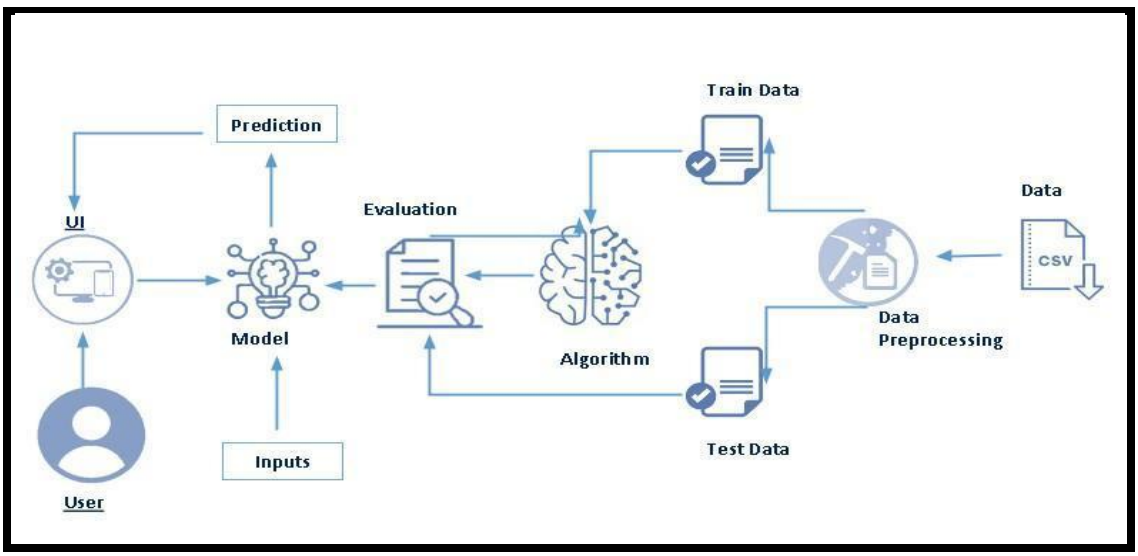
PREDICTING PERSONAL LOAN APPROVAL USING MACHINE LEARNING

1.INTRODUCTION

1.1 OVERVIEW

A loan is a sum of money that is borrowed and repaid over a period of time, typically with interest. There are various types of loans available to individuals and businesses, such as personal loans, mortgages, auto loans, student loans, business loans and many more. They are offered by banks, credit unions, and other financial institutions, and the terms of the loan, such as interest rate, repayment period, and fees, vary depending on the lender and the type of loan.A personal loan is a type of unsecured loan that can be used for a variety of expenses such as home repairs, medical expenses, debt consolidation, and more. The loan amount, interest rate, and repayment period vary depending on the lender and the borrower's creditworthiness. To qualify for a personal loan, borrowers typically need to provide proof of income and have a good credit score.Predicting personal loan approval using machine learning analyses a borrower's financial data and credit history to determine the likelihood of loan approval. This can help financial institutions to make more informed decisions about which loan applications to approve and which to deny.

Technical Architecture



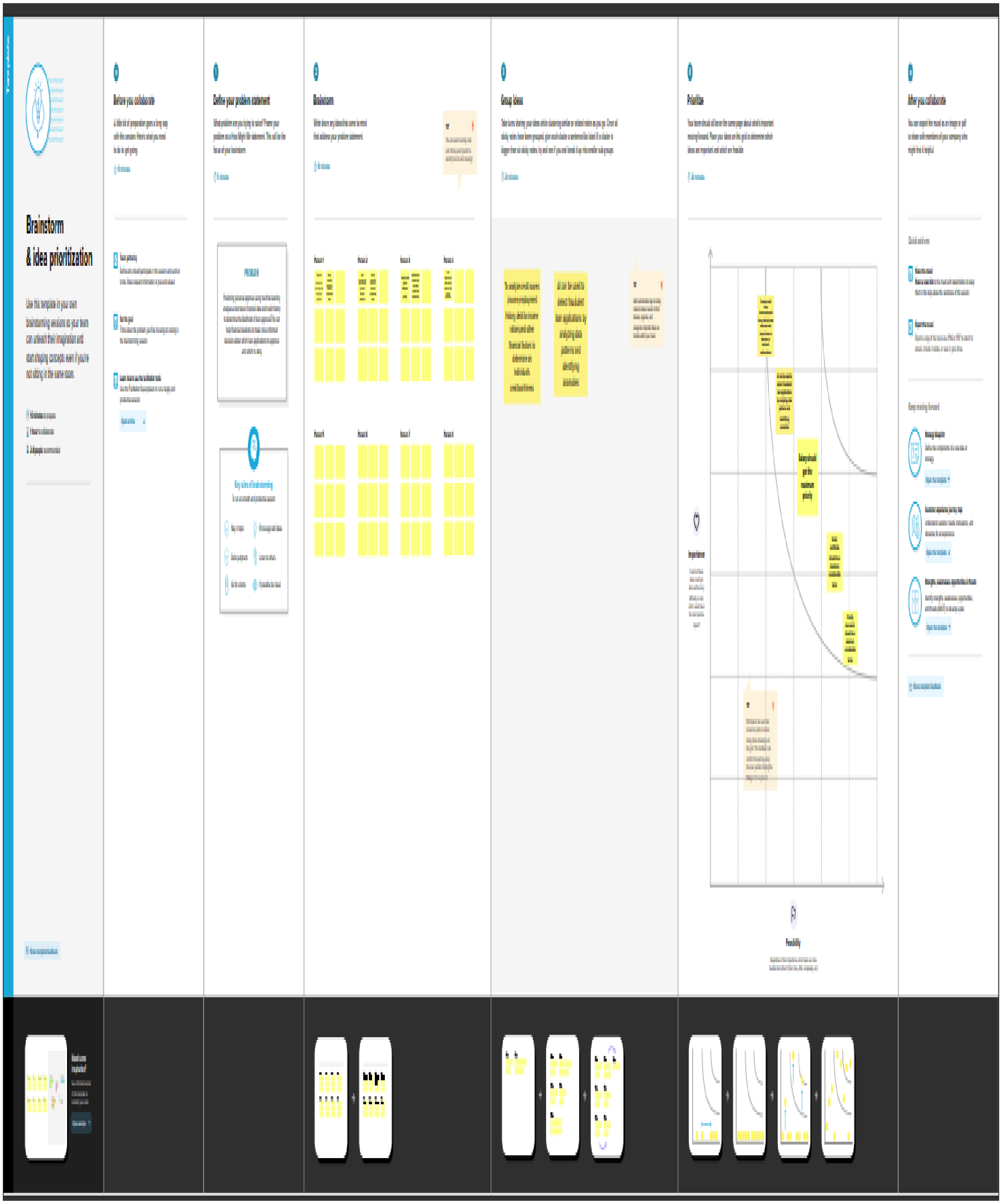
1.2 PURPOSE

It is done by predicting if the loan can be given to that person on the basis of various parameters like credit score, income, age, marital status, gender, etc. The prediction model not only helps the applicant but also **helps the bank by minimizing the risk and reducing the number of defaulters** .

2. PROBLEM DEFINITION AND DESIGN THINKING

2.1 EMPATHY MAP

2.2 IDEATION & BRAINSTORMING MAP



```
data = pd.read_csv('loan_prediction.csv')
data
```

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

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```
data.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
```

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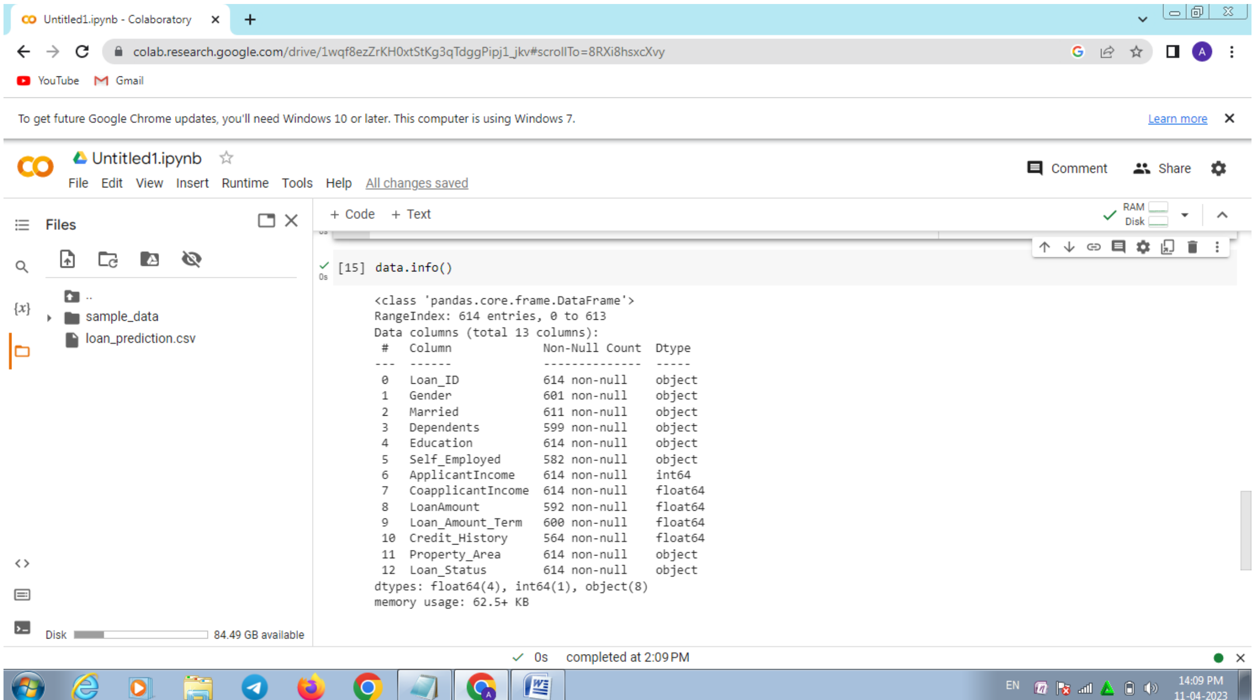
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colab.research.google.com/drive/1wqf8ezZrKH0xtStKg3qTdggPipj1_jkv#scrollTo=8RXi8hsxcXvy
YouTube
Gmail
To get future Google Chrome updates, you'll need Windows 10 or later. This computer is using Windows 7.
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RAM
Disk
sample_data
loan_prediction.csv
[15] data.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
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84.49 GB available
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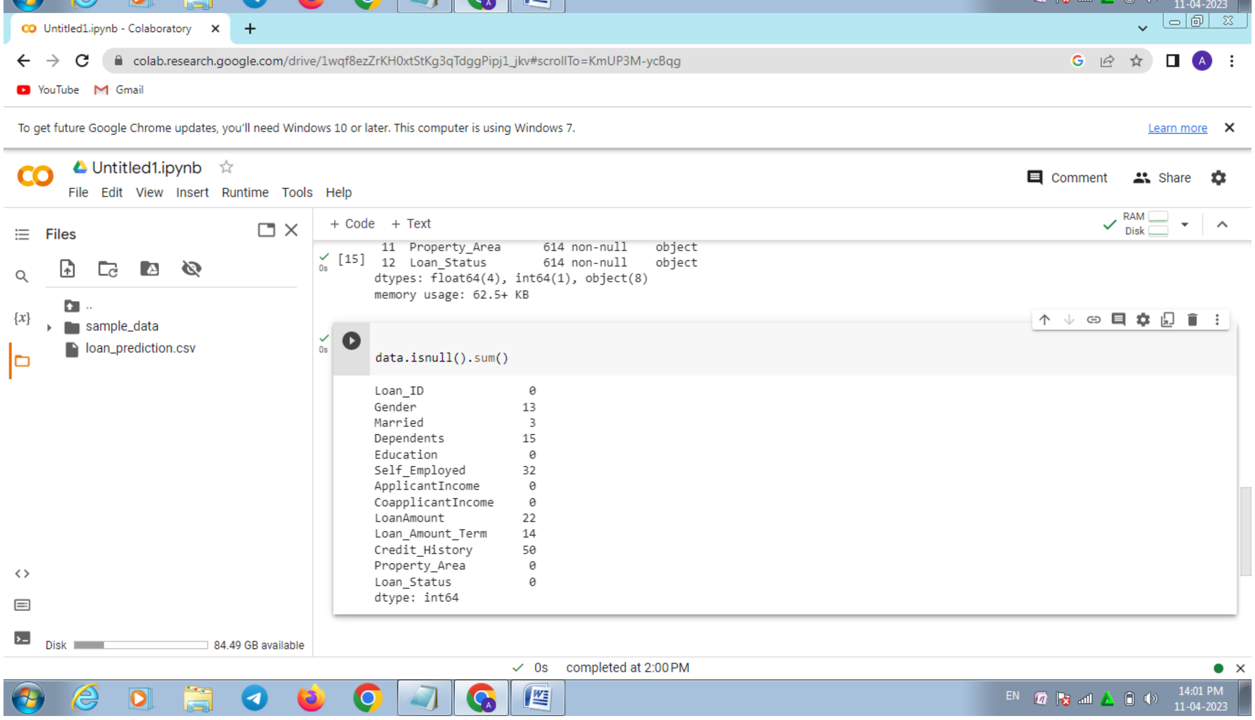
11-04-2023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YouTube
Gmail
To get future Google Chrome updates, you'll need Windows 10 or later. This computer is using Windows 7.
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RAM
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loan_prediction.csv
11 Property_Area 614 non-null object
[15] 12 Loan_Status 614 non-null object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
data.isnull().sum()
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
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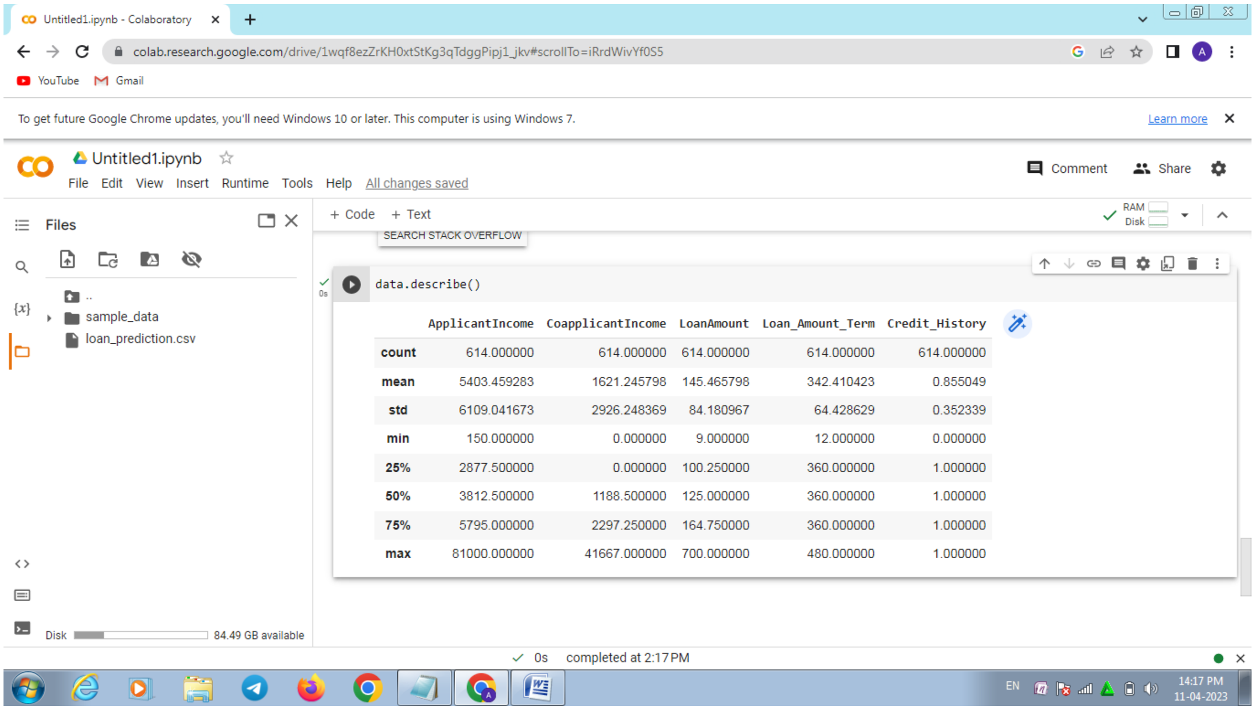
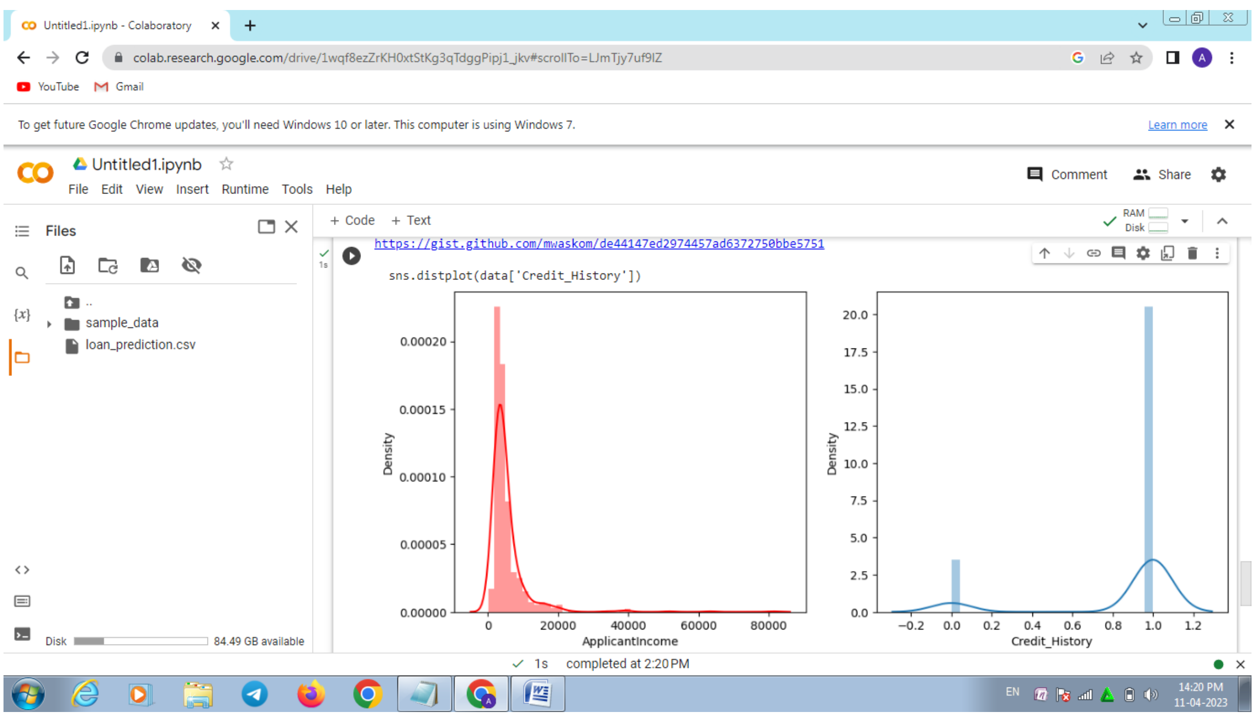


```
data.describe()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	145.465798	342.410423	0.855049
std	6109.041673	2926.248369	84.180967	64.428629	0.352339
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	125.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000



4. ADVANTAGES & DISADVANTAGES

- **ADVANTAGES**
  - Accuracy—one of the primary benefits of using machine learning for credit scoring is **its accuracy.**
  - Unlike human manual processing, ML-based models are automated and less likely to make mistakes.
  - This means that loan processing becomes not only faster but more accurate too

- **DISADVANTAGES**
  - It emphasize different weights to each factor but in real life sometime loan can be approved on the basis of single strong factor only, which is not possible through this system.
  - Loan Prediction is very helpful for employee of banks as well as for the applicant also.

5. APPLICATIONS

- In banking sector.
- Co-operate sectors which provides loans to their employees.
- An individual/applicant who wants to know about his capability of taking loans.

6. CONCLUSION

The system approved or rejects the loan applications. Recovery of loans is a major contributing parameter in the financial statements of a ban. It is very difficult to predict the possibility of payment of loan by the customer. Machine Learning (ML) techniques are very useful in predicting outcomes for large amount of data. In our project,three machine learning algorithms ,Logistics Regression(LR),Decision Tree(DT) and Random Forest(RF) are applied to predict the loan approval of customers. The experimental results conducts that the accuracy of Random Forest machine algorithm is better than compared to Logistic Regression and decision tree machine learning approaches.

7. FUTURE SCOPE

In near future this module of prediction can be integrate with the module of automated processing system. The system is trained on old training dataset in future software can be made such that new testing date should also take part in training data after some fix time.

8.APPENDIX

A. SOURCE CODE

```
import pandas as pd
import numpy as np
import pickle
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sklearn
from sklearn.tree import DecisionTreeClassifier ensemble
from.sklearn.ensemble import
GradientBoostingClassifier,RandomForestClassifier
from sklearn.neighbours import KNeighborsClassifier
from sklearn.model_selection import RandomizedSearchCV
import imblearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrices import
accurancy_score,classfication_report,confusion_matrix,f1_score


data = pd.read_csv('loan_prediction.csv')

data.info()

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'].fillna(data['Dependents'].mode()[0])
data['Dependents'] =
data['Dependents'].fillna(data['Dependents'].mode()[0])
data['Self_Employed'] =
data['Self_Employed'].fillna(data['Self_Employed'].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('int64')
data['Married'] = data['Married'].astype('int64')
data['Dependents'] = data['Dependents'].astype('int64')
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')

from imblearn.combine import SMOTETomek
smote = SMOTETomek(0.90)
y = data['Loan_Status']
x = data.drop(coiumns=['Loan_Status'],axis=1)
x_bal,y_bal = smote.fit_resample(x,y)
print(y.value_counts())
print(y_bal.value_counts())

data.describe()

plt.figure(figsize=(12.5))
plt.subplot(121)
sns.distplot(data['ApplicantIncome'],color='r)
plt.subplot(122)
sns.displot(data['credit_History'])
plt.show()


plt.figure(figsize=((18,24))
plt.subplot(1,4,1)
sns.countplot(data['Gender'])
plt.subplot(1,4,2)
sns.countplot(data['Education'])
plt.show()



plt.figure(figsize=(20,5))
plt.subplot(131)
sns.countplot(data['Married'], hue=data['Gender'])
plt.subplot(132)
sns.countplot(data['self_Employed'], hue=data['Education'])
plt.figure(figsize=((18,24))
plt.subplot(133)
sns.countplot(data['Property_Area'], hue=data['Loan_Amount_Term'])
```

```
sns.swarmplot(data['Gender'],data['ApplicantIncome'],
hue=data['Loan_Status'])



sc=StandardScalar()
x_bal=sc.fit_transform(x_bal)
x_bal pd.DataFrame(x_bal,columns=names)
x_train,x_test,y_train,y_test = train_test_split(
x_bal,y_bal,test_size=0.33,random_state=42)

def decisionTree(x_train,X_test,y_train,y_test)
dt=DecisionTreeClassifier()
dt.fit(x_train,y_train)
yPred = dt.predict(x_test)
print('***DecisionTreeClassifier***')
print('Confusion matrix')
print('confusion matrix(y_test,yPred))
print(Classification report')
print(classification_report(y_test,yPred))

def randomForest(x_train,x_test,y_train,y_test):
  rf = RondomForestClassifier()
  rf.fit(x_train,y_train)
  yPred = rf.predict(x_test)
  print('***RondomForestClassifier ***')
  print('Confusion matrix')
  print(confusion_matrix(y_test,yPred))
  print('Classification report')
  print(classification_report(y_test,yPred))

def KNN(x_train,x_test,y_train,y_test):
    knn = KNeighboursClassfier()
    knn.fit(x_train,y_train)
    yPred = knn.predict(x_test)
    print('***KNeighboursClassifier***')
    print('Confusion matrix')
    print(confusion_matrix(y_test,yPred))
    print('Classification report')
    print(classification_report(y_test,yPred))

def xgboost(x_train,x_test,y_train,y_test):
    xg= GradientBoostingClassfier()
    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))

import tensortflow
from tensortflow.keras.models import sequential
from tensortflow.keras.layers import Dense
```

```
classifier = Sequential()

Classifier.add(Dence(units=100,activation='relu',input_dim=11))

classifier.add (Dence(units=50,activation='relu')

classifier.add (Dence(units=1,activation='sigmoid')

classifier.compile(optimizer='adam',loss='binary_crossentropy',matrices=['
accurancy'])

model_history =
classifier.fit(x_train,y_train,batch_size=100,validation_split=0.2,epochs=
100)

dtr.predict([[1,1,0,1,1,4276,1542,145,240,0,1]])

rfr.predict([[1,1,0,1,1,4276,1542,145,240,0,1]])
knn.predict([[1,1,0,1,1,4276,1542,145,240,0,1]])
xgb.predict([[1,1,0,1,1,4276,1542,145,240,0,1]])
_
classfier.save("loan.h5)
y_pred = classifier.predict(x_test)
[237] y_pred
[238] y_pred = (y_pred > 0.5)
      y_pred

[244] def predict_exit(sample_value):
sample_value = np.array(sample_value)
sample_value=sample_value.reshape(1,-1)
sample_value = sc.transform(sample_value)

return classifier.predict(sample_value)
sample_value = [[1,1,0,1,1,4276,1542,145,240,0,1]]
if predict_exit(sample_value)>0.5:
  print('Prediction: High chance of loan Approval!')
  else:
   print('Prediction: Low chance of loan Approval.')

sample_value = [[1,1,0,1,1,4276,1542,145,240,0,1]]
if predict_exit(sample_value)>0.5:
  print('Prediction: High chance of loan Approval!')
  else:
   print('Prediction: Low chance of loan Approval.')
 def  compareModel(x_train,x_test,y_train,y_test):
 decisionTree(x_train,x_test,y_train,y_test)
print('_'*100)
RandomForest(x_train,x_test,y_train,y_test)
print('_'*100)
XGB(x_train,x_test,y_train,y_test)
print('_'*100)
KNN(x_train,x_test,y_train,y_test)
```

```
print('_'*100)


compareModel(x_train,x_test,y_train,y_test)

 yPred = classifier.predict(x_test)
    print(accurancy_score(y_pred,y_test)
    print("ANN Model")
    print('Confusion matrix')
    print(confusion_matrix(y_test,yPred))
    print('Classification report')
    print(classification_report(y_test,yPred))

rf = RandomForestClassifier()
rf.fit(x_train,y_train)
ypred = rf.predict(x_test)
f1_score(yPred,y_test,average='weighted')
cv = cross_val_score(rf,x,y,cv=5)
np.mean(cv)

pickle.dump(model,open('rdf.pk1','wb'))

from flask import Flask,render_template,request
import numpy as np
import pickle

app = Flask(_name_)
model = pickle.load(open(r'rdf.pkl','rb'))
scale = pickle.load(open(r'scale.pkl','rb'))

@app.route('/')
def home():
 return render_template('home.html')

@app.route('/submit',methods=["POST","GET"])
def submit():
# reading the inputs given by the user
input_feature=[int(x) for x in request.form.values() ]
#input_feature = np.transponse(input_feature)
input_feature=[np.array(input_feature) ]
print(input_feature)
names =
['Gender','Married','Dependents','Education','Self_Employed',ApplicantInco
me','CoapplicantIncome','LoadAmount_Term','Credit_History','Property_Area'
]
data = pandas.DataFrame(input_feature,column=names)
print(data)
#data_scaled = scale_fit_transform(data)
#data = pandas.DataFrame(,columns=names)

#predictions using the loaded  model file
prediction=model.predict(data)
print(prediction)
prediction = int(prediction)
```

```
print(type(prediction))

if(prediction == 0):
  return render_template("output.html"result ="Loan will Not be Apporved")
 else:
   return render_template("output.html"result ="Loan will Not be
Apporved")
#showing the prediction results in a UI

if__name__=="__main__" :
 # app.run(host='0.0.0.0',port=8000,debug=True)   #running the app
 port=int(Os.environ.get(PORT',5000))
 app.run(debug=False)
```