Importing Dependencies import pandas as pd data = pd.read csv('/content/train u6lujuX CVtuZ9i (1).csv') # Loan_ID : Unique Loan ID # Gender : Male/ Female # Married : Applicant married (Y/N) # Dependents : Number of dependents # Education : Applicant Education (Graduate/ Under Graduate) # Self_Employed : Self employed (Y/N) # ApplicantIncome : Applicant income

ApplicantIncome : Applicant income

CoapplicantIncome : Coapplicant income

LoanAmount : Loan amount in thousands of dollars

Loan_Amount_Term : Term of loan in months

Credit_History : Credit history meets guidelines yes or no

Property_Area : Urban/ Semi Urban/ Rural

Loan_Status : Loan approved (Y/N) this is the target variable

1. Displaying Top 5 rows in the Dataset

data.head()

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cred
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	

2.Displaying last 5 rows in the Dataset

data.tail()

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cr
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	
4											•

3. Find Shape of Our Dataset (Number of Rows And Number of Columns)

```
data.shape
     (614, 13)

print('No of Rows :', data.shape[0])
print('No of Columns :', data.shape[1])

    No of Rows : 614
    No of Columns : 13
```

4. Get Information About Our Dataset Like Total Number Rows, Total Number of Columns, Datatypes of Each Column And Memory Requirement

```
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
dtyp	es: float64(4), int	64(1), object(8)	

memory usage: 62.5+ KB

5. Check Null Values In The Dataset

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	

Getting %age of Null values in each columns data.isnull().sum()*100/ len(data)

```
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
```

6. Handling The missing Values

```
# Droping Loan_ID as it is not relevent
data = data.drop('Loan_ID',axis=1)
data.head(1)
```

ApplicantIncome

LoanAmount

CoapplicantIncome

Loan_Amount_Term

Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term Credit_History

Male No 0 Graduate No 5849 0.0 NaN 360.0 1.0

0.000000

0.000000

0.000000

0.000000

```
Credit_History
                          8.679928
                          0.000000
     Property Area
                          0.000000
     Loan Status
     dtype: float64
data['Self_Employed'].mode()[0]
     'No'
data['Self_Employed'] =data['Self_Employed'].fillna(data['Self_Employed'].mode()[0])
data.isnull().sum()*100/len(data)
                          0.000000
     Gender
     Married
                          0.000000
                          0.000000
     Dependents
                          0.000000
     Education
     Self_Employed
                          0.000000
     ApplicantIncome
                          0.000000
                          0.000000
     CoapplicantIncome
     LoanAmount
                          0.000000
     Loan_Amount_Term
                          0.000000
     Credit_History
                          8.679928
                          0.000000
     Property_Area
     Loan_Status
                          0.000000
     dtype: float64
data['Gender'].unique()
     array(['Male', 'Female'], dtype=object)
data['Self_Employed'].unique()
     array(['No', 'Yes'], dtype=object)
data['Credit_History'].unique()
     array([ 1., 0., nan])
data['Credit_History'].mode()[0]
     1.0
```

```
data.isnull().sum()*100 / len(data)
                          0.0
     Gender
     Married
                          0.0
     Dependents
                          0.0
     Education
                          0.0
     Self_Employed
                          0.0
     ApplicantIncome
                          0.0
     CoapplicantIncome
                          0.0
     LoanAmount
                          0.0
     Loan_Amount_Term
                          0.0
     Credit_History
                          0.0
     Property_Area
                          0.0
     Loan Status
                          0.0
     dtype: float64
```

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

7. Handling Categorical Columns

data.sample(5)

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_Histo
191	Male	No	0	Graduate	No	12000	0.0	164.0	360.0	,
440	Male	No	0	Graduate	No	3660	5064.0	187.0	360.0	
542	Female	No	1	Graduate	No	3652	0.0	95.0	360.0	
241	Male	Yes	1	Not Graduate	No	2510	1983.0	140.0	180.0	,
582	Female	Yes	0	Graduate	No	3166	0.0	36.0	360.0	
4										•

```
data['Dependents'] =data['Dependents'].replace(to_replace="3+",value='4')

data['Dependents'].unique()

array(['1', '0', '2', '4'], dtype=object)

data['Loan_Status'].unique()
```

```
data['Gender'] = data['Gender'].map({'Male':1,'Female':0}).astype('int')
data['Married'] = data['Married'].map({'Yes':1,'No':0}).astype('int')
data['Education'] = data['Education'].map({'Graduate':1,'Not Graduate':0}).astype('int')
data['Self_Employed'] = data['Self_Employed'].map({'Yes':1,'No':0}).astype('int')
data['Property_Area'] = data['Property_Area'].map({'Rural':0,'Semiurban':2,'Urban':1}).astype('int')
data['Loan_Status'] = data['Loan_Status'].map({'Y':1,'N':0}).astype('int')
```

data.head()

array(['N', 'Y'], dtype=object)

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
1	1	1	1	1	0	4583	1508.0	128.0	360.0	1.0
2	1	1	0	1	1	3000	0.0	66.0	360.0	1.0
3	1	1	0	0	0	2583	2358.0	120.0	360.0	1.0
4	1	0	0	1	0	6000	0.0	141.0	360.0	1.0
5	1	1	2	1	1	5417	4196.0	267.0	360.0	1.0
4										>

8. Store Feature Matrix In X And Response (Target) In Vector y

```
X = data.drop('Loan_Status',axis=1)

y = data['Loan_Status']

y

1 0
```

1 1 1

9. Feature Scaling

data.head()

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
1	1	1	1	1	0	4583	1508.0	128.0	360.0	1.0
2	1	1	0	1	1	3000	0.0	66.0	360.0	1.0
3	1	1	0	0	0	2583	2358.0	120.0	360.0	1.0
4	1	0	0	1	0	6000	0.0	141.0	360.0	1.0
5	1	1	2	1	1	5417	4196.0	267.0	360.0	1.0
4										•

```
cols = ['ApplicantIncome','CoapplicantIncome','Loan_Amount_Term']
```

```
from sklearn.preprocessing import StandardScaler
st = StandardScaler()
X[cols]=st.fit_transform(X[cols])
```

		Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_Histo			
	1	1	1	1	1	0	-0.128694	-0.049699	-0.214368	0.279961	,			
	2	1	1	0	1	1	-0.394296	-0.545638	-0.952675	0.279961	,			
	3	1	1	0	0	0	-0.464262	0.229842	-0.309634	0.279961	,			
	4	1	0	0	1	0	0.109057	-0.545638	-0.059562	0.279961	,			
	5	1	1	2	1	1	0.011239	0.834309	1.440866	0.279961	,			
from from	10. Splitting The Dataset Into The Training Set And Test Set & Applying K-Fold Cross Validation from sklearn.model_selection import train_test_split from sklearn.model_selection import cross_val_score from sklearn.metrics import accuracy_score													
	t num	py as np	•	,_										
	613	U	U	U	Т	1	-0.128694	-U.545b38	-0.154828	0.279961	ι			
def m X m y p	<pre>model_df={} def model_val(model,X,y):</pre>													
model	_df {}													

11. Logistic Regression

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model_val(model,X,y)
```

```
LogisticRegression() accuracy is 0.8018018018018
     LogisticRegression() Avg cross val score is 0.8047829647829647
  12. SVC
from sklearn import svm
model = svm.SVC()
model val(model,X,y)
     SVC() accuracy is 0.7927927927928
     SVC() Avg cross val score is 0.7938902538902539
  13. Decision Tree Classifier
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model val(model,X,y)
     DecisionTreeClassifier() accuracy is 0.7477477477477478
     DecisionTreeClassifier() Avg cross val score is 0.7106797706797707
  14. Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
model =RandomForestClassifier()
model_val(model,X,y)
     RandomForestClassifier() accuracy is 0.7747747747747747
     RandomForestClassifier() Avg cross val score is 0.7848484848484848
  15. Gradient Boosting Classifier
from sklearn.ensemble import GradientBoostingClassifier
model =GradientBoostingClassifier()
model_val(model,X,y)
     GradientBoostingClassifier() accuracy is 0.7927927927927928
     GradientBoostingClassifier() Avg cross val score is 0.7721539721539721
```

16. Hyperparameter Tuning

```
from sklearn.model selection import RandomizedSearchCV
Logistic Regression
log_reg_grid= {"C": np.logspace(-4,4,20),
               "solver":['liblinear']}
rs_log_reg=RandomizedSearchCV(LogisticRegression(),
                   param_distributions=log_reg_grid,
                  n_iter=20,cv=5,verbose=True)
rs_log_reg.fit(X,y)
     Fitting 5 folds for each of 20 candidates, totalling 100 fits
             RandomizedSearchCV
      ▶ estimator: LogisticRegression
            ▶ LogisticRegression
rs_log_reg.best_score_
     0.8047829647829647
rs_log_reg.best_params_
     {'solver': 'liblinear', 'C': 0.23357214690901212}
SVC
svc_grid = {'C':[0.25,0.50,0.75,1],"kernel":["linear"]}
rs svc=RandomizedSearchCV(svm.SVC(),
                  param_distributions=svc_grid,
                   cv=5,
```

```
n_iter=20,
                  verbose=True)
rs_svc.fit(X,y)
     /usr/local/lib/python3.8/dist-packages/sklearn/model selection/ search.py:305: UserWarning: The total space of parameters 4 is smaller th
       warnings.warn(
     Fitting 5 folds for each of 4 candidates, totalling 20 fits
       ► RandomizedSearchCV
        ▶ estimator: SVC
              ► SVC
rs_svc.best_score_
     0.8066011466011467
rs svc.best params
     {'kernel': 'linear', 'C': 0.25}
Random Forest Classifier
RandomForestClassifier()
      ▼ RandomForestClassifier
     RandomForestClassifier()
rf_grid={'n_estimators':np.arange(10,1000,10),
  'max_features':['auto','sqrt'],
 'max_depth':[None,3,5,10,20,30],
 'min_samples_split':[2,5,20,50,100],
 'min_samples_leaf':[1,2,5,10]
rs_rf=RandomizedSearchCV(RandomForestClassifier(),
                  param distributions=rf grid,
                   cv=5,
```

n_iter=20,
verbose=True)

rs_rf.fit(X,y)

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
  warn(
/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/ forest.py:424: FutureWarning: `max fe
```

```
rs rf.best score
    0.8066175266175266
    /USI//IOCAI/IID/python3.8/UISt-packageS/Skiedrh/enSemble/ ToreSt.py:424: Futurewarning: max Te
rs rf.best params
    {'n estimators': 760,
     'min samples split': 20,
     'min samples leaf': 1,
     'max features': 'sqrt',
     'max depth': 5}
    / USI / TOCAT/ TID/ PYCHOHO.O/ UTSC-PACKAGES/ SKIEALH/EHSEMBIE/ _ FOLESC.PY.424. FUCULEWALHING. HAA_ FE
LogisticRegression score Before Hyperparameter Tuning: 80.48
LogisticRegression score after Hyperparameter Tuning: 80.48
SVC score Before Hyperparameter Tuning: 79.38
SVC score after Hyperparameter Tuning: 80.66
RandomForestClassifier score Before Hyperparameter Tuning: 77.76
RandomForestClassifier score after Hyperparameter Tuning: 80.66
    /USI//IOCAI/IID/pythons.o/UISt-packageS/Skiedrh/ensembie/ ToreSt.py.424. Futurewarniing. max re
Save Model
           X = data.drop('Loan_Status',axis=1)
y = data['Loan Status']
           rf = RandomForestClassifier(n estimators=270,
 min samples split=5,
 min samples leaf=5,
 max features='sqrt',
 max depth=5)
         D | E | (6) | (6)
rf.fit(X,y)
```

warn(

```
RandomForestClassifier
import joblib
joblib.dump(rf,'loan_status_predict')
     ['loan status predict']
model = joblib.load('loan_status_predict')
import pandas as pd
df = pd.DataFrame({
    'Gender':1,
    'Married':1,
    'Dependents':2,
    'Education':0,
    'Self_Employed':0,
    'ApplicantIncome':2889,
    'CoapplicantIncome':0.0,
    'LoanAmount':45,
    'Loan_Amount_Term':180,
    'Credit_History':0,
    'Property Area':1
},index=[0])
df
```

Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term Credit_History

1 1 2 0 0 2889 0.0 45 180 0

result = model.predict(df)

if result==1:
 print("Loan Approved")

else:
 print("Loan Not Approved")

 Loan Not Approved

```
from tkinter import *
import joblib
import pandas as pd
def show_entry():
    p1 = float(e1.get())
    p2 = float(e2.get())
    p3 = float(e3.get())
    p4 = float(e4.get())
    p5 = float(e5.get())
    p6 = float(e6.get())
    p7 = float(e7.get())
    p8 = float(e8.get())
    p9 = float(e9.get())
    p10 = float(e10.get())
    p11 = float(e11.get())
    model = joblib.load('loan status predict')
    df = pd.DataFrame({
    'Gender':p1,
    'Married':p2,
    'Dependents':p3,
    'Education':p4,
    'Self Employed':p5,
    'ApplicantIncome':p6,
    'CoapplicantIncome':p7,
    'LoanAmount':p8,
    'Loan_Amount_Term':p9,
    'Credit_History':p10,
    'Property_Area':p11
},index=[0])
    result = model.predict(df)
    if result == 1:
        Label(master, text="Loan approved").grid(row=31)
    else:
        Label(master, text="Loan Not Approved").grid(row=31)
master =Tk()
master.title("Loan Status Prediction Using Machine Learning")
label = Label(master,text = "Loan Status Prediction",bg = "black",
               fg = "white").grid(row=0,columnspan=2)
```

```
Label(master,text = "Gender [1:Male ,0:Female]").grid(row=1)
Label(master,text = "Married [1:Yes,0:No]").grid(row=2)
Label(master,text = "Dependents [1,2,3,4]").grid(row=3)
Label(master,text = "Education").grid(row=4)
Label(master,text = "Self Employed").grid(row=5)
Label(master,text = "ApplicantIncome").grid(row=6)
Label(master,text = "CoapplicantIncome").grid(row=7)
Label(master,text = "LoanAmount").grid(row=8)
Label(master,text = "Loan Amount Term").grid(row=9)
Label(master,text = "Credit History").grid(row=10)
Label(master,text = "Property Area").grid(row=11)
e1 = Entry(master)
e2 = Entry(master)
e3 = Entry(master)
e4 = Entry(master)
e5 = Entry(master)
e6 = Entry(master)
e7 = Entry(master)
e8 = Entry(master)
e9 = Entry(master)
e10 = Entry(master)
e11 = Entry(master)
e1.grid(row=1,column=1)
e2.grid(row=2,column=1)
e3.grid(row=3,column=1)
e4.grid(row=4,column=1)
e5.grid(row=5,column=1)
e6.grid(row=6,column=1)
e7.grid(row=7,column=1)
e8.grid(row=8,column=1)
e9.grid(row=9,column=1)
e10.grid(row=10,column=1)
e11.grid(row=11,column=1)
Button(master,text="Predict",command=show entry).grid()
mainloop()
```

```
TclError
                                          Traceback (most recent call last)
<ipython-input-75-5a835c3cf813> in <module>
    35
    36
---> 37 master =Tk()
    38 master.title("Loan Status Prediction Using Machine Learning")
    39 label = Label(master,text = "Loan Status Prediction",bg = "black",
/usr/lib/python3.8/tkinter/__init__.py in __init__(self, screenName, baseName, className, useTk, sync, use)
   2268
                        baseName = baseName + ext
   2269
               interactive = 0
               self.tk = _tkinter.create(screenName, baseName, className, interactive, wantobjects, useTk, sync, use)
-> 2270
               if useTk:
   2271
  2272
                    self. loadtk()
```

TclFrror: no display name and no \$DTSPLAY environment variable

OLANOITOTAON OVENTEON