IMPORTING MODULES

In [102…

```
import numpy as np

# dataa split
from sklearn.model_selection import train_test_split

# model Evaluation
from sklearn import metrics

#navie bayesian and accuracy
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

#pandas
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('seaborn')
```

In [103…

```
import seaborn as sns
import plotly.express as px

# SMOTE
from imblearn.over_sampling import SMOTE

# scaling
from sklearn.preprocessing import StandardScaler

# tune
from sklearn.model_selection import RandomizedSearchCV
```

READING THE DATASET

In [104…

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

Out[104…

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
0	9046	Male	67	0	1	Yes	Private	Urban
1	31112	Male	80	0	1	Yes	Private	Rural
2	60182	Female	49	0	0	Yes	Private	Urban
3	1665	Female	79	1	0	Yes	Self-employed	Rural
4	56669	Male	81	0	0	Yes	Private	Urban
...	...	...	...	...	...	...	...	...
3421	68398	Male	82	1	0	Yes	Self-employed	Rural
3422	45010	Female	57	0	0	Yes	Private	Rural
3423	44873	Female	81	0	0	Yes	Self-employed	Urban

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type
3424	19723	Female	35	0	0	Yes	Self-employed	Rural
3425	37544	Male	51	0	0	Yes	Private	Rural

3426 rows × 12 columns

DATA ENCODING (PREPARATION)

In [105…

```
# convert string to numeric using map

# gender
data['gender'] = data['gender'].map({
'Male': int(0),
'Female':int(1),
'Other':int(2)})

# ever_married
data['ever_married'] =data['ever_married'].map({
'Yes':int(1),
'No':int(0)})

# work_type
data['work_type'] = data['work_type'].map({
'Private':int(3),
'Self-employed':int(4),
'Govt_job':int(2),
'children':int(1),
'Never_worked':int(0)})

# Residence_type
data['Residence_type'] = data['Residence_type'].map({
'Urban':int(2),
'Rural':int(1)})

# smoking_status
data['smoking_status'] = data['smoking_status'].map({
'formerly smoked':int(1),
'never smoked':int(2),
'smokes':int(3),
'Unknown':int(0)})
```

In [106…

```
### attributes used in the classification
```

In [107…

```
x=data[['gender','age','hypertension','heart_disease','ever_married','work_ty
y=data[['stroke']]
x=x.values
y=y.values
```

SPLIT DATASET

In [108…

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.datasets import load_iris
```

In [109…

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.20,ra
```

In [110…

```
print(X_train.shape)
print(X_test.shape)
```

```
(2740, 10)
(686, 10)
```

In [111…

```
y_train=y_train.flatten()
y_test=y_test.flatten()
print(y_train.shape)
print(y_test.shape)
```

```
(2740,)
(686,)
```

RELU activation function

In [112…

```
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense
import matplotlib.pyplot as plt
```

In [113…

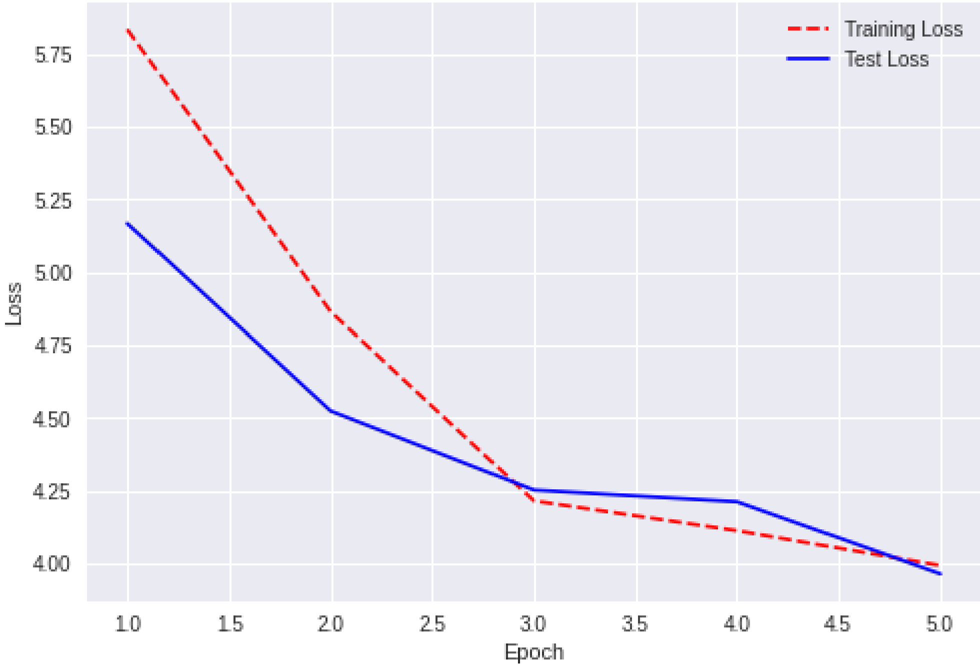
```
# define keras model
model=tf.keras.Sequential()

model.add(tf.keras.layers.Dense(units=25,activation='relu'))

#compile keras model
model.compile('adam','binary_crossentropy',metrics=['accuracy'])
```

In [114…

```
#fitting ANN model into training data
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),epochs

# Get training and test loss histories
training_loss = history.history['loss']
test_loss = history.history['val_loss']

# Create count of the number of epochs
epoch_count = range(1, len(training_loss) + 1)

# Visualize loss history
plt.plot(epoch_count, training_loss, 'r--')
plt.plot(epoch_count, test_loss, 'b-')
plt.legend(['Training Loss', 'Test Loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show();
```

```
Epoch 1/5
86/86 [==============================] - 0s 3ms/step - loss: 6.2830 - accurac
y: 0.0000e+00 - val_loss: 5.1664 - val_accuracy: 0.0000e+00
Epoch 2/5
```

```
86/86 [==============================] - 0s 1ms/step - loss: 4.9580 - accurac
y: 0.0000e+00 - val_loss: 4.5233 - val_accuracy: 0.0000e+00
Epoch 3/5
86/86 [==============================] - 0s 2ms/step - loss: 4.2441 - accurac
y: 0.0000e+00 - val_loss: 4.2516 - val_accuracy: 0.0000e+00
Epoch 4/5
86/86 [==============================] - 0s 1ms/step - loss: 4.1304 - accurac
y: 0.0000e+00 - val_loss: 4.2113 - val_accuracy: 0.0000e+00
Epoch 5/5
86/86 [==============================] - 0s 1ms/step - loss: 4.0605 - accurac
y: 0.0000e+00 - val_loss: 3.9634 - val_accuracy: 0.0000e+00
```



INFERENCE

From the above graph we can see that the Loss of Training almost touches 5.75 where as the test touchesto 5.15 at Epoch 1.0 And Also they intersected at Epoch 3.0 and 5.0 .The loss is really high at the intial values of epoch and it gradually decreased as the value of the epoch increased.The modern default activation function for hidden layers is the ReLU function.

TANH activation function

In [115…

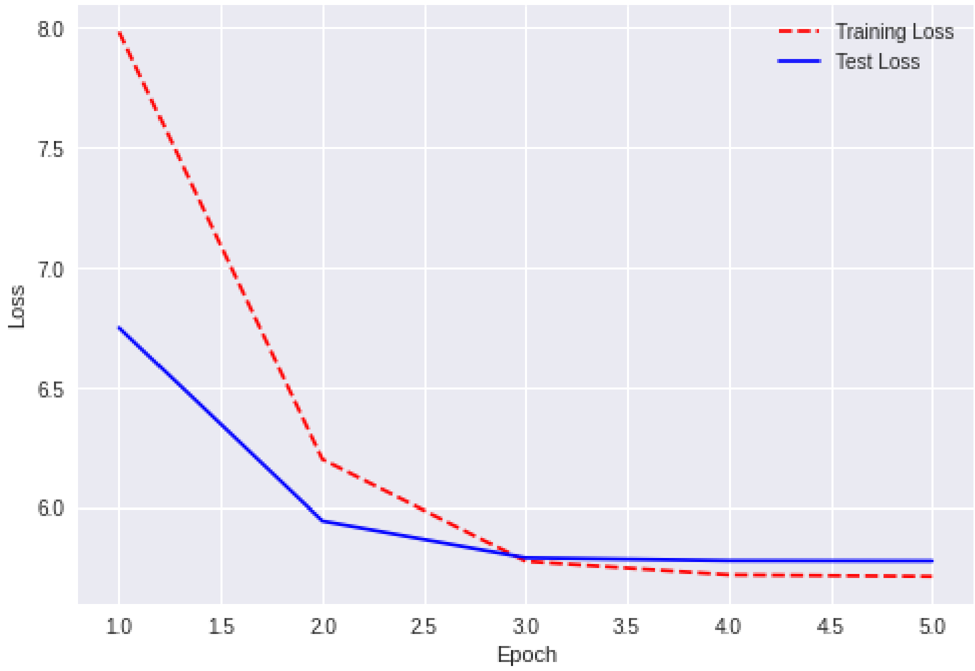
```
# define keras model
model=tf.keras.Sequential()

model.add(tf.keras.layers.Dense(units=25,activation='tanh'))

#compile keras model
model.compile('adam','binary_crossentropy',metrics=['accuracy'])
```

In [116…

```
#fitting ANN model into training data
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),epochs

# Get training and test loss histories
training_loss = history.history['loss']
test_loss = history.history['val_loss']

# Create count of the number of epochs
epoch_count = range(1, len(training_loss) + 1)
```

```
# Visualize loss history
plt.plot(epoch_count, training_loss, 'r--')
plt.plot(epoch_count, test_loss, 'b-')
plt.legend(['Training Loss', 'Test Loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show();
```

```
Epoch 1/5
86/86 [==============================] - 1s 5ms/step - loss: 8.6138 - accurac
y: 0.1481 - val_loss: 6.7507 - val_accuracy: 0.0641
Epoch 2/5
86/86 [==============================] - 0s 2ms/step - loss: 6.4024 - accurac
y: 0.0443 - val_loss: 5.9461 - val_accuracy: 0.0641
Epoch 3/5
86/86 [==============================] - 0s 1ms/step - loss: 5.8417 - accurac
y: 0.0530 - val_loss: 5.7929 - val_accuracy: 0.0641
Epoch 4/5
86/86 [==============================] - 0s 1ms/step - loss: 5.7052 - accurac
y: 0.0458 - val_loss: 5.7810 - val_accuracy: 0.0641
Epoch 5/5
86/86 [==============================] - 0s 1ms/step - loss: 5.7271 - accurac
y: 0.0530 - val_loss: 5.7797 - val_accuracy: 0.0641
```



INFERENCE

From the above graph we can see that the Loss of Training almost touches 8.0 where as the test touchesto 6.5 at Epoch 1.0 And Also they intersected at Epoch 2.8 .The loss is really high at the intial values of epoch and it gradually decreased as the value of the epoch increased and it became constant after some particular value of epochso.They are basically used in feed-forward nets.

SIGMOID activation function

In [117…

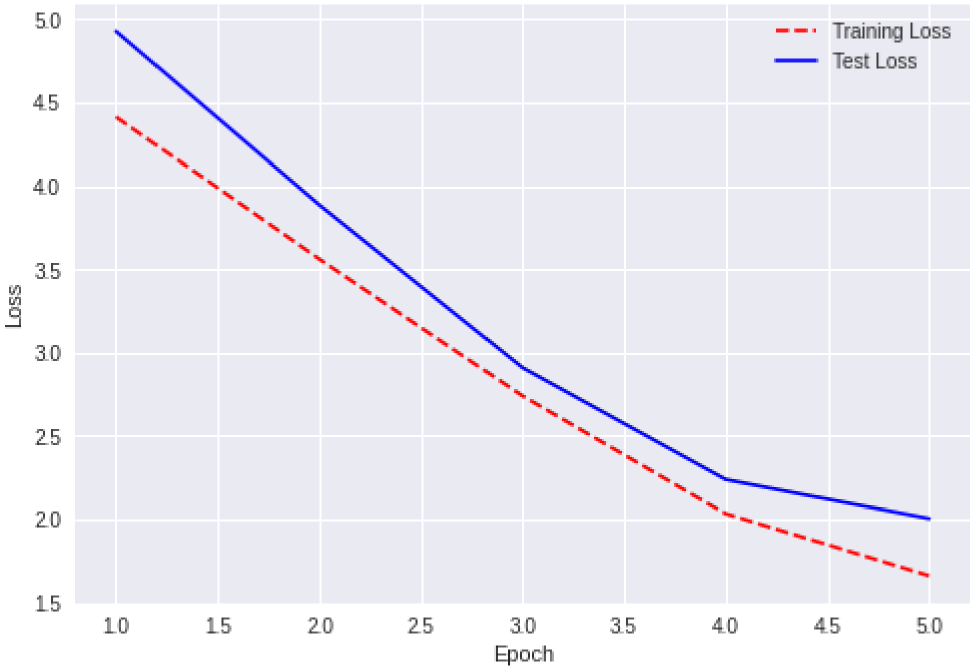
```
# define keras model
model=tf.keras.Sequential()

model.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))
```

```
#compile keras model
model.compile('adam','binary_crossentropy',metrics=['accuracy'])
```

In [118…

```
#fitting ANN model into training data
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),epochs

# Get training and test loss histories
training_loss = history.history['loss']
test_loss = history.history['val_loss']

# Create count of the number of epochs
epoch_count = range(1, len(training_loss) + 1)

# Visualize loss history
plt.plot(epoch_count, training_loss, 'r--')
plt.plot(epoch_count, test_loss, 'b-')
plt.legend(['Training Loss', 'Test Loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show();
```

```
Epoch 1/5
86/86 [==============================] - 0s 3ms/step - loss: 4.7389 - accurac
y: 0.9495 - val_loss: 4.9263 - val_accuracy: 0.9359
Epoch 2/5
86/86 [==============================] - 0s 1ms/step - loss: 3.1974 - accurac
y: 0.9542 - val_loss: 3.8860 - val_accuracy: 0.9329
Epoch 3/5
86/86 [==============================] - 0s 1ms/step - loss: 3.1916 - accurac
y: 0.9471 - val_loss: 2.9092 - val_accuracy: 0.9257
Epoch 4/5
86/86 [==============================] - 0s 2ms/step - loss: 2.4610 - accurac
y: 0.9386 - val_loss: 2.2396 - val_accuracy: 0.8950
Epoch 5/5
86/86 [==============================] - 0s 1ms/step - loss: 1.6536 - accurac
y: 0.9114 - val_loss: 2.0050 - val_accuracy: 0.8746
```



INFERENCE

From the above graph we can see that the Loss of Training don't meet. so it usually does not perform well apparently it is used only for the output layer for the binary classification.