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In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

import tensorflow as tf
from tensorflow import keras
```

Import Library yang akan dipakai

In [2]:
```python
data = pd.read_csv('insurance.csv')
data.info()
data.head(15)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             1338 non-null   int64  
 1   sex             1338 non-null   int64  
 2   bmi             1338 non-null   float64
 3   steps           1338 non-null   int64  
 4   children        1338 non-null   int64  
 5   smoker          1338 non-null   int64  
 6   region          1338 non-null   int64  
 7   charges         1338 non-null   float64
 8   insuranceclaim  1338 non-null   int64  
dtypes: float64(2), int64(7)
memory usage: 94.2 KB
```

Out[2]:

	age	sex	bmi	steps	children	smoker	region	charges	insuranceclaim
0	19	0	27.900	3009	0	1	3	16884.92400	1
1	18	1	33.770	3008	1	0	2	1725.55230	1
2	28	1	33.000	3009	3	0	2	4449.46200	0
3	33	1	22.705	10009	0	0	1	21984.47061	0
4	32	1	28.880	8010	0	0	1	3866.85520	1
5	31	0	25.740	8005	0	0	2	3756.62160	0
6	46	0	33.440	3002	1	0	2	8240.58960	1
7	37	0	27.740	8007	3	0	1	7281.50560	0
8	37	1	29.830	8002	2	0	0	6406.41070	0
9	60	0	25.840	5008	0	0	1	28923.13692	0
10	25	1	26.220	8006	0	0	0	2721.32080	1
11	62	0	26.290	5004	0	1	2	27808.72510	1
12	23	1	34.400	3008	0	0	3	1826.84300	1
13	56	0	39.820	4001	0	0	2	11090.71780	1
14	27	1	42.130	4006	0	1	2	39611.75770	1

Membaca data insurance. Lalu melihat 15 teratas

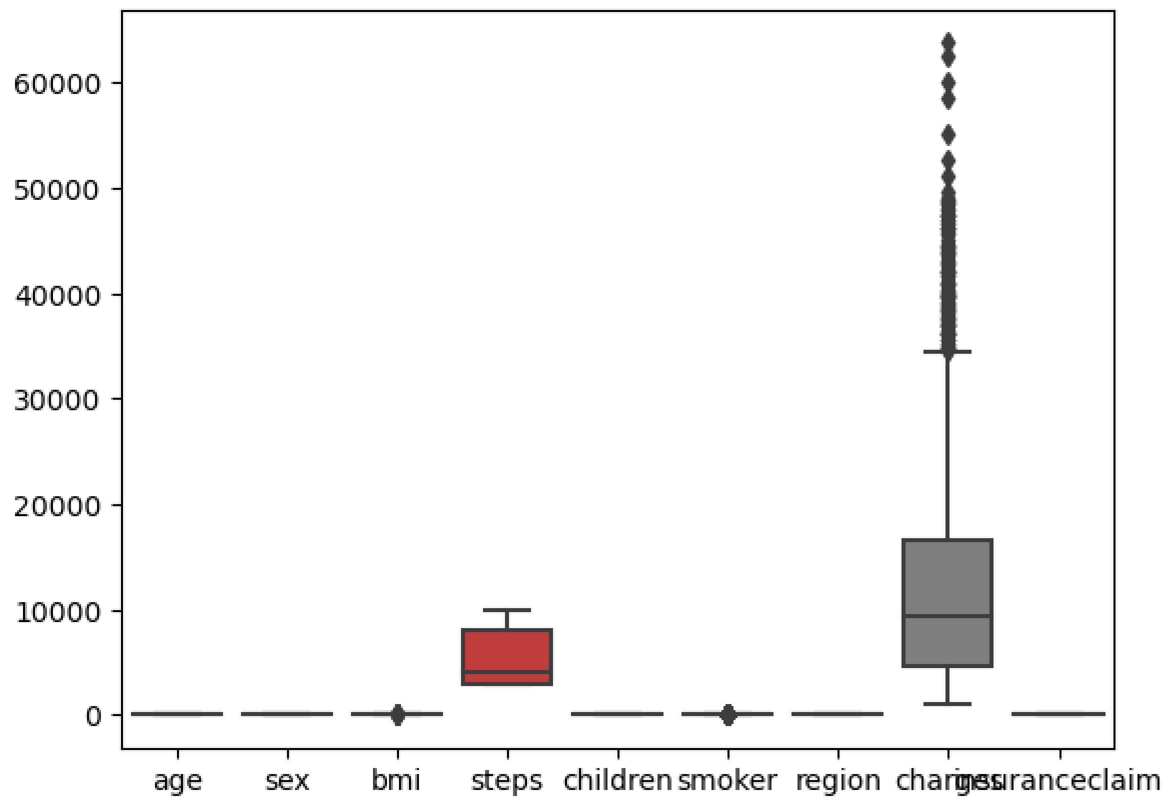
In [3]:
```
data.isnull().sum()
```

Out[3]:
```
age              0
sex              0
bmi              0
steps            0
children         0
smoker           0
region           0
charges          0
insuranceclaim   0
dtype: int64
```

Mengecek apakah ad datan yang kosong

In [4]:
```
sns.boxplot(data=data)
```

Out[4]: <AxesSubplot:>



B

Adanya masalah di dalam data yang diambil. Bila kita lihat outlier, akan terlihat kalau banyak adanya outlier. Cara termudah untuk mengatasi hal itu adalah dengan membuang outlier menggunakan teknik seperti IQR

In [5]:
```
X = data.drop('insuranceclaim', axis=1)
y = data['insuranceclaim']

scaler = StandardScaler()
X = scaler.fit_transform(X)
```

Membagi data menjadi X dan y

In [6]:
```
#Split data inti 80% train, 10% test, 10% validation
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.2, ranc

testing_X, valid_X, testing_y, valid_y = train_test_split(test_X, test_y, test_
```

Membagi data dengan Validasi 80%, test 10% dan validasi 10%

C

In [7]:
```
n = train_X.shape[1]
n_class = len(np.unique(train_y))

model = keras.Sequential([
    keras.layers.Dense(2 * n, input_shape = (n,), activation='relu'),
    keras.layers.Dense(2 * n, activation='relu'),
    keras.layers.Dense(n_class, activation='sigmoid')
])
```

In [8]:
```
#n
```

In [9]:
```
#n_class
```

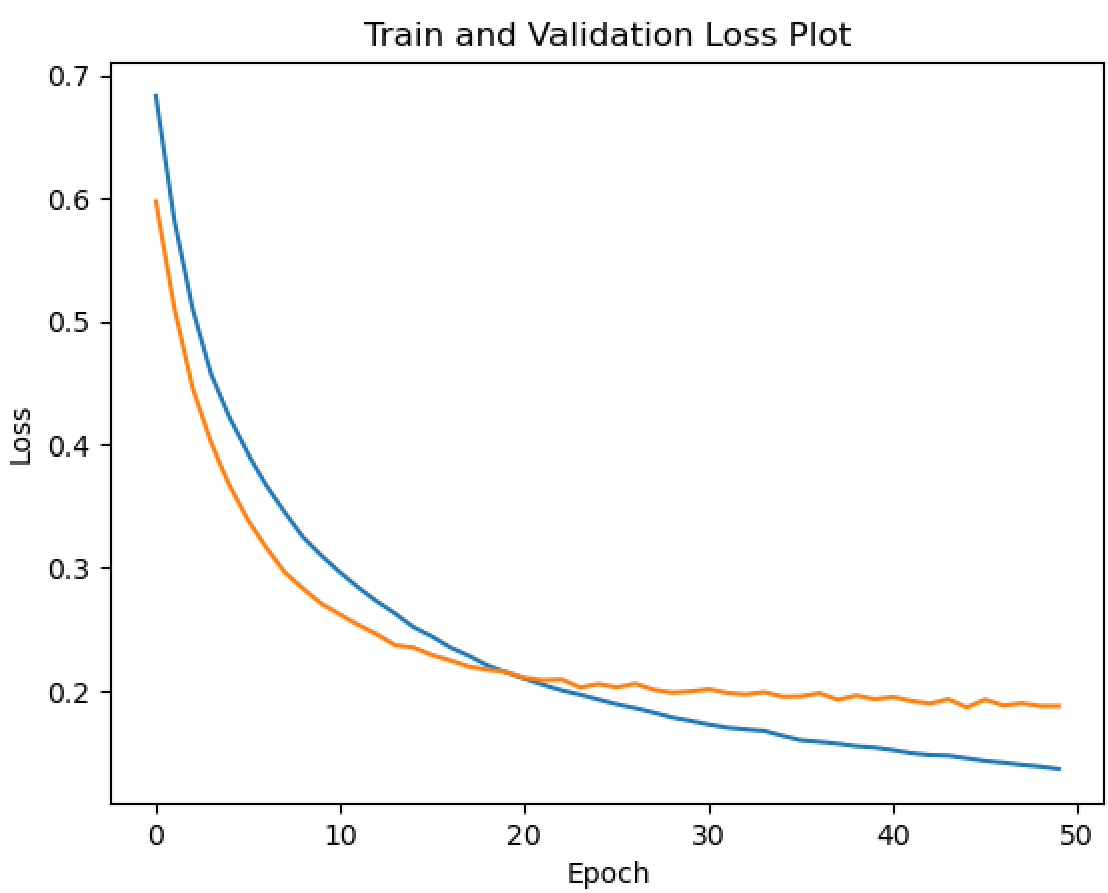
In [10]:
```
model.compile(optimizer='adam', loss = 'sparse_categorical_crossentropy', metri
```

In [11]:
```
model.fit(train_X, train_y, epochs = 50, validation_data = (valid_X, valid_y))
```

```
Epoch 1/50
34/34 [==============================] - 1s 5ms/step - loss: 0.6834 - accur
acy: 0.5645 - val_loss: 0.5976 - val_accuracy: 0.7239
Epoch 2/50
34/34 [==============================] - 0s 1ms/step - loss: 0.5825 - accur
acy: 0.6944 - val_loss: 0.5110 - val_accuracy: 0.7612
Epoch 3/50
34/34 [==============================] - 0s 1ms/step - loss: 0.5099 - accur
acy: 0.7533 - val_loss: 0.4455 - val_accuracy: 0.7836
Epoch 4/50
34/34 [==============================] - 0s 1ms/step - loss: 0.4570 - accur
acy: 0.7897 - val_loss: 0.4014 - val_accuracy: 0.8284
Epoch 5/50
34/34 [==============================] - 0s 1ms/step - loss: 0.4216 - accur
acy: 0.8234 - val_loss: 0.3673 - val_accuracy: 0.8582
Epoch 6/50
34/34 [==============================] - 0s 1ms/step - loss: 0.3926 - accur
acy: 0.8495 - val_loss: 0.3393 - val_accuracy: 0.8731
Epoch 7/50
```

In [12]:
```
plt.plot(model.history.history['loss'], label='Training Loss')
plt.plot(model.history.history['val_loss'], label='Validation Loss')
plt.title('Train and Validation Loss Plot')
plt.xlabel('Epoch')
plt.ylabel('Loss')
```

Out[12]: Text(0, 0.5, 'Loss')



In [13]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report

test_predictions = np.argmax(model.predict(testing_X), axis=1).round()
accuracy = accuracy_score(testing_y, test_predictions)
print("Accuracy: {}".format(accuracy), "\n")

print(classification_report(testing_y, test_predictions))
```

```
5/5 [==============================] - 0s 750us/step
Accuracy: 0.9104477611940298

              precision    recall  f1-score   support

           0       0.86      0.89      0.88        47
           1       0.94      0.92      0.93        87

    accuracy                           0.91       134
   macro avg       0.90      0.91      0.90       134
weighted avg       0.91      0.91      0.91       134
```

Membuat arsitektur suai dengan soal, lalu mengecek report menggunakan calssification_report yang akan nanti dibandingkan dengan setelah dimodifikasi

D

In [14]:
```
model = keras.Sequential([
    keras.layers.Dense(10, input_dim = 8, activation='relu'),
    keras.layers.Dense(10, activation='relu'),
    keras.layers.Dense(2, activation='softmax')
])
```

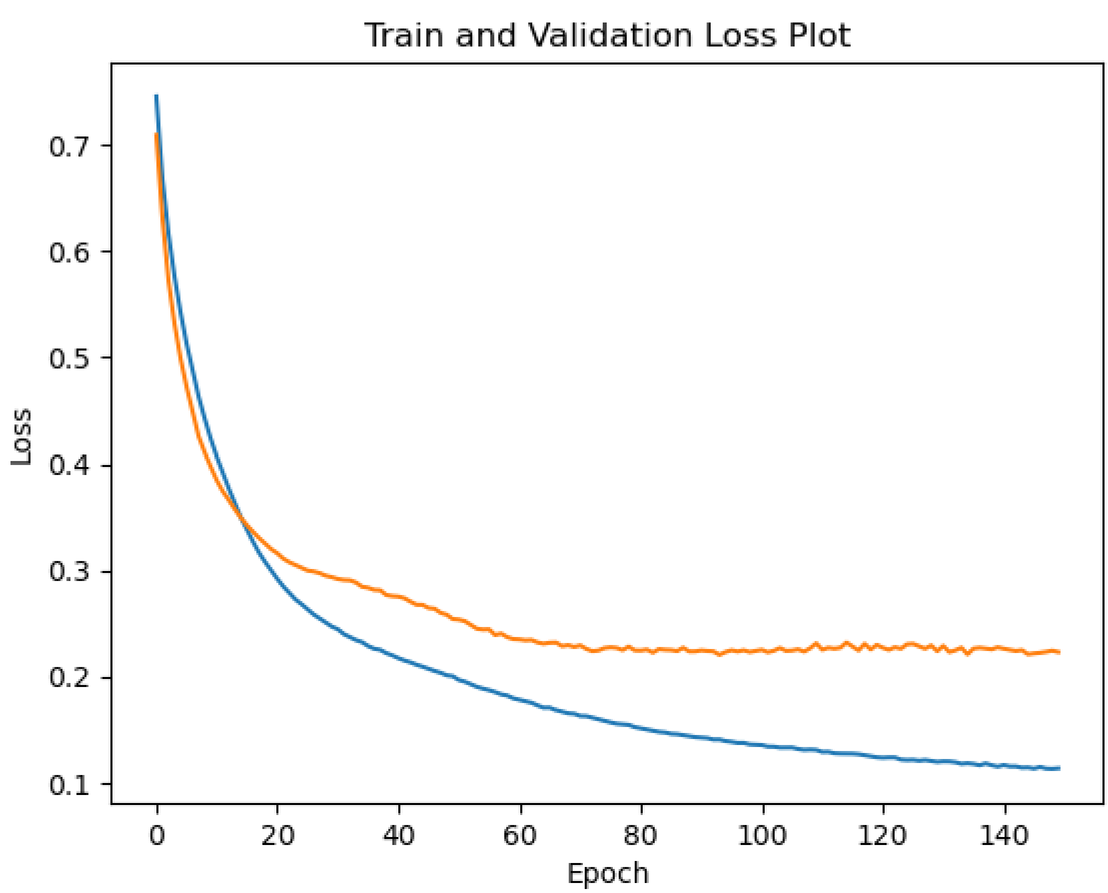
In [15]:
```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics
```

In [16]:
```
model.fit(train_X, train_y, epochs = 150, batch_size =  40, validation_data = (
```

```
Epoch 1/150
27/27 [==============================] - 0s 4ms/step - loss: 0.7458 - accur
acy: 0.4897 - val_loss: 0.7093 - val_accuracy: 0.4627
Epoch 2/150
27/27 [==============================] - 0s 1ms/step - loss: 0.6686 - accur
acy: 0.5944 - val_loss: 0.6316 - val_accuracy: 0.6642
Epoch 3/150
27/27 [==============================] - 0s 2ms/step - loss: 0.6171 - accur
acy: 0.7150 - val_loss: 0.5729 - val_accuracy: 0.7761
Epoch 4/150
27/27 [==============================] - 0s 2ms/step - loss: 0.5765 - accur
acy: 0.7701 - val_loss: 0.5320 - val_accuracy: 0.8060
Epoch 5/150
27/27 [==============================] - 0s 2ms/step - loss: 0.5426 - accur
acy: 0.7841 - val_loss: 0.4992 - val_accuracy: 0.8060
Epoch 6/150
27/27 [==============================] - 0s 2ms/step - loss: 0.5132 - accur
acy: 0.7804 - val_loss: 0.4723 - val_accuracy: 0.8060
Epoch 7/150
```

In [17]:
```
plt.plot(model.history.history['loss'], label='Training Loss')
plt.plot(model.history.history['val_loss'], label='Validation Loss')
plt.title('Train and Validation Loss Plot')
plt.xlabel('Epoch')
plt.ylabel('Loss')
```

Out[17]:
```
Text(0, 0.5, 'Loss')
```



In [18]:

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report

test_predictions = np.argmax(model.predict(test_X), axis=1).round()

accuracy = accuracy_score(test_y, test_predictions)
print("Accuracy: {}".format(accuracy), "\n")

print(classification_report(test_y, test_predictions))
```

```
9/9 [==============================] - 0s 500us/step
Accuracy: 0.9029850746268657

              precision    recall  f1-score   support

           0       0.86      0.90      0.88       107
           1       0.93      0.91      0.92       161

    accuracy                           0.90       268
   macro avg       0.90      0.90      0.90       268
weighted avg       0.90      0.90      0.90       268
```

Mengganti arsitektur n * 2 dengan angka yang lain seperti 10 dan menambahkan batch_size dengan jumlah 40. Dengan menambahkan batch_size bisa mengecek beberapa sample sekaligus sehinga lebih cepat dan efisien. Epoch juga ditambahkan dari 50 ke 150. Dengan menambahkan epoch, model machine learning dapat mempelajari pola dengna lebih mudah

E

Bisa dilihat dari kedua model, setelah diganti beberapa angka di arsitektur dan ditambahkan batch_size dan ditambahkan jumlah epoch, hasil akurasinya meningkat dari 0.89 menjadi 0.92. Nilai presisi recall dan F1-score juga lebih besar dibandingkan sebelumnya. Hal ini menandakan kalau perubahan yang dilakukan memperbagus baseline arsitektur yang sudah dibuat.