```
import pandas as pd
df = pd.read_csv("/content/diabetes_data_upload.csv")
df. dropna ( axis = 0 , inplace = True )
print(df)
print(df.isnull())
```

```
     Age  Gender Polyuria Polydipsia sudden weight loss weakness Polyphagia  \
0     40    Male       No        Yes                 No      Yes         No
1     58    Male       No         No                 No      Yes         No
2     41    Male      Yes         No                 No      Yes        Yes
3     45    Male       No         No                Yes      Yes        Yes
4     60    Male      Yes        Yes                Yes      Yes        Yes
..   ...     ...      ...        ...                ...      ...        ...
515   39  Female      Yes        Yes                Yes       No        Yes
516   48  Female      Yes        Yes                Yes      Yes        Yes
517   58  Female      Yes        Yes                Yes      Yes        Yes
518   32  Female       No         No                 No      Yes         No
519   42    Male       No         No                 No       No         No

    Genital thrush visual blurring Itching Irritability delayed healing  \
0               No              No     Yes           No             Yes
1               No             Yes      No           No              No
2               No              No     Yes           No             Yes
3              Yes              No     Yes           No             Yes
4               No             Yes     Yes          Yes             Yes
..             ...             ...     ...          ...             ...
515             No              No     Yes           No             Yes
516             No              No     Yes          Yes             Yes
517             No             Yes      No           No              No
518             No             Yes     Yes           No             Yes
519             No              No      No           No              No

    partial paresis muscle stiffness Alopecia Obesity     class
0                No              Yes      Yes     Yes  Positive
1               Yes               No      Yes      No  Positive
2                No              Yes      Yes      No  Positive
3                No               No       No      No  Positive
4               Yes              Yes      Yes     Yes  Positive
..              ...              ...      ...     ...       ...
515             Yes               No       No      No  Positive
516             Yes               No       No      No  Positive
517             Yes              Yes       No     Yes  Positive
518              No               No      Yes      No  Negative
519              No               No       No      No  Negative

[520 rows x 17 columns]
       Age  Gender  Polyuria  Polydipsia  sudden weight loss  weakness  \
0    False   False     False       False               False     False
1    False   False     False       False               False     False
2    False   False     False       False               False     False
3    False   False     False       False               False     False
4    False   False     False       False               False     False
..     ...     ...       ...         ...                 ...       ...
515  False   False     False       False               False     False
516  False   False     False       False               False     False
517  False   False     False       False               False     False
518  False   False     False       False               False     False
519  False   False     False       False               False     False

     Polyphagia  Genital thrush  visual blurring  Itching  Irritability  \
0         False           False            False    False         False
1         False           False            False    False         False
2         False           False            False    False         False
3         False           False            False    False         False
```

```
df = df.replace("Yes", 1)
```

```
df = df.replace("No",0)
```

```
df
```

	Age	Gender	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching	Irrita
0	40	Male	0	1	0	1	0	0	0	1	
1	58	Male	0	0	0	1	0	0	1	0	
2	41	Male	1	0	0	1	1	0	0	1	
3	45	Male	0	0	1	1	1	1	0	1	
4	60	Male	1	1	1	1	1	0	1	1	
...	...	...	...	...	...	...	...	...	...	...	
515	39	Female	1	1	1	0	1	0	0	1	
516	48	Female	1	1	1	1	1	0	0	1	
517	58	Female	1	1	1	1	1	0	1	0	
518	32	Female	0	0	0	1	0	0	1	1	
519	42	Male	0	0	0	0	0	0	0	0	

520 rows × 17 columns

```
df.info()
```

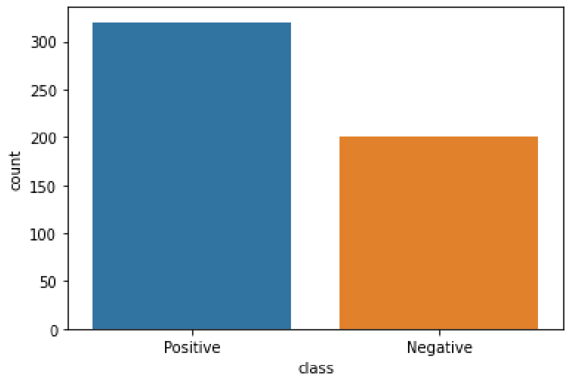
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Age                 520 non-null    int64
 1   Gender              520 non-null    object
 2   Polyuria            520 non-null    int64
```

```
 3   Polydipsia          520 non-null    int64
 4   sudden weight loss  520 non-null    int64
 5   weakness            520 non-null    int64
 6   Polyphagia          520 non-null    int64
 7   Genital thrush      520 non-null    int64
 8   visual blurring     520 non-null    int64
 9   Itching             520 non-null    int64
 10  Irritability        520 non-null    int64
 11  delayed healing     520 non-null    int64
 12  partial paresis     520 non-null    int64
 13  muscle stiffness    520 non-null    int64
 14  Alopecia            520 non-null    int64
 15  Obesity             520 non-null    int64
 16  class               520 non-null    object
dtypes: int64(15), object(2)
memory usage: 73.1+ KB
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
import numpy as np
```

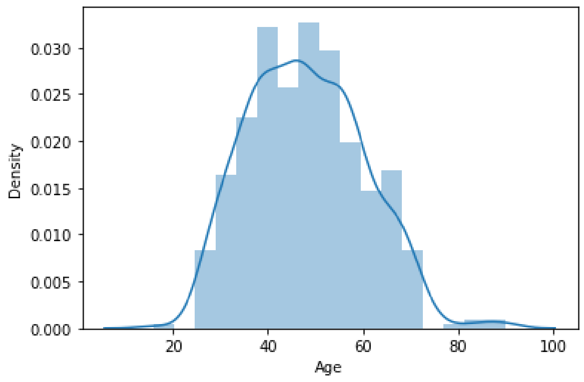
```
sns.countplot(df['class'],)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following var
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fce529dbe50>
```




```
sns.distplot(df['Age'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a de
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7fce52918c10>
```




```
df = df.drop('Gender', axis=1)
df = df.replace("Positive", 1)
df = df.replace("Negative", 0)
X = df.drop('class', axis=1)
y = df['class']
X_train,X_test,y_train,y_test = train_test_split(X,y)
```

```
X_train.head()
```

	Age	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching	Irritability
150	50	1	1	1	1	1	0	0	1	1
143	53	1	0	1	0	0	0	0	0	0
425	62	1	1	0	1	1	0	1	0	1
113	79	0	1	1	1	1	1	0	1	1
376	43	0	0	0	1	0	1	0	1	0

```
y_train.head()
```

```
150    1
143    1
425    1
113    1
376    0
Name: class, dtype: int64
```

Keras is an open source neural network library written in Python.

There are two ways to build Keras models: sequential API, functional API

```
from keras.models import Sequential
from keras.layers import Dense, Dropout
```

The model design:

- 4 layers.
- 27 total neurons
- Relu & Sigmoid activation functions.

[link text]

.

```
model = Sequential()

model.add(Dense(15, input_dim=15, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(3, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss="mse", optimizer="adam", metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 15)                240

 dense_5 (Dense)             (None, 8)                 128

 dense_6 (Dense)             (None, 3)                 27

 dense_7 (Dense)             (None, 1)                 4

=================================================================
Total params: 399
Trainable params: 399
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(X_train, y_train, epochs = 2500, batch_size=15, validation_data=(X_test, y_test))
```

```
Streaming output truncated to the last 5000 lines.
26/26 [==============================] - 1s 9ms/step - loss: 0.3932 - accuracy: 0.6051 - val_loss: 0.3463 - val_accuracy: 0.6462
Epoch 2/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.2592 - accuracy: 0.7026 - val_loss: 0.1913 - val_accuracy: 0.7692
Epoch 3/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.1838 - accuracy: 0.8051 - val_loss: 0.1749 - val_accuracy: 0.6846
Epoch 4/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.1672 - accuracy: 0.8128 - val_loss: 0.1607 - val_accuracy: 0.8000
Epoch 5/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.1529 - accuracy: 0.8410 - val_loss: 0.1524 - val_accuracy: 0.8000
Epoch 6/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1423 - accuracy: 0.8564 - val_loss: 0.1450 - val_accuracy: 0.8077
Epoch 7/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.1334 - accuracy: 0.8590 - val_loss: 0.1386 - val_accuracy: 0.7846
Epoch 8/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1317 - accuracy: 0.8513 - val_loss: 0.1341 - val_accuracy: 0.8077
Epoch 9/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.1218 - accuracy: 0.8718 - val_loss: 0.1303 - val_accuracy: 0.8462
Epoch 10/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1141 - accuracy: 0.8667 - val_loss: 0.1244 - val_accuracy: 0.8308
Epoch 11/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1135 - accuracy: 0.8615 - val_loss: 0.1210 - val_accuracy: 0.8462
Epoch 12/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1088 - accuracy: 0.8744 - val_loss: 0.1226 - val_accuracy: 0.8692
Epoch 13/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.1047 - accuracy: 0.8821 - val_loss: 0.1160 - val_accuracy: 0.8846
Epoch 14/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.0991 - accuracy: 0.8692 - val_loss: 0.1161 - val_accuracy: 0.8000
Epoch 15/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.0971 - accuracy: 0.8897 - val_loss: 0.1128 - val_accuracy: 0.8077
Epoch 16/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0944 - accuracy: 0.8821 - val_loss: 0.1216 - val_accuracy: 0.8000
Epoch 17/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0944 - accuracy: 0.8769 - val_loss: 0.1129 - val_accuracy: 0.8615
Epoch 18/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.0920 - accuracy: 0.8872 - val_loss: 0.1089 - val_accuracy: 0.8692
Epoch 19/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0927 - accuracy: 0.8846 - val_loss: 0.1035 - val_accuracy: 0.8846
Epoch 20/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0881 - accuracy: 0.8897 - val_loss: 0.1026 - val_accuracy: 0.8846
Epoch 21/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0877 - accuracy: 0.8897 - val_loss: 0.1008 - val_accuracy: 0.8846
Epoch 22/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0879 - accuracy: 0.8974 - val_loss: 0.1062 - val_accuracy: 0.8538
Epoch 23/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0876 - accuracy: 0.8949 - val_loss: 0.1066 - val_accuracy: 0.8538
Epoch 24/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0845 - accuracy: 0.8974 - val_loss: 0.0991 - val_accuracy: 0.8846
Epoch 25/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0826 - accuracy: 0.9154 - val_loss: 0.1071 - val_accuracy: 0.8538
Epoch 26/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0824 - accuracy: 0.9026 - val_loss: 0.0962 - val_accuracy: 0.8923
Epoch 27/2500
26/26 [==============================] - 0s 3ms/step - loss: 0.0798 - accuracy: 0.9051 - val_loss: 0.1062 - val_accuracy: 0.8538
Epoch 28/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.0831 - accuracy: 0.8923 - val_loss: 0.0954 - val_accuracy: 0.8923
Epoch 29/2500
26/26 [==============================] - 0s 4ms/step - loss: 0.0826 - accuracy: 0.8949 - val_loss: 0.0943 - val_accuracy: 0.8923
```

Saving the model Keras also supports a simpler interface to save both the model weights and model architecture together into a single H5 file.

Saving the model in this way includes everything we need to know about the model, including:

Model weights. Model architecture. Model compilation details (loss and metrics). Model optimizer state. This means that we can load and use the model directly, without having to re-compile it.

```
model.save('model.h5')
```

```
from keras.models import load_model
model = load_model('model.h5')
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 15)                240

 dense_5 (Dense)             (None, 8)                 128

 dense_6 (Dense)             (None, 3)                 27

 dense_7 (Dense)             (None, 1)                 4

=================================================================
Total params: 399
Trainable params: 399
Non-trainable params: 0
_________________________________________________________________
```

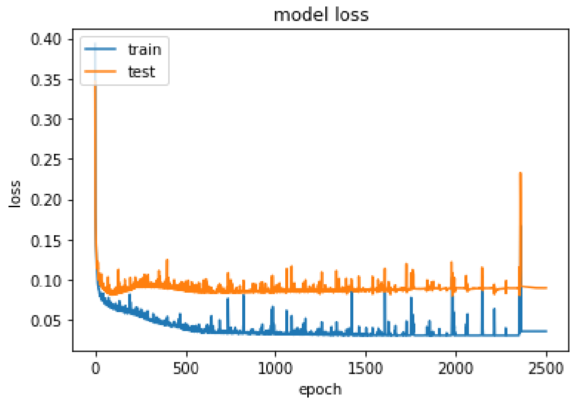
```
print(model.predict(np.array([53,0,1,0,1,0,1,0,0,0,1,0,0,1,1]).reshape((1,15))))
```

```
1/1 [==============================] - 0s 33ms/step
[[0.4941433]]
```

```
_, accuracy = model.evaluate(X_train, y_train)
print('Accuracy: %.2f' % (accuracy*100))
```

```
13/13 [==============================] - 0s 8ms/step - loss: 0.0359 - accuracy: 0.9641
Accuracy: 96.41
```

```
import matplotlib.pyplot as plt
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```




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