LOAN APPROVAL PREDICTION

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GOVERNMENT ARTS AND COLLEGE ,

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INDEX

1.INTRODUCTION

1.1 OVERVIEW

Loan approval prediction refers to the process of using machine learning algorithms to predict the likelihood of a loan being approved or rejected. This involves analyzing a variety of factors related to the borrower, such as their credit history, income, employment status, and other relevant information.

The goal of loan approval prediction is to help lenders make informed decisions about whether to approve or deny loan applications. By using advanced analytics techniques, lenders can improve their accuracy in predicting which borrowers are likely to default on their loans, and adjust their lending criteria accordingly.

Loan approval prediction can be applied in various industries, including banking, finance, and insurance. It has become increasingly important in recent years as more and more people are applying for loans and lenders need to efficiently manage their risk exposure.

1.2 PURPOSE

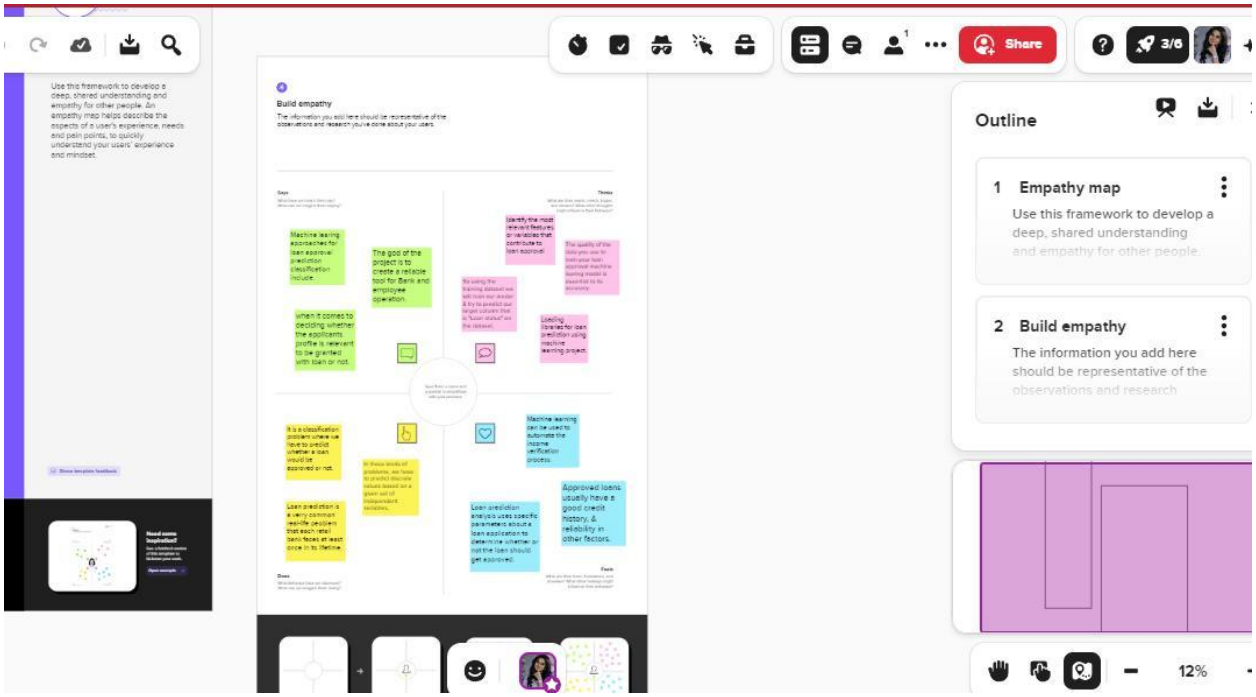
If you're looking to predict loan approvals, you can use machine learning algorithms to analyze data related to past loan applications and outcomes to create a model that can predict the likelihood of loan approval for a new application.

To do this, you would need a dataset that includes information about past loan applications, including features such as credit scores, income, employment status, loan amounts, and other relevant information. You can use this data to train a machine learning algorithm, such as logistic regression or a decision tree, to identify patterns in the data that are associated with loan approval or rejection.

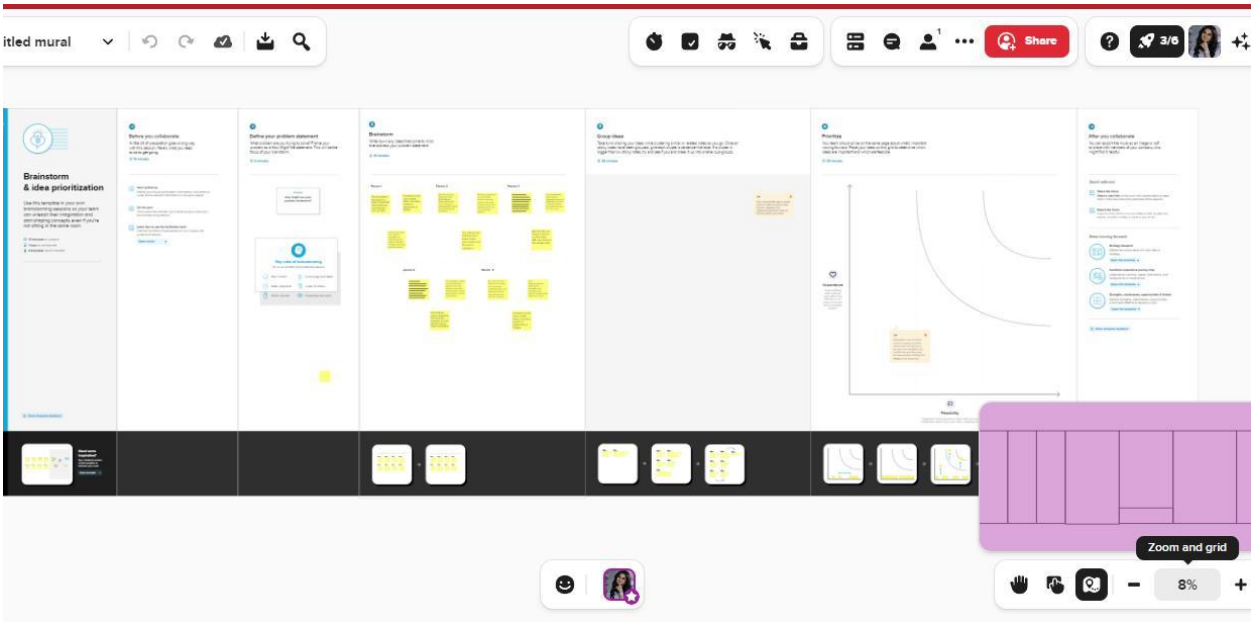
Once you have trained your model, you can use it to predict the likelihood of loan approval for new loan applications. This can be useful for lenders who want to automate their loan approval process and reduce the time and cost associated with manual review of loan applications. It can also be useful for borrowers who want to get a sense of their likelihood of approval before applying for a loan.

2.PROBLEM DEFINITION &DESIGN THINKING

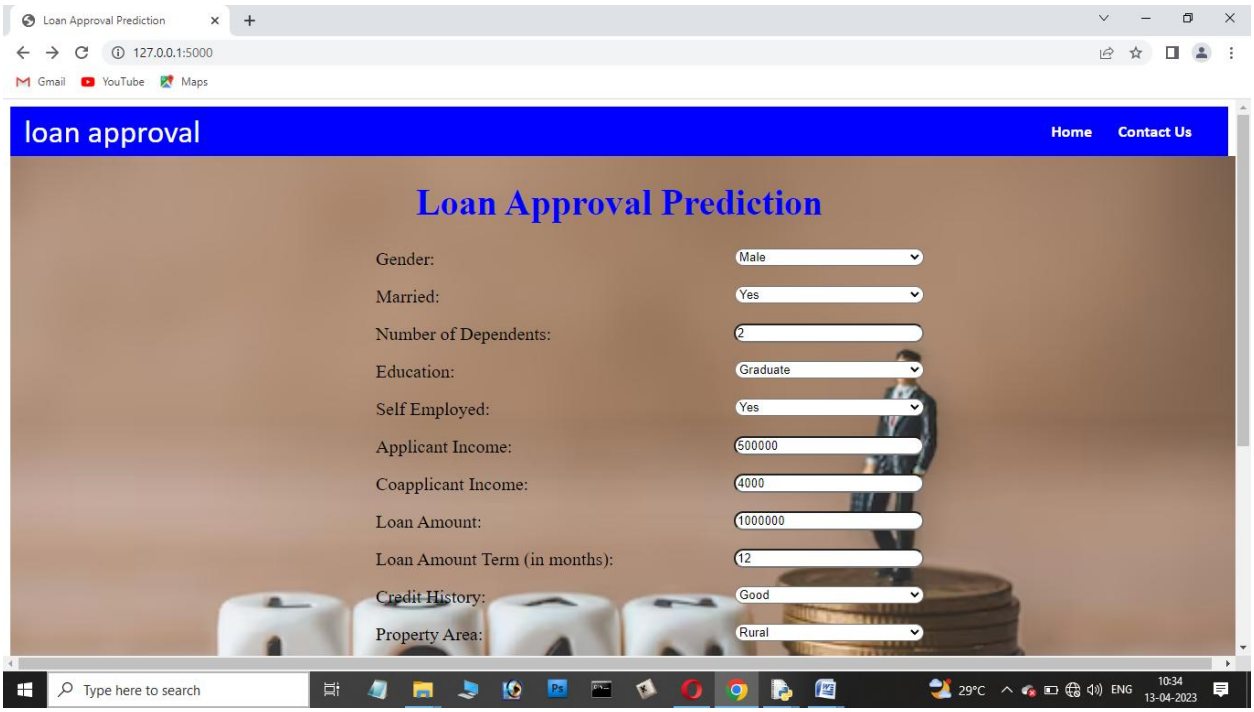
EMPATHY MAP



IDEATION & BRAINSTORMING MAP



3.RESULT


Loan Approval Prediction
127.0.0.1:5000
Gmail
YouTube
Maps
loan approval
Home
Contact Us
Loan Approval Prediction
Gender:
Male
Married:
Yes
Number of Dependents:
2
Education:
Graduate
Self Employed:
Yes
Applicant Income:
500000
Coapplicant Income:
4000
Loan Amount:
1000000
Loan Amount Term (in months):
12
Credit History:
Good
Property Area:
Rural
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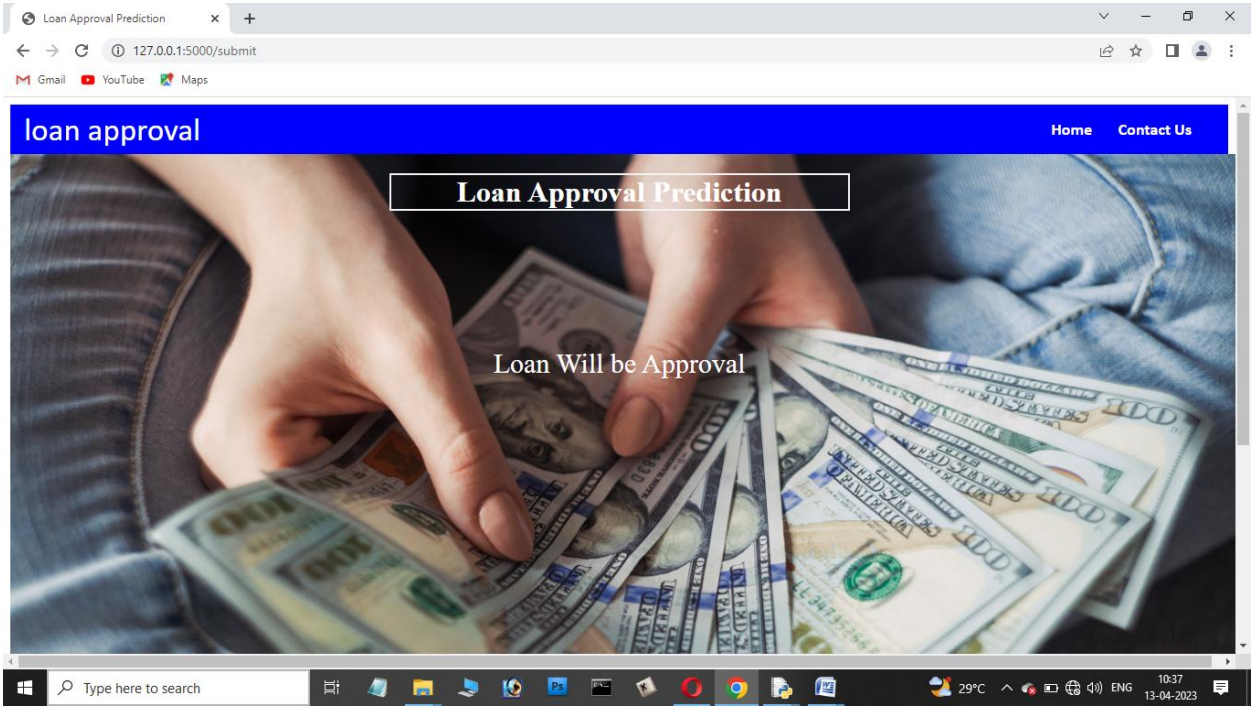
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Home
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Loan Approval Prediction
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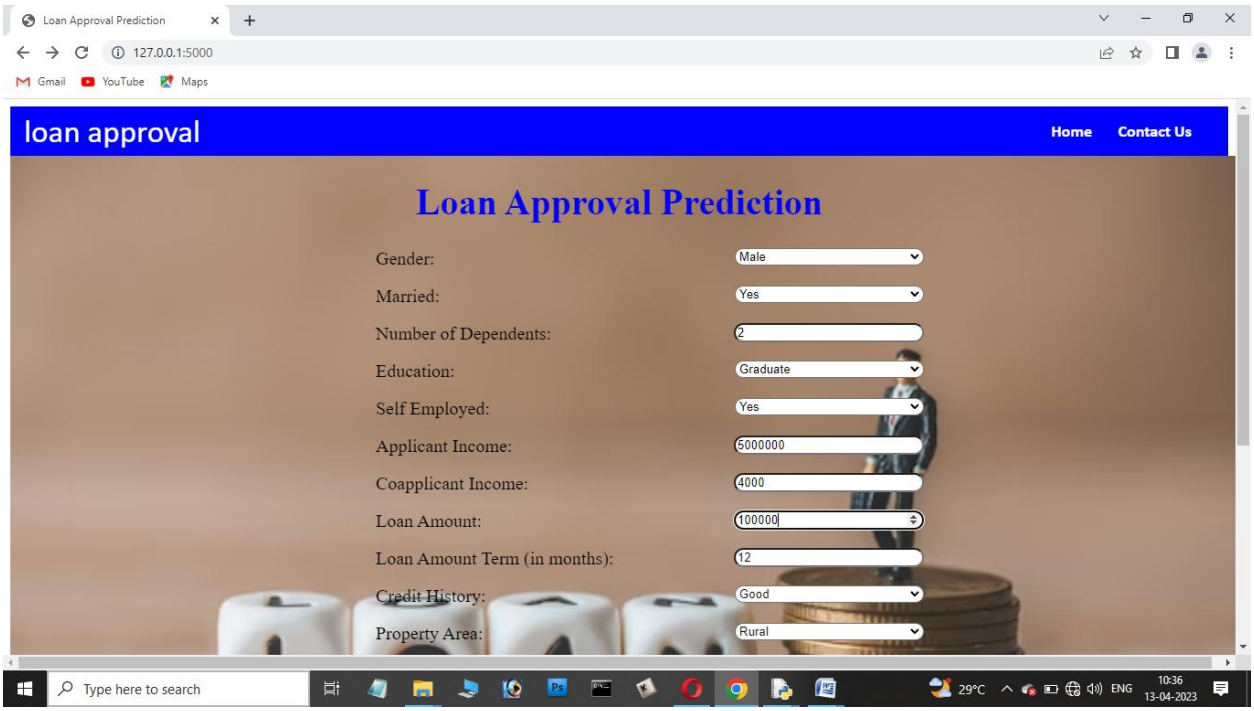
Loan Approval Prediction
127.0.0.1:5000
Gmail
YouTube
Maps
loan approval
Home
Contact Us
Loan Approval Prediction
Gender:
Male
Married:
Yes
Number of Dependents:
2
Education:
Graduate
Self Employed:
Yes
Applicant Income:
5000000
Coapplicant Income:
4000
Loan Amount:
100000
Loan Amount Term (in months):
12
Credit History:
Good
Property Area:
Rural
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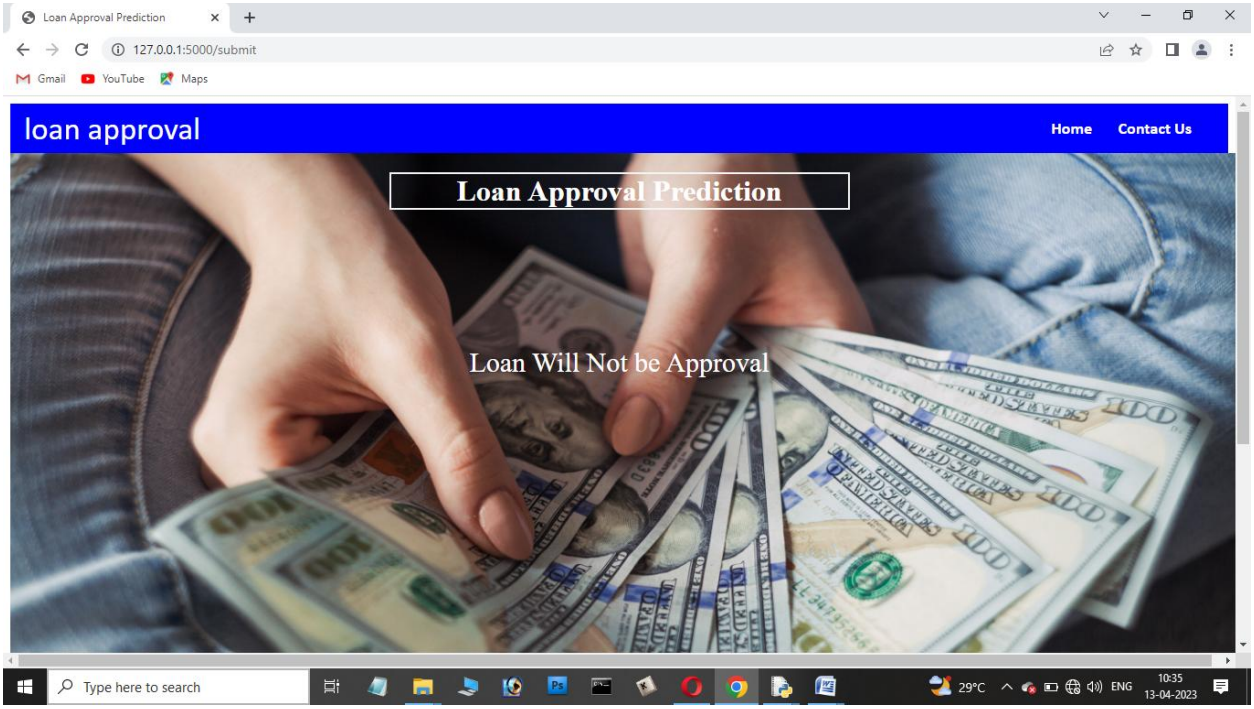
13-04-2023


Loan Approval Prediction
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Gmail
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Maps
loan approval
Home
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Loan Approval Prediction
Loan Will Not be Approval
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4.ADVANDAGES AND DISADVANDAGES

ADVANDAGES:

Improved accuracy: Loan approval prediction can help lenders make more accurate decisions by analyzing a wide range of variables and factors that may impact the borrower's ability to repay the loan.

Time-saving: Predictive models can analyze vast amounts of data and provide results quickly, which can save time for both lenders and borrowers.

Reduced bias: Loan approval prediction can help reduce bias in the lending process by relying on data-driven decisions rather than relying on subjective judgments.

Lower default rates: By accurately predicting the likelihood of loan repayment, lenders can reduce the risk of default and improve their overall loan portfolio performance.

DISADVANDAGES:

Over-reliance on data: Predictive models rely heavily on historical data, which may not always reflect current economic conditions or changes in borrower behavior.

Complexity: Predictive models can be complex and difficult to understand, which can make it challenging for lenders to explain their decisions to borrowers.

Data privacy concerns: Loan approval prediction requires access to sensitive data such as credit scores, income levels, and employment histories, which can raise privacy concerns.

Potential for errors: Predictive models may not always be accurate, and errors can lead to incorrect decisions that may negatively impact borrowers.

5.APPLICATIONS

Collect data: Collect relevant data about loan applicants, such as their credit score, income, employment history, loan amount requested, loan purpose, and other relevant factors.

Preprocess the data: Clean the data by removing missing or inconsistent values, normalize numeric values, and encode categorical variables.

Split the data: Split the data into a training set and a test set. The training set will be used to train the machine learning model, while the test set will be used to evaluate the model's performance.

Train the model: Train a machine learning model using the training set. There are several machine learning algorithms you can use, such as logistic regression, decision trees, random forests, or neural networks. Choose the algorithm that best fits your data and problem.

Evaluate the model: Evaluate the performance of the trained model on the test set. Measure metrics such as accuracy, precision, recall, and F1-score to determine how well the model is performing.

Deploy the model: Deploy the model in a production environment. You can either integrate the model into an existing loan approval system or build a new loan approval system around the model.

Monitor and improve the model: Monitor the performance of the deployed model and improve it over time. Collect feedback from users and use it to refine the model and make it more accurate.

6.CONCLUSION

So here, it can be concluded with confidence that the Naïve Bayes model is extremely efficient and gives a better result when compared to other models. It works correctly and fulfills all requirements of bankers. This system properly and accurately calculate the result. It predicts the loan is approve or reject to loan applicant or customer very accuratly.

7.REFERENCES

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2) Aboobyda Jafar Hamid and Tarig Mohammed Ahmed,―Developing Prediction Model of Loan Risk in Banks using Data Mining‖, Machine Learning and Applications: An International Journal (MLAIJ), Vol.3, No.1, pp. 1-9, March 2016.

3) S. Vimala, K.C. Sharmili, ―Prediction of Loan Risk using NB and Support Vector Machine‖, International Conference on Advancements in Computing Technologies (ICACT 2018), vol. 4, no. 2, pp. 110-113, 2018.

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8.APPENDIX

tamil.py - C:\Users\pc\Desktop\project\Tamil\tamil.py (3.10.4)

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```
import pandas as pd
import numpy as np
import pickle
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import RandomizedSearchCV
import imblearn
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, f1_score
from sklearn.preprocessing import LabelEncoder
from imblearn.combine import SMOTETomek
import warnings
warnings.filterwarnings("ignore", category=UserWarning)



data = pd.read_csv('C:/Users/pc/Desktop/project/Tamil/dataset/train_u6lujuX_CVtuZ9i.csv')
print(data)
print(data.info())
print(data.isnull().sum())

data['Gender'] = data['Gender'].fillna(data['Gender'].mode()[0])
data['Married'] = data['Married'].fillna(data['Married'].mode()[0])
data['Dependents'] = data['Dependents'].str.replace('+', '', regex=False)
data['Dependents'] = data['Dependents'].fillna(data['Dependents'].mode()[0])
data['Self_Employed'] = data['Self_Employed'].fillna(data['Self_Employed'].mode()[0])
data['LoanAmount'] = data['LoanAmount'].fillna(data['LoanAmount'].mode()[0])
data['Loan_Amount_Term'] = data['Loan_Amount_Term'].fillna(data['Loan_Amount_Term'].mode()[0])
data['Credit_History'] = data['Credit_History'].fillna(data['Credit_History'].mode()[0])

data['Gender'] = data['Gender'].astype('category')
data['Gender'] = data['Gender'].replace({'Male': 0, 'Female': 1}).astype('int64')
data['Married'] = data['Married'].replace({'No': 0, 'Yes': 1}).astype('int64')
data['Dependents'] = data['Dependents'].astype('int64')
data['Self_Employed'] = data['Self_Employed'].map({'Yes': 1, 'No': 0})
```

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```
data['Credit_History'] = data['Credit_History'].fillna(data['Credit_History'].mode()[0])

data['Gender'] = data['Gender'].astype('category')
data['Gender'] = data['Gender'].replace({'Male': 0, 'Female': 1}).astype('int64')
data['Married'] = data['Married'].replace({'No': 0, 'Yes': 1}).astype('int64')
data['Dependents'] = data['Dependents'].astype('int64')
data['Self_Employed'] = data['Self_Employed'].map({'Yes': 1, 'No': 0})
data['Self_Employed'] = data['Self_Employed'].astype('int64')
data['CoapplicantIncome'] = data['CoapplicantIncome'].astype('int64')
data['LoanAmount'] = data['LoanAmount'].astype('int64')
data['Loan_Amount_Term'] = data['Loan_Amount_Term'].astype('int64')
data['Credit_History'] = data['Credit_History'].astype('int64')



le = LabelEncoder()
for col in data.columns:
    if data[col].dtype == 'object':
        data[col] = le.fit_transform(data[col].astype(str))

# Split the data into X and y
y = data['Loan_Status']
X = data.drop('Loan_Status', axis=1)

# Apply SMOTETomek
smote = SMOTETomek(sampling_strategy=0.90)
X_bal, y_bal = smote.fit_resample(X, y)

# Print the class distribution before and after SMOTETomek
print("Before SMOTETomek: ", y.value_counts())
print("After SMOTETomek: ", y_bal.value_counts())


plt.figure(figsize=(12,5))
plt.subplot(121)
sns.histplot(data['ApplicantIncome'], color='r')
plt.title('Applicant Income Distribution')
plt.subplot(122)
sns.histplot(data['Credit_History'])
plt.title('Credit History Distribution')
```

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```
plt.show()

plt.figure(figsize=(10,5))
sns.countplot(x='Gender', hue='Loan_Status', data=data)
plt.title('Gender vs Loan Status')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()

plt.figure(figsize=(20,5))
plt.subplot(131)
sns.countplot(x=data['Married'], hue=data['Gender'])
plt.subplot(132)
sns.countplot(x="Self_Employed", hue="Education", data=data)
plt.subplot(133)
sns.countplot(x='Property_Area', hue='Loan_Amount_Term', data=data)
plt.show()


sns.stripplot(x='Gender', y='ApplicantIncome', data=data, hue='Loan_Status', jitter=True)
plt.show()


sc = StandardScaler()
names = list(X_bal.columns)
X_bal = sc.fit_transform(X_bal)
X_bal = pd.DataFrame(X_bal, columns=names)


from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_bal, y_bal, test_size=0.25, random_state=42)
X_train.head()

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report
```

Task View

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tamil.py - C:\Users\pc\Desktop\project\Tamil\tamil.py (3.10.4)

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```
def decisionTree(X_train, X_test, y_train, y_test):
    dt = DecisionTreeClassifier()
    dt.fit(X_train, y_train)
    y_pred = dt.predict(X_test)
    print('*** DecisionTreeClassifier ***')
    print('Confusion matrix')
    print(confusion_matrix(y_test, y_pred))
    print('Classification report')
    print(classification_report(y_test, y_pred))
    return dt

# Retrain the model with only 11 features
dt = DecisionTreeClassifier(max_features=11)
dt.fit(X_train, y_train)

# Make prediction with 11 features
dt.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report

def randomForest(X_train, X_test, y_train, y_test):
    rf = RandomForestClassifier()
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    print('*** RandomForestClassifier ***')
    print('Confusion matrix')
    print(confusion_matrix(y_test, y_pred))
    print('Classification report')
    print(classification_report(y_test, y_pred))
    return rf

rf = randomForest(X_train, X_test, y_train, y_test)
rf.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])


from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report

def KNN(X_train, X_test, y_train, y_test):
```

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```
import xgboost

def xgboost(X_train, X_test, y_train, y_test):
    xg=GradientBoostingClassifier()
    xg.fit(X_train,y_train)
    yPred=xg.predict(X_test)
    print('***GradientBoostingClassifier***')
    print('Confusion matrix')
    print(confusion_matrix(y_test,yPred))
    print('classification report')
    print(classification_report(y_test,yPred))
    return xg


import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
classifier = Sequential()
classifier.add(Dense(units=100, activation='relu', input_dim=12))
classifier.add(Dense(units=50, activation='relu'))
classifier.add(Dense(units=1, activation='sigmoid'))
classifier.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model_history = classifier.fit(X_train, y_train, batch_size=100, validation_split=0.2, epochs=100)


dt = decisionTree(X_train, X_test, y_train, y_test)
# Make prediction with 11 features
dt.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])
rf = randomForest(X_train, X_test, y_train, y_test)
rf.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])
knn = KNN(X_train, X_test, y_train, y_test)
knn.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])
xg = xgboost(X_train, X_test, y_train, y_test)
xg.predict([[1,1,0,1,1,4276,1542,145,240,0,0,1]])

classifier.save("loan.h5")

y_pred = classifier.predict(X_test)

print(y_pred)
```

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```
y_pred = (y_pred > 0.5)

print(y_pred)

unsqueezed_text = y_pred.squeeze()

print(unsqueezed_text)

import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier

def predict_exit(sample_value, sc, model):
    sample_value = np.array(sample_value)
    sample_value = sample_value.reshape(1, -1)
    sample_value = sc.transform(sample_value)
    # add return statement to return the predicted value
    return model.predict(sample_value)

sample_value = [[1, 1, 0, 1, 1, 4276, 1542, 145, 240, 0, 0]]

# Define and train a logistic regression model
X_train = X_bal.iloc[:, :-1]  # exclude the last column
y_train = y_bal
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
model = LogisticRegression()
model.fit(X_train, y_train)

# Call predict_exit and store the predicted value
prediction = predict_exit(sample_value, sc, model)

# Print the prediction
if prediction > 0.5:
    print('Prediction: High chance of loan approval!')
else:
```

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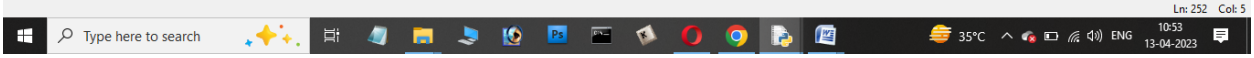

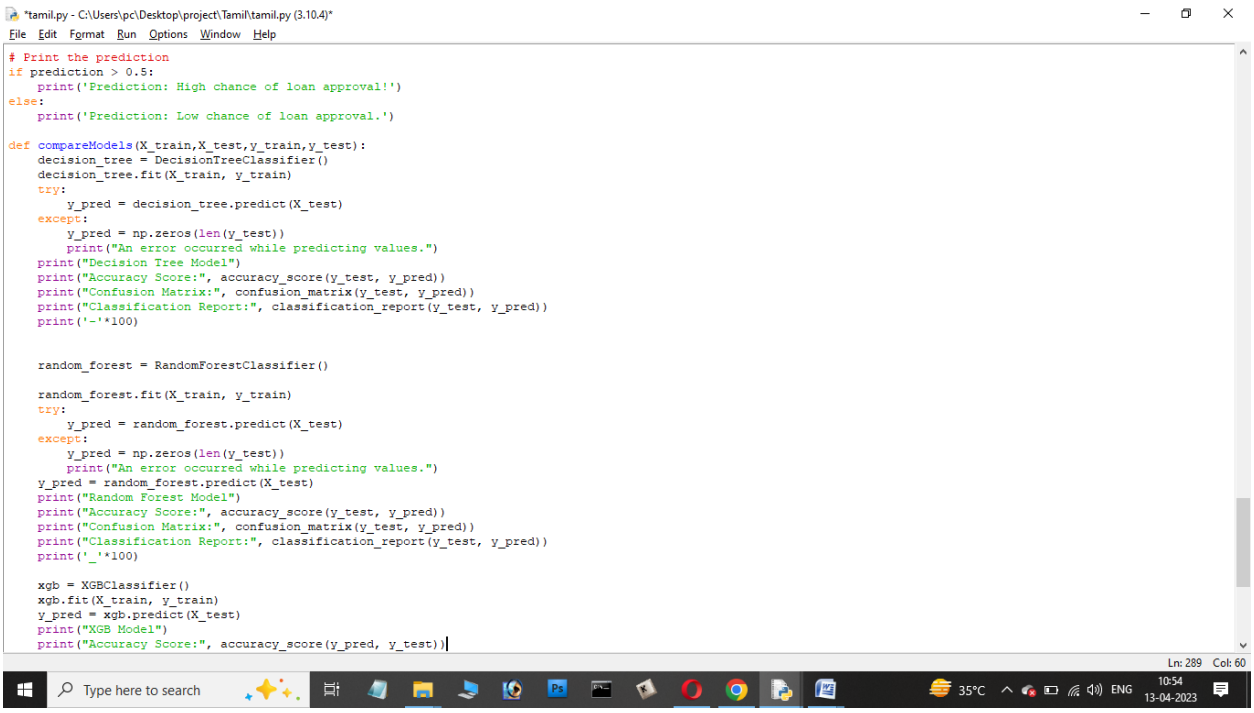
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# Print the prediction
if prediction > 0.5:
print('Prediction: High chance of loan approval!')
else:
print('Prediction: Low chance of loan approval.')
def compareModels(X_train,X_test,y_train,y_test):
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)
try:
y_pred = decision_tree.predict(X_test)
except:
y_pred = np.zeros(len(y_test))
print("An error occurred while predicting values.")
print("Decision Tree Model")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:", classification_report(y_test, y_pred))
print('-'*100)
random_forest = RandomForestClassifier()
random_forest.fit(X_train, y_train)
try:
y_pred = random_forest.predict(X_test)
except:
y_pred = np.zeros(len(y_test))
print("An error occurred while predicting values.")
y_pred = random_forest.predict(X_test)
print("Random Forest Model")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:", classification_report(y_test, y_pred))
print('_'*100)
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
print("XGB Model")
print("Accuracy Score:", accuracy_score(y_pred, y_test))
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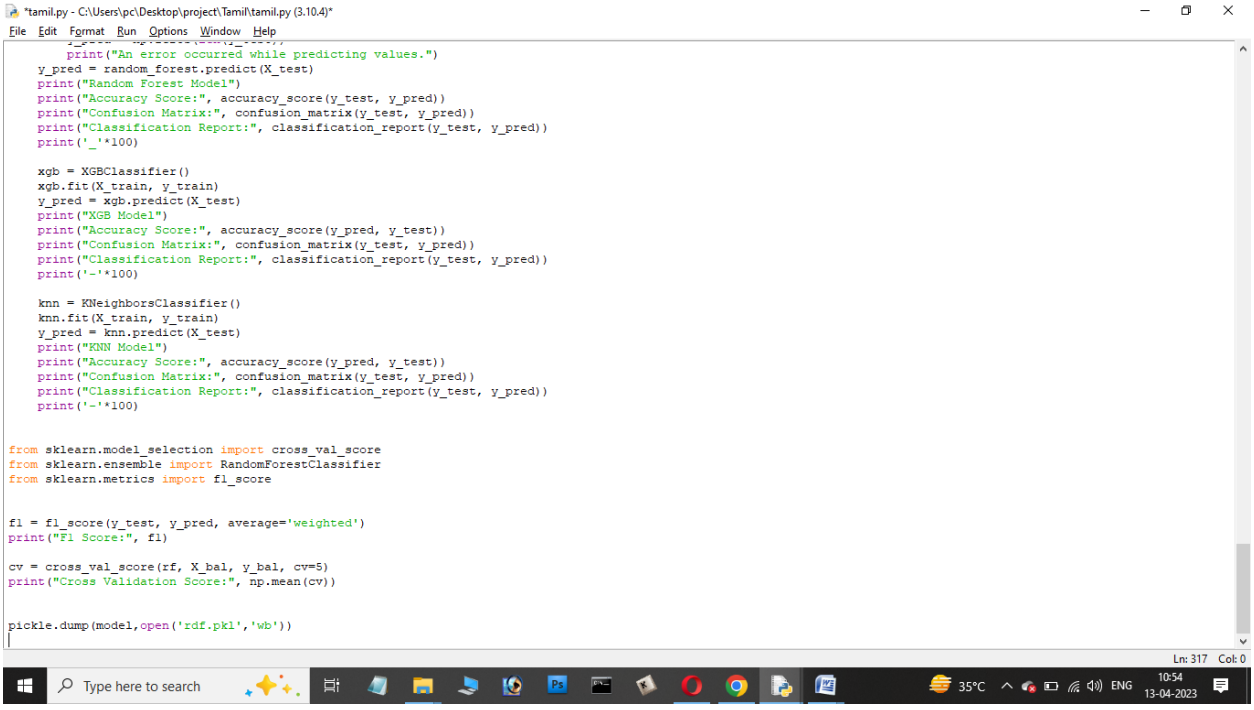
tamil.py - C:\Users\pc\Desktop\project\Tamil\tamil.py (3.10.4)
File Edit Format Run Options Window Help
print("An error occurred while predicting values.")
y_pred = random_forest.predict(X_test)
print("Random Forest Model")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:", classification_report(y_test, y_pred))
print('_'*100)
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
print("XGB Model")
print("Accuracy Score:", accuracy_score(y_pred, y_test))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:", classification_report(y_test, y_pred))
print('-'*100)
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print("KNN Model")
print("Accuracy Score:", accuracy_score(y_pred, y_test))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:", classification_report(y_test, y_pred))
print('-'*100)
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred, average='weighted')
print("F1 Score:", f1)
cv = cross_val_score(rf, X_bal, y_bal, cv=5)
print("Cross Validation Score:", np.mean(cv))
pickle.dump(model,open('rdf.pkl','wb'))
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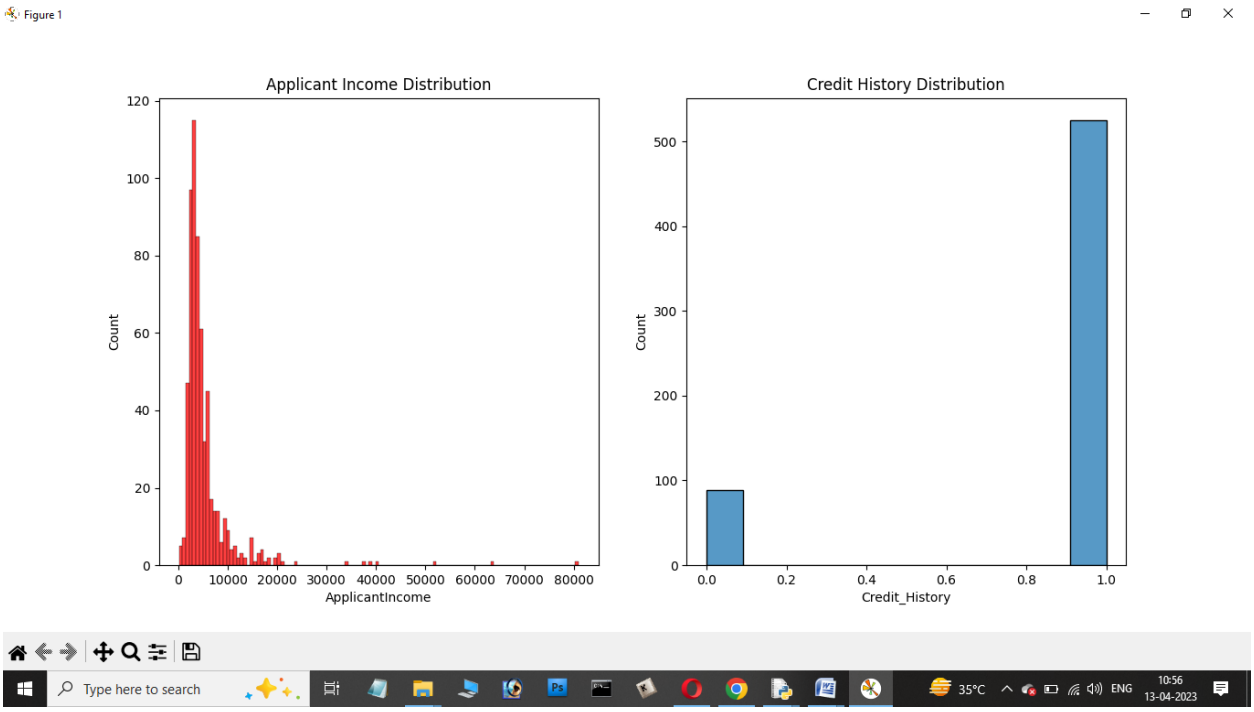


Figure 1
Applicant Income Distribution
Count
ApplicantIncome
0
20
40
60
80
100
120
0
10000
20000
30000
40000
50000
60000
70000
80000
Credit History Distribution
Count
Credit_History
0
100
200
300
400
500
0.0
0.2
0.4
0.6
0.8
1.0
Type here to search
35°C
ENG
10:56
13-04-2023

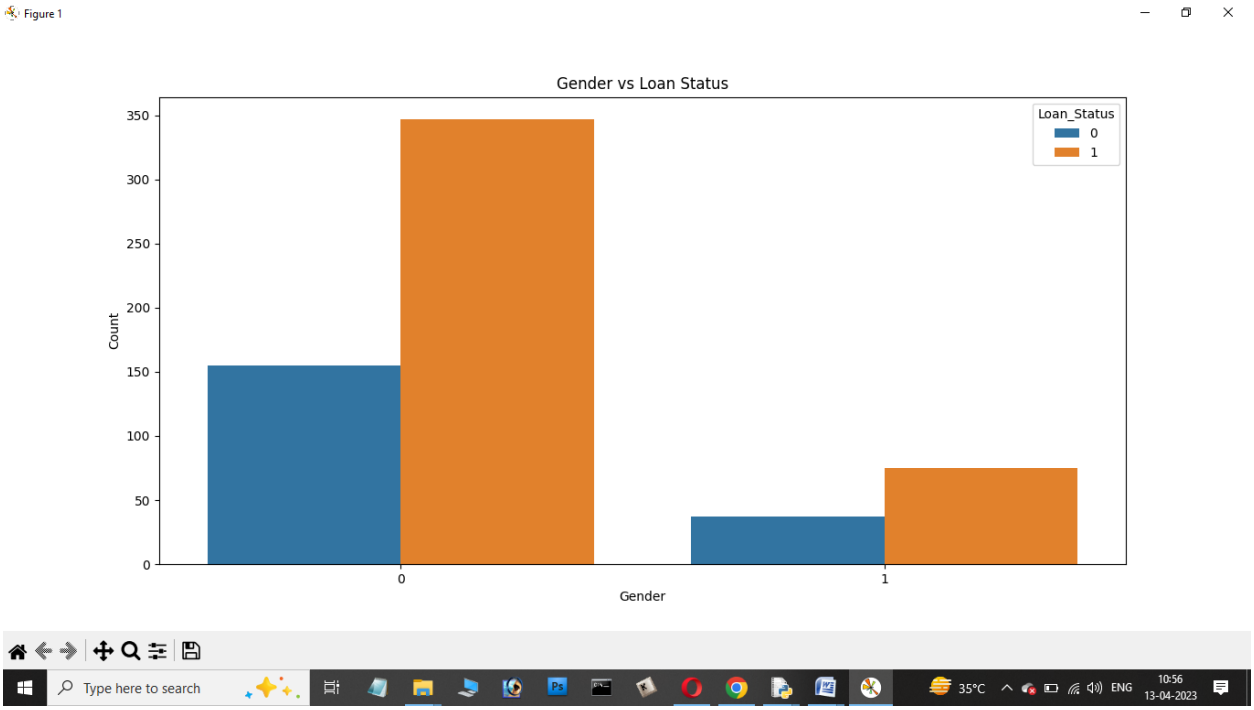


Figure 1
Gender vs Loan Status
Loan_Status
0
1
Count
Gender
0
50
100
150
200
250
300
350
0
1
Type here to search
35°C
ENG
10:56
13-04-2023

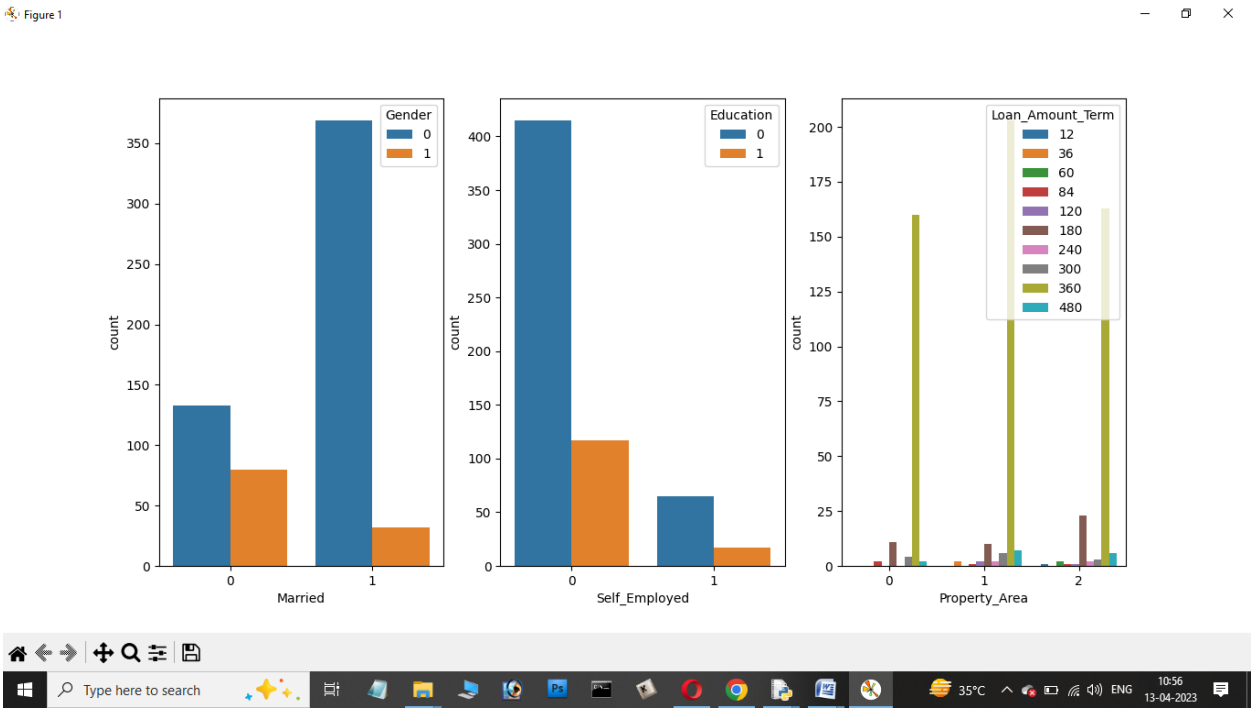


Figure 1
Gender
0
1
Education
0
1
Loan_Amount_Term
12
36
60
84
120
180
240
300
360
480
count
Married
Self_Employed
Property_Area
Type here to search
35°C
ENG
10:56
13-04-2023

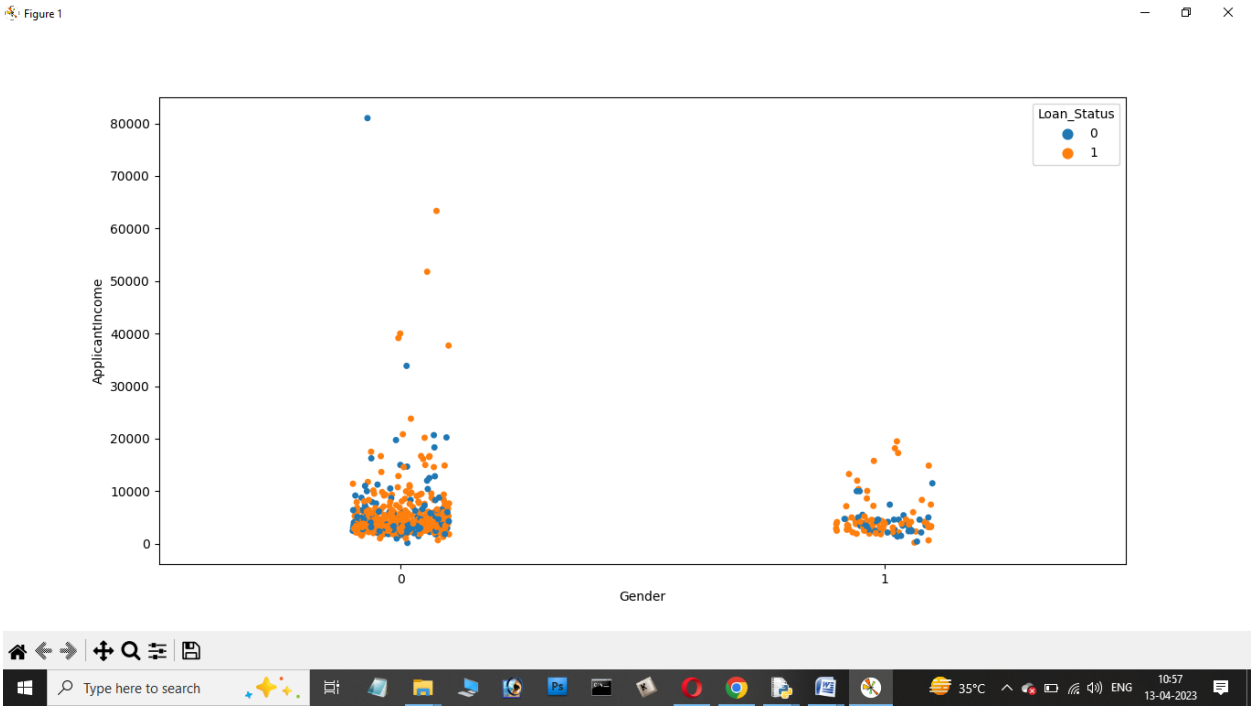
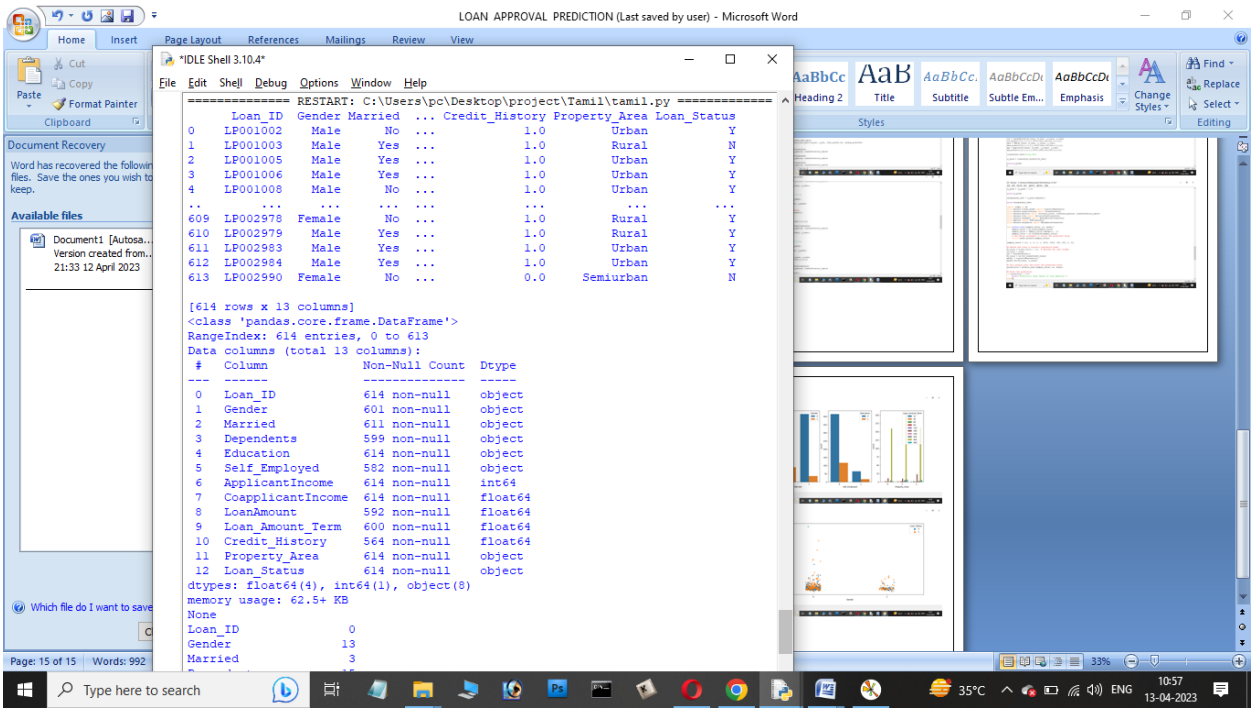
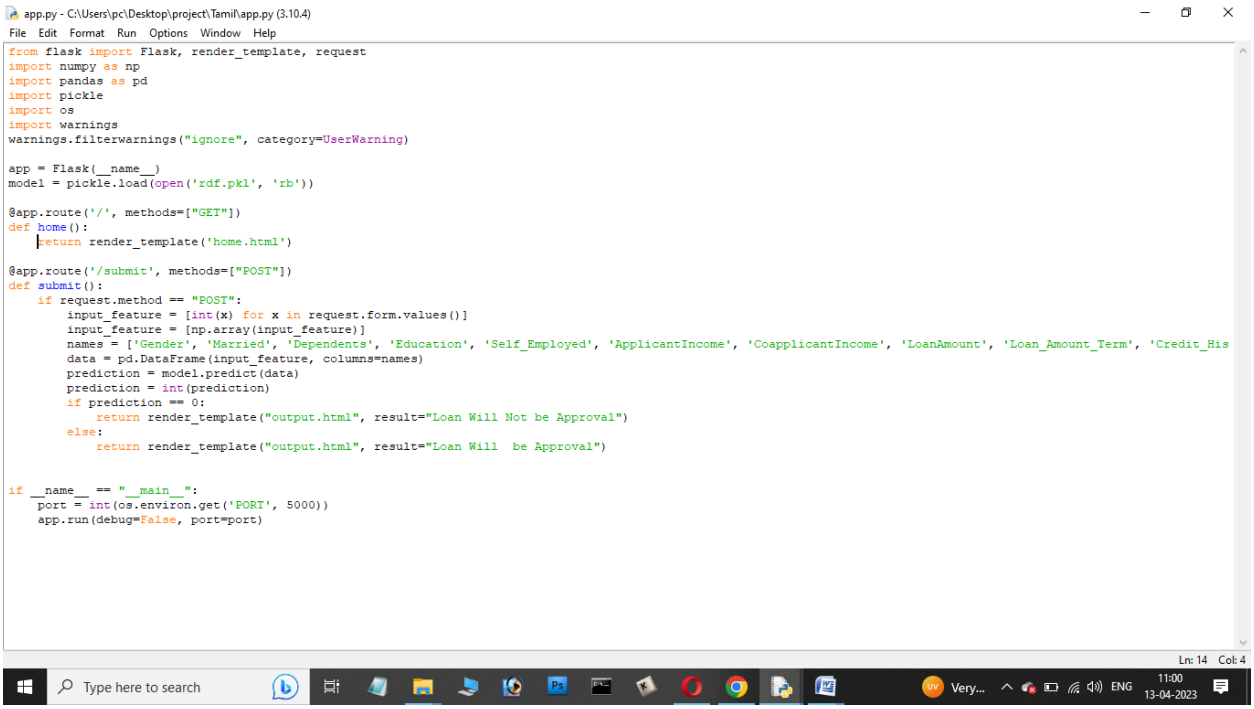
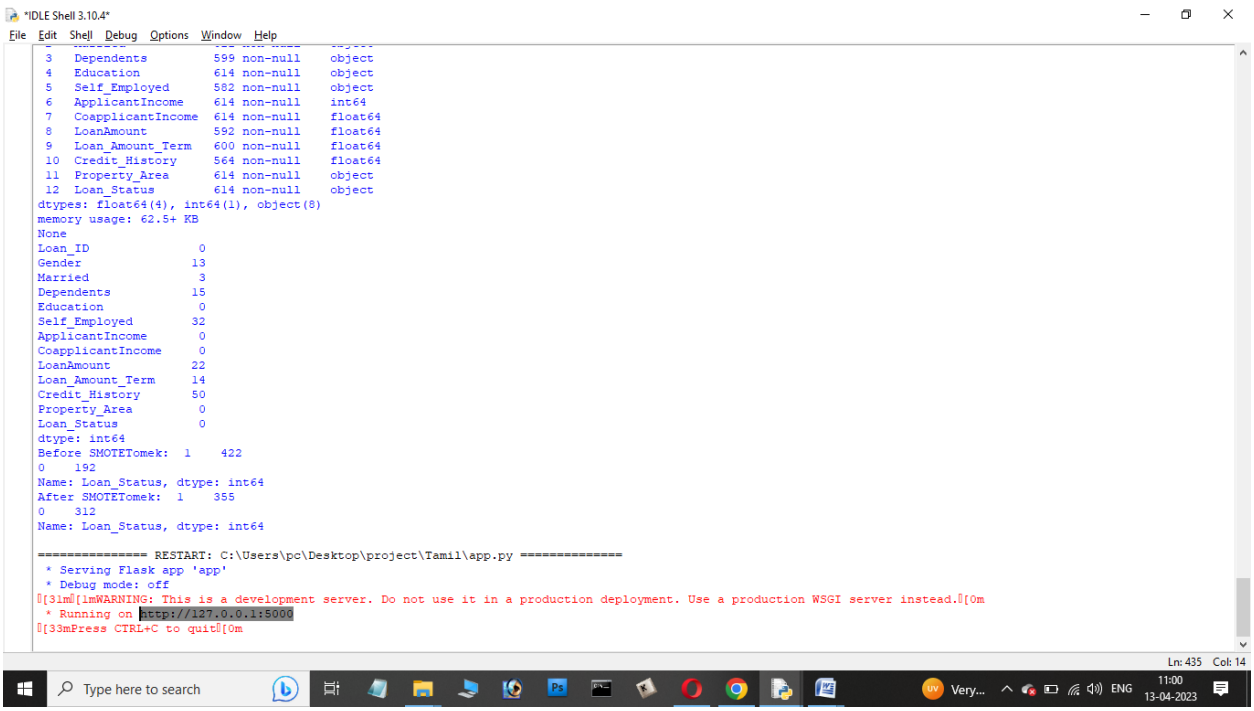


Figure 1
Loan_Status
0
1
Applicantincome
Gender
Type here to search
35°C
ENG
10:57
13-04-2023



Python flask file:




IDLE Shell 3.10.4
File Edit Shell Debug Options Window Help
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
None
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
Before SMOTETomek: 1 422
0 192
Name: Loan_Status, dtype: int64
After SMOTETomek: 1 355
0 312
Name: Loan_Status, dtype: int64
========== RESTART: C:\Users\pc\Desktop\project\Tamil\app.py ==========
* Serving Flask app 'app'
* Debug mode: off
[31m[1mWARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.[0m
* Running on http://127.0.0.1:5000
[33mPress CTRL+C to quit[0m
Ln: 435 Col: 14
Type here to search
Very...
ENG
11:00
13-04-2023