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PREDICT LOAN APPROVAL WITH MACHINE LEARNING



```
In [1]: import pandas as pd
```

```
In [2]: data = pd.read_csv('loan_prediction.csv')
```

```
In [3]: # 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  
# 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. Display Top 5 Rows of The Dataset

In [4]: `data.head()`

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
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	

2. Check Last 5 Rows of The Dataset

In [5]: `data.tail()`

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
609	LP002978	Female	No	0	Graduate	No	2900	0.0	
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	

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

In [6]: `data.shape`

Out[6]: `(614, 13)`

In [7]: `print("Number of Rows", data.shape[0])
print("Number of Columns", data.shape[1])`

```
Number of Rows 614  
Number of Columns 13
```

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

In [8]: `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
```

5. Check Null Values In The Dataset

```
In [9]: data.isnull().sum()
```

```
Out[9]:
```

Loan_ID	0
Gender	13
Married	3
Dependents	15
Education	0
Self_Employed	32
ApplicantIncome	0
CoapplicantIncome	0
LoanAmount	22
Loan_Amount_Term	14
Credit_History	50
Property_Area	0
Loan_Status	0

dtype: int64

```
In [10]: data.isnull().sum()*100 / len(data)
```

```
Out[10]:
```

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

```
In [11]: data = data.drop('Loan_ID', axis=1)
```

```
In [12]: data.head(1)
```

```
Out[12]:
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount
0	Male	No	0	Graduate		No	5849	0.0

```
In [13]: columns = ['Gender', 'Dependents', 'LoanAmount', 'Loan_Amount_Term']
```

```
In [14]: data = data.dropna(subset=columns)
```

```
In [15]: data.isnull().sum()*100 / len(data)
```

```
Out[15]: Gender          0.000000  
Married          0.000000  
Dependents       0.000000  
Education         0.000000  
Self_Employed    5.424955  
ApplicantIncome   0.000000  
CoapplicantIncome 0.000000  
LoanAmount        0.000000  
Loan_Amount_Term 0.000000  
Credit_History    8.679928  
Property_Area     0.000000  
Loan_Status        0.000000  
dtype: float64
```

```
In [16]: data['Self_Employed'].mode()[0]
```

```
Out[16]: 'No'
```

```
In [17]: data['Self_Employed'] = data['Self_Employed'].fillna(data['Self_Employed'].mode()[0])
```

```
In [18]: data.isnull().sum()*100 / len(data)
```

```
Out[18]: Gender          0.000000  
Married          0.000000  
Dependents       0.000000  
Education         0.000000  
Self_Employed    0.000000  
ApplicantIncome   0.000000  
CoapplicantIncome 0.000000  
LoanAmount        0.000000  
Loan_Amount_Term 0.000000  
Credit_History    8.679928  
Property_Area     0.000000  
Loan_Status        0.000000  
dtype: float64
```

```
In [19]: data['Gender'].unique()
```

```
Out[19]: array(['Male', 'Female'], dtype=object)
```

```
In [20]: data['Self_Employed'].unique()
```

```
Out[20]: array(['No', 'Yes'], dtype=object)
```

```
In [21]: data['Credit_History'].mode()[0]
```

```
Out[21]: 1.0
```

```
In [22]: data['Credit_History'] = data['Credit_History'].fillna(data['Credit_History'].mode()[0])
```

```
In [23]: data.isnull().sum()*100 / len(data)
```

```
Out[23]: Gender          0.0  
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
```

7. Handling Categorical Columns

```
In [24]: data.sample(5)
```

```
Out[24]:   Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome LoanAmou  
 244    Male     Yes         0  Not Graduate        No           3406          4417.0      123  
 155    Male     Yes        3+  Graduate        No           39999            0.0      600  
 502    Male     Yes         2  Graduate        No           4865          5624.0      208  
 161    Male     Yes         0  Graduate        No           7933            0.0      275  
 329  Female    No         0  Graduate        No           2500            0.0      67
```

```
In [25]: data['Dependents'] = data['Dependents'].replace(to_replace="3+", value='4')
```

```
In [26]: data['Dependents'].unique()
```

```
Out[26]: array(['1', '0', '2', '4'], dtype=object)
```

```
In [27]: data['Loan_Status'].unique()
```

```
Out[27]: array(['N', 'Y'], dtype=object)
```

```
In [28]: 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}).a  
data['Loan_Status'] = data['Loan_Status'].map({'Y':1, 'N':0}).astype('int')
```

```
In [33]: data.head()
```

```
Out[33]:   Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome LoanAmount  
 1        1       1         1         1          0           4583          1508.0      128.0  
 2        1       1         0         1          1           3000            0.0      66.0  
 3        1       1         0         0          0           2583          2358.0      120.0  
 4        1       0         0         1          0           6000            0.0      141.0  
 5        1       1         2         1          1           5417          4196.0      267.0
```

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

```
In [34]: X = data.drop('Loan_Status', axis=1)
```

```
In [36]: y = data['Loan_Status']
```

```
In [37]: y
```

```
Out[37]: 1      0  
2      1  
3      1
```

```
4      1
5      1
...
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 553, dtype: int32
```

9. Feature Scaling

```
In [38]: data.head()
```

```
Out[38]:
```

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

```
In [39]: cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term']
```

```
In [41]: from sklearn.preprocessing import StandardScaler
st = StandardScaler()
X[cols]=st.fit_transform(X[cols])
```

```
In [42]: X
```

```
Out[42]:
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmou
1	1	1	1	1	0	-0.128694	-0.049699	-0.2143
2	1	1	0	1	1	-0.394296	-0.545638	-0.9526
3	1	1	0	0	0	-0.464262	0.229842	-0.3096
4	1	0	0	1	0	0.109057	-0.545638	-0.0595
5	1	1	2	1	1	0.011239	0.834309	1.4408
...
609	0	0	0	1	0	-0.411075	-0.545638	-0.8931
610	1	1	4	1	0	-0.208727	-0.545638	-1.2622
611	1	1	1	1	0	0.456706	-0.466709	1.2741
612	1	1	2	1	0	0.374659	-0.545638	0.4882
613	0	0	0	1	1	-0.128694	-0.545638	-0.1548

553 rows × 11 columns

10. Splitting The Dataset Into The Training Set And Test Set & Applying K-Fold Cross Validation

```
In [46]: from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
```

```
from sklearn.metrics import accuracy_score
import numpy as np

In [47]: model_df={}
def model_val(model,X,y):
    X_train,X_test,y_train,y_test=train_test_split(X,y,
                                                    test_size=0.20,
                                                    random_state=42)
    model.fit(X_train,y_train)
    y_pred=model.predict(X_test)
    print(f"{model} accuracy is {accuracy_score(y_test,y_pred)}")

    score = cross_val_score(model,X,y,cv=5)
    print(f"{model} Avg cross val score is {np.mean(score)}")
    model_df[model]=round(np.mean(score)*100,2)
```

```
In [58]: model_df
```

```
Out[58]: {LogisticRegression(): 80.48,
          SVC(): 79.39,
          DecisionTreeClassifier(): 70.89,
          RandomForestClassifier(): 77.76,
          GradientBoostingClassifier(): 77.4}
```

11. Logistic Regression

```
In [49]: from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model_val(model,X,y)

LogisticRegression() accuracy is 0.8018018018018018
LogisticRegression() Avg cross val score is 0.8047829647829647
```

12. SVC

```
In [51]: from sklearn import svm
model = svm.SVC()
model_val(model,X,y)

SVC() accuracy is 0.7927927927927928
SVC() Avg cross val score is 0.7938902538902539
```

13. Decision Tree Classifier

```
In [53]: from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model_val(model,X,y)

DecisionTreeClassifier() accuracy is 0.7117117117117117
DecisionTreeClassifier() Avg cross val score is 0.7089434889434889
```

14. Random Forest Classifier

```
In [55]: from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model_val(model,X,y)

RandomForestClassifier() accuracy is 0.7567567567567568
RandomForestClassifier() Avg cross val score is 0.7776412776412777
```

15. Gradient Boosting Classifier

```
In [57]: from sklearn.ensemble import GradientBoostingClassifier  
model =GradientBoostingClassifier()  
model_val(model,X,y)  
  
GradientBoostingClassifier() accuracy is 0.7927927927927928  
GradientBoostingClassifier() Avg cross val score is 0.774004914004914
```

In []:

16. Hyperparameter Tuning

```
In [59]: from sklearn.model_selection import RandomizedSearchCV
```

Logistic Regression

```
In [60]: log_reg_grid={"C":np.logspace(-4,4,20),  
                  "solver":['liblinear']}
```

```
In [61]: rs_log_reg=RandomizedSearchCV(LogisticRegression(),  
                                     param_distributions=log_reg_grid,  
                                     n_iter=20, cv=5, verbose=True)
```

```
In [62]: rs_log_reg.fit(X,y)
```

Fitting 5 folds for each of 20 candidates, totalling 100 fits

```
Out[62]: RandomizedSearchCV(cv=5, estimator=LogisticRegression(), n_iter=20,  
                           param_distributions={'C': array([1.00000000e-04, 2.63665090e-04, 6.95  
                           192796e-04, 1.83298071e-03,  
                           4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,  
                           2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,  
                           1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,  
                           5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),  
                           'solver': ['liblinear']},  
                           verbose=True)
```

```
In [63]: rs_log_reg.best_score_
```

```
Out[63]: 0.8047829647829647
```

```
In [64]: rs_log_reg.best_params_
```

```
Out[64]: {'solver': 'liblinear', 'C': 0.23357214690901212}
```

SVC

```
In [65]: svc_grid = {'C':[0.25,0.50,0.75,1], "kernel":["linear"]}
```

```
In [66]: rs_svc=RandomizedSearchCV(svm.SVC(),  
                               param_distributions=svc_grid,  
                               cv=5,  
                               n_iter=20,  
                               verbose=True)
```

```
In [67]: rs_svc.fit(X,y)
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:296: UserWarning: Found no available metrics. Using 'accuracy' as default metric.

```
arning: The total space of parameters 4 is smaller than n_iter=20. Running 4 iterations.  
For exhaustive searches, use GridSearchCV.
```

```
UserWarning,
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
```

```
Out[67]: RandomizedSearchCV(cv=5, estimator=SVC(), n_iter=20,  
                           param_distributions={'C': [0.25, 0.5, 0.75, 1],  
                           'kernel': ['linear']},  
                           verbose=True)
```

```
In [68]: rs_svc.best_score_
```

```
Out[68]: 0.8066011466011467
```

```
In [69]: rs_svc.best_params_
```

```
Out[69]: {'kernel': 'linear', 'C': 0.25}
```

Random Forest Classifier

```
In [ ]: RandomForestClassifier()
```

```
In [73]: 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]  
            }
```

```
In [74]: rs_rf=RandomizedSearchCV(RandomForestClassifier(),  
                               param_distributions=rf_grid,  
                               cv=5,  
                               n_iter=20,  
                               verbose=True)
```

```
In [76]: rs_rf.fit(X,y)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
Out[76]: RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=20,  
                           param_distributions={'max_depth': [None, 3, 5, 10, 20, 30],  
                           'max_features': ['auto', 'sqrt'],  
                           'min_samples_leaf': [1, 2, 5, 10],  
                           'min_samples_split': [2, 5, 20, 50,  
                           100],  
                           'n_estimators': array([ 10,  20,  30,  40,  50,  
                           60,  70,  80,  90, 100, 110, 120, 130,  
                           140, 150, 160, 170, 180, 190, 200, 210, 220, 230, 240, 250, 260,  
                           270, 280, 290, 300, 310, 320, 330, 340, 350, 360, 370, 380, 390,  
                           400, 410, 420, 430, 440, 450, 460, 470, 480, 490, 500, 510, 520,  
                           530, 540, 550, 560, 570, 580, 590, 600, 610, 620, 630, 640, 650,  
                           660, 670, 680, 690, 700, 710, 720, 730, 740, 750, 760, 770, 780,  
                           790, 800, 810, 820, 830, 840, 850, 860, 870, 880, 890, 900, 910,  
                           920, 930, 940, 950, 960, 970, 980, 990])},  
                           verbose=True)
```

```
In [78]: rs_rf.best_score_
```

```
Out[78]: 0.8066011466011467
```

```
In [79]: rs_rf.best_params_
```

```
Out[79]: {'n_estimators': 270,  
          'min_samples_split': 5,
```

```
'min_samples_leaf': 5,  
'max_features': 'sqrt',  
'max_depth': 5}
```

```
In [ ]: 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
```

17. Save The Model

```
In [80]: X = data.drop('Loan_Status', axis=1)  
y = data['Loan_Status']
```

```
In [84]: rf = RandomForestClassifier(n_estimators=270,  
                               min_samples_split=5,  
                               min_samples_leaf=5,  
                               max_features='sqrt',  
                               max_depth=5)
```

```
In [85]: rf.fit(X,y)
```

```
Out[85]: RandomForestClassifier(max_depth=5, max_features='sqrt', min_samples_leaf=5,  
                               min_samples_split=5, n_estimators=270)
```

```
In [86]: import joblib
```

```
In [87]: joblib.dump(rf, 'loan_status_predict')
```

```
Out[87]: ['loan_status_predict']
```

```
In [88]: model = joblib.load('loan_status_predict')
```

```
In [89]: 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])
```

```
In [90]: df
```

```
Out[90]:   Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  CoapplicantIncome  LoanAmount  
0         1        1           1            2            0                 0             2889                  0.0            45
```

```
In [92]: result = model.predict(df)
```

In [93]:

```
if result==1:  
    print("Loan Approved")  
else:  
    print("Loan Not Approved")
```

Loan Not Approved

GUI

In [94]:

```
from tkinter import *  
import joblib  
import pandas as pd
```

In []:

```
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()
```

In []: