488
2	XGBoost	0.780488
0	Decision Tree	0.768293
3	Logistic Regression	0.743902
4	SVC	0.743902

Comparison of AUC for Different Methods

In [139]:

```
Score = [auc1, auc2, auc3, auc4, auc5]
Models = pd.DataFrame({
    'n_neighbors': ["Decision Tree","Random Forest","XGBoost", "Logistic Regression", "SVC"],
    'Score': Score})
Models.sort_values(by='Score', ascending=False)
```

Out[139]:

	n_neighbors	Score
2	XGBoost	0.883700
1	Random Forest	0.860648
0	Decision Tree	0.830235
3	Logistic Regression	0.798780
4	SVC	0.756990

Conclusion:

- Credit_History is a very important variable because of its high correlation with Loan Status therefor showing high Dependancy for for predicting the loan getting approved or not.
- The Random Forest algorithm and XGBoost Algorithm provides highest accuracy and also XGBoost algorithm gives the AUC highest in comparison to other methods.

In [140]:

```
df.head()
```

Out[140]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmo
0	1	0	0	0	0	5849	0.0	12
1	1	1	1	0	0	4583	1508.0	12
2	1	1	0	0	1	3000	0.0	6
3	1	1	0	1	0	2583	2358.0	12
4	1	0	0	0	0	6000	0.0	14

Checking the model is able to perform Loan Status Prediction

In [96]:

```
input_data = (1,1,0,1,1,2000,0.0,66.0,180.0,1.0,2)

input_data = np.array(input_data) # changing the input_data to numpy array

input_data_reshaped = input_data.reshape(1,-1) # reshape the array

prediction = rfc.predict(input_data_reshaped)
print(prediction)

if (prediction[0] == 0):
  print('The person is not eligible for loan')
else:
  print('\nThe person is eligible for loan')
```

```
[1]

The person is eligible for loan
```

In [ ]: