

```
# importing the required libraries
import pandas as pd
import numpy as np
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
%matplotlib inline

#CHECKING VERSION OF SKLEARN
print(sklearn.__version__)

0.22.2.post1

#loading the preprocessed dataset
data=pd.read_csv("/content/Loan_Prediction_New_Data.csv")

data.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001002	0.0	0.0	0.000000	1.0	0.0	0.0704
1	LP001003	0.0	1.0	0.333333	1.0	0.0	0.0548
2	LP001005	0.0	1.0	0.000000	1.0	1.0	0.0352
3	LP001006	0.0	1.0	0.000000	0.0	0.0	0.0300
4	LP001008	0.0	0.0	0.000000	1.0	0.0	0.0723

```
#checking missing values
data.isnull().sum()
```

```
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
```

```
#checking data types
data.dtypes
```

```
Loan_ID      object
Gender       float64
Married      float64
Dependents   float64
Education    float64
Self_Employed float64
ApplicantIncome float64
CoapplicantIncome float64
LoanAmount   float64
Loan_Amount_Term float64
Credit_History float64
Property_Area float64
Loan_Status   float64
dtype: object
```

```
#dropint the loan id since it is just a unique value
data=data.drop("Loan_ID",axis=1)
```

```
data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappli
0	0.0	0.0	0.000000	1.0	0.0	0.070489	
1	0.0	1.0	0.333333	1.0	0.0	0.054830	
2	0.0	1.0	0.000000	1.0	1.0	0.035250	
3	0.0	1.0	0.000000	0.0	0.0	0.030093	
4	0.0	0.0	0.000000	1.0	0.0	0.072356	

```
data.shape
```

```
(614, 12)
```

```
#SEPERATE THE DATA INTO DEPENDENT AND INDEPENDENT
x=data.drop("Loan_Status",axis=1)
```

```
#independent variable
x
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	0.0	0.0	0.000000	1.0	0.0	0.070489	
1	0.0	1.0	0.333333	1.0	0.0	0.054830	
2	0.0	1.0	0.000000	1.0	1.0	0.035250	
3	0.0	1.0	0.000000	0.0	0.0	0.030093	
4	0.0	0.0	0.000000	1.0	0.0	0.072356	
...
609	1.0	0.0	0.000000	1.0	0.0	0.034014	
610	0.0	1.0	1.000000	1.0	0.0	0.048930	
611	0.0	1.0	0.333333	1.0	0.0	0.097984	
612	0.0	1.0	0.666667	1.0	0.0	0.091936	

```
y=data["Loan_Status"]
```

```
614 rows x 11 columns
```

```
#dependent variable(target variable)
```

```
y
```

```
0      1.0
1      0.0
2      1.0
3      1.0
4      1.0
```

```
...
```

```
609    1.0
610    1.0
611    1.0
612    1.0
613    0.0
```

```
Name: Loan_Status, Length: 614, dtype: float64
```

```
#shape of independent and dependent variable
```

```
x.shape,y.shape
```

```
((614, 11), (614,))
```

CREATING TEST AND TRAINING DATA

```
xtrain,xtest,ytrain,ytest=train_test_split(x,y,stratify=data["Loan_Status"],random_state=10,train_size=0.8)
```

```
#shape of training and test set
```

```
(xtrain.shape,ytrain.shape),(xtest.shape,ytest.shape)
```

((491, 11), (491,)), ((123, 11), (123,)))

xtrain

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
164	0.0	1.0	0.000000	1.0	0.0	0.113457	0.000000
171	0.0	1.0	1.000000	1.0	0.0	0.638380	0.000000
546	0.0	0.0	0.000000	0.0	0.0	0.039678	0.000000
226	0.0	1.0	0.000000	0.0	1.0	0.056710	0.000000
176	0.0	1.0	0.666667	1.0	0.0	0.023438	0.000000
...
560	0.0	1.0	0.666667	0.0	0.0	0.043599	0.000000
503	0.0	1.0	0.333333	0.0	0.0	0.048237	0.000000
343	0.0	1.0	1.000000	0.0	0.0	0.037390	0.000000
148	1.0	0.0	0.000000	1.0	0.0	0.121831	0.000000
303	0.0	1.0	0.333333	1.0	0.0	0.018244	0.000000

491 rows × 11 columns

xtest

```

Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  Coap
ytrain
164      1.0
171      1.0
546      0.0
226      0.0
176      1.0
...
560      1.0
503      0.0
343      1.0
148      0.0
303      1.0
Name: Loan_Status, Length: 491, dtype: float64
369      0.0      1.0      0.000000      1.0      0.0      0.242177
ytest
507      0.0
493      1.0
434      1.0
125      1.0
294      1.0
...
82       0.0
295      1.0
369      0.0
450      0.0
363      1.0
Name: Loan_Status, Length: 123, dtype: float64

```

DEFINING ARCHITECTURE OF THE MODL

```

#importing keras
import keras

#checking the version of the keras
print(keras.__version__)

2.6.0

#importting tensorflow
import tensorflow as tf

#checking the version of the tensorflow
print(tf.__version__)

2.6.0

```

```
#importing sequential function from keras
from keras.models import Sequential
```

```
#importing different layers
from keras.layers import InputLayer,Dense
```

DEFINING THE NUMBER OF INPUT NEURONS

```
xtrain.shape
```

```
(491, 11)
```

```
xtrain.shape[1]
```

```
11
```

```
#defining the input neurons
input_neurons=xtrain.shape[1]
```

```
#defining the no of output neurons
#binary classification problem - output neuron = 1
output_neurons=1
```

```
#defining hidden layer and no of neurons in each layer
number_of_hidden_layers=2
neuron_hidden_layer_1=10
neuron_hidden_layer_2=5
```

```
#defining the architecture of the model
model = Sequential()
model.add(InputLayer(input_shape=(input_neurons,)))
model.add(Dense(units=neuron_hidden_layer_1, activation='relu'))
model.add(Dense(units=neuron_hidden_layer_2, activation='relu'))
model.add(Dense(units=output_neurons, activation='sigmoid'))
```

```
#summary of the model
model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
=====		
dense (Dense)	(None, 10)	120
=====		
dense_1 (Dense)	(None, 5)	55

dense_2 (Dense)	(None, 1)	6
-----------------	-----------	---

=====
 Total params: 181
 Trainable params: 181
 Non-trainable params: 0

```
#no of parameter between input and first hidden layer
input_neurons*neuron_hidden_layer_1
```

```
110
```

```
#Adding bias for each neurons for first hidden layer
input_neurons*neuron_hidden_layer_1+10
```

```
120
```

```
#no.of parameter between first and second hidden layer
neuron_hidden_layer_1*neuron_hidden_layer_2+5
```

```
55
```

```
#no.of parameter between second hidden layer and output layer
neuron_hidden_layer_2*output_neurons+1
```

```
6
```

COMPILING THE MODEL (DEFINING LOSS AND OPTIMIZER)

```
#compiling the model
# loss as binary_crossentropy, since we have binary classification problem
# defining the optimizer as adam
# Evaluation metric as accuracy
model.compile(loss="binary_crossentropy",optimizer="Adam",metrics=["accuracy"])
```

```
# training the model
```

```
# passing the independent and dependent features for training set for training the model
```

```
# validation data will be evaluated at the end of each epoch
```

```
# setting the epochs as 50
```

```
# storing the trained model in model_history variable which will be used to visualize the tra
```

```
model_history = model.fit(xtrain, ytrain, validation_data=(xtest, ytest), epochs=50)
```

```
Epoch 22/50
16/16 [=====] - 0s 4ms/step - loss: 0.4850 - accuracy: 0.810
Epoch 23/50
16/16 [=====] - 0s 3ms/step - loss: 0.4822 - accuracy: 0.810
Epoch 24/50
16/16 [=====] - 0s 4ms/step - loss: 0.4791 - accuracy: 0.812
Epoch 25/50
16/16 [=====] - 0s 5ms/step - loss: 0.4764 - accuracy: 0.812
Epoch 26/50
16/16 [=====] - 0s 4ms/step - loss: 0.4752 - accuracy: 0.812
Epoch 27/50
16/16 [=====] - 0s 4ms/step - loss: 0.4731 - accuracy: 0.812
Epoch 28/50
16/16 [=====] - 0s 4ms/step - loss: 0.4722 - accuracy: 0.810
Epoch 29/50
16/16 [=====] - 0s 4ms/step - loss: 0.4710 - accuracy: 0.812
Epoch 30/50
16/16 [=====] - 0s 4ms/step - loss: 0.4698 - accuracy: 0.810
Epoch 31/50
16/16 [=====] - 0s 5ms/step - loss: 0.4693 - accuracy: 0.810
Epoch 32/50
16/16 [=====] - 0s 4ms/step - loss: 0.4688 - accuracy: 0.810
Epoch 33/50
16/16 [=====] - 0s 5ms/step - loss: 0.4678 - accuracy: 0.810
Epoch 34/50
16/16 [=====] - 0s 4ms/step - loss: 0.4671 - accuracy: 0.810
Epoch 35/50
16/16 [=====] - 0s 4ms/step - loss: 0.4668 - accuracy: 0.810
Epoch 36/50
16/16 [=====] - 0s 5ms/step - loss: 0.4664 - accuracy: 0.810
Epoch 37/50
16/16 [=====] - 0s 5ms/step - loss: 0.4657 - accuracy: 0.810
Epoch 38/50
16/16 [=====] - 0s 5ms/step - loss: 0.4654 - accuracy: 0.810
Epoch 39/50
16/16 [=====] - 0s 5ms/step - loss: 0.4650 - accuracy: 0.810
Epoch 40/50
16/16 [=====] - 0s 4ms/step - loss: 0.4659 - accuracy: 0.812
Epoch 41/50
16/16 [=====] - 0s 4ms/step - loss: 0.4638 - accuracy: 0.810
Epoch 42/50
16/16 [=====] - 0s 3ms/step - loss: 0.4641 - accuracy: 0.810
Epoch 43/50
16/16 [=====] - 0s 4ms/step - loss: 0.4638 - accuracy: 0.810
Epoch 44/50
16/16 [=====] - 0s 4ms/step - loss: 0.4631 - accuracy: 0.810
Epoch 45/50
16/16 [=====] - 0s 4ms/step - loss: 0.4630 - accuracy: 0.810
Epoch 46/50
16/16 [=====] - 0s 4ms/step - loss: 0.4629 - accuracy: 0.810
Epoch 47/50
16/16 [=====] - 0s 4ms/step - loss: 0.4625 - accuracy: 0.810
Epoch 48/50
16/16 [=====] - 0s 4ms/step - loss: 0.4626 - accuracy: 0.810
Epoch 49/50
```



```
16/16 [=====] - 0s 4ms/step - loss: 0.4622 - accuracy: 0.810
Epoch 50/50
16/16 [=====] - 0s 4ms/step - loss: 0.4623 - accuracy: 0.810
```

PREDICTIONS

```
prediction = model.predict(xtest)
```

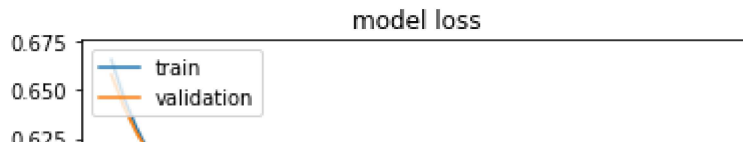
```
#calculating accuracy
accuracy_score(ytest,prediction)
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-48-e66ad745415c> in <module>()
      1 #calculating accuracy
----> 2 accuracy_score(ytest,prediction)

----- 1 frames -----
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py in
_check_targets(y_true, y_pred)
    88     if len(y_type) > 1:
    89         raise ValueError("Classification metrics can't handle a mix of
{0} "
---> 90                                "and {1} targets".format(type_true, type_pred))
    91
    92     # We can't have more than one value on y_type => The set is no more
needed
```

```
ValueError: Classification metrics can't handle a mix of binary and continuous
```

```
# summarize history for loss
plt.plot(model_history.history['loss'])
plt.plot(model_history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



```
# summarize history for accuracy
plt.plot(model_history.history['acc'])
plt.plot(model_history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

```
-----
KeyError                                Traceback (most recent call last)
<ipython-input-52-b7dd9c61dd7c> in <module>()
      1 # summarize history for accuracy
----> 2 plt.plot(model_history.history['acc'])
      3 plt.plot(model_history.history['val_acc'])
      4 plt.title('model accuracy')
      5 plt.ylabel('accuracy')
```

KeyError: 'acc'

SEARCH STACK OVERFLOW