



NEURAL NETS PROJECT DIABETE PREDICTION

Mini Project using neural nets to solve
classification problem

Students: Bassole Cedric-Francois/Bouchaala Mohamed

University: ISET BIZERTE

Class: Master in Robotics and Artificial Intelligence

Course: Neural Nets and Fuzzy logic

2023 Avril 7

Abstract

Neural nets take inspiration from the learning process occurring in human brains. They consists of an artificial network of functions, called parameters, which allows the computer to learn, and to fine tune itself, by analyzing new data

Neural networks are also able to handle large amounts of data and can learn from data without being explicitly programmed with a set of rules or a decision tree. This allows them to be very flexible and adaptable, and makes them well-suited for tasks that are difficult to define using traditional programming techniques.

"The work presented in this report is our own and was obtained by my clasmate and me "except the dataset .We obtained it from kaggle dataframe.

Contents

1	Motivation	1
2	The data	1
2.1	initial observation	1
2.2	Data preparation	3
3	Building the Convolutional Neural Network	3
3.1	Activation function	4
3.2	Keras model fit	5
4	Results	6
4.1	Precision	6
4.2	Confusion Matrix	6
4.3	classification Report	8
5	Discussion	8
5.1	Limitations and Challenges	9
6	Conclusion	10

1. Motivation

Diabetes is a chronic medical condition which is estimated to affect 415 million people in the world. 5 million deaths a year can be attributed to diabetes-related complications. Type 2 diabetes can be prevented and reversed if diagnosed early. Why not using machine learning to predict diabetes in patients using vital statistics by using datasets where patients have been diagnosed. By training a neural network, we can use it to make predictions on new patients.

2. The data

First, we use this data set from Kaggle which tracks diabetes in Pima Native Americans. We use it to build a predictive model of how likely someone is to get or have diabetes given their age, body mass index, glucose and insulin levels, skin thickness, etc.

2.1 initial observation

-Import the dataframe with pandas

We have several categories along with the outcome which is binary .

Importing the data set

```
Entrée [249]: np.set_printoptions(precision=2)
```

```
Entrée [136]: df = pd.read_csv("C:/Users/user/Python/Jupyter_notebooks/diabetes.csv")
```

```
Entrée [137]: df = df.dropna(how="any", axis=0)
```

```
Entrée [138]: df.head()
```

Out[138]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Figure 1: An exampl image

-Browse the data, listing maximum and minimum and average values

Entrée [274]: `df.describe()`

Out[274]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

Figure 2: An example

The data also needs to be scaled in order to allow the neural network to work effectively. we will talk about the Data cleaning and preprocessing in the following part.

-Check correlation with heatmap graph

That is not important for the final model but is useful to gain further insight into the data. This is the code we used for correlation map:

```
import seaborn as sns
corr = df.corr()
sns.heatmap(corr, xticklabels=corr.columns.values,
            yticklabels=corr.columns.values)
```

Out[260]: <AxesSubplot:>

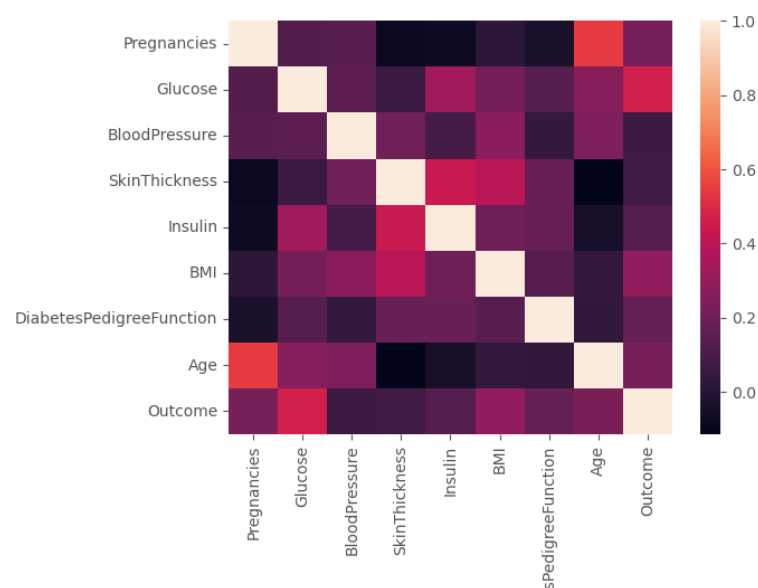


Figure 3: correlation

There's not a lot of orange squares in the chart. So, you can say that no single value is 80%. likely to give you diabetes (outcome). There does not seem to be much correlation between these individual variables. But, we will see that when taken in the aggregate we can predict with almost 75% accuracy who will develop diabetes given all of these factors together.

2.2 Data preparation

Splitting the dataset into training set and test set

```
labels=df['Outcome']
features = df.iloc[:,1:8]
from sklearn.model_selection import train_test_split
X=features
y=np.ravel(labels)
X_train, X_test, y_train, y_test = train_test_split(X,
    y, test_size=0.33, random_state=42)
```

- **Outcome** is the column with the label (0 or 1).
- The rest of the columns except the first one are the features.
- We use the scikit-learn function `train-test-split(X, y, testsize=0.33, random-state=42)` to split the data into training and test data sets, given 33% of the records to the test data set. The training data set is used to train the model, meaning find the weights and biases. The test data set is used to check its accuracy.
- **Label** is not an array. It is a column in a dataset. So we use the NumPy `np.ravel()` function to convert that to an array.

Transform data in the same scale

StandardScaler does this in two steps: `fit()` and `transform()` .

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler().fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

3. Building the Convolutional Neural Network

This neural network will be built with Keras by using the Sequential class.

```
from keras.models import Sequential
from keras.layers import Dense
model = Sequential()
```

```
model.add(Dense(7, activation='relu', input_shape=(7,)))
model.add(Dense(7, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

3.1 Activation function

Pick an activation function for each layer

For the first two layers we use a relu (rectified linear unit) activation function. That choice means nothing, as you could have picked sigmoid. relu is 1 for all positive values and 0 for all negative ones

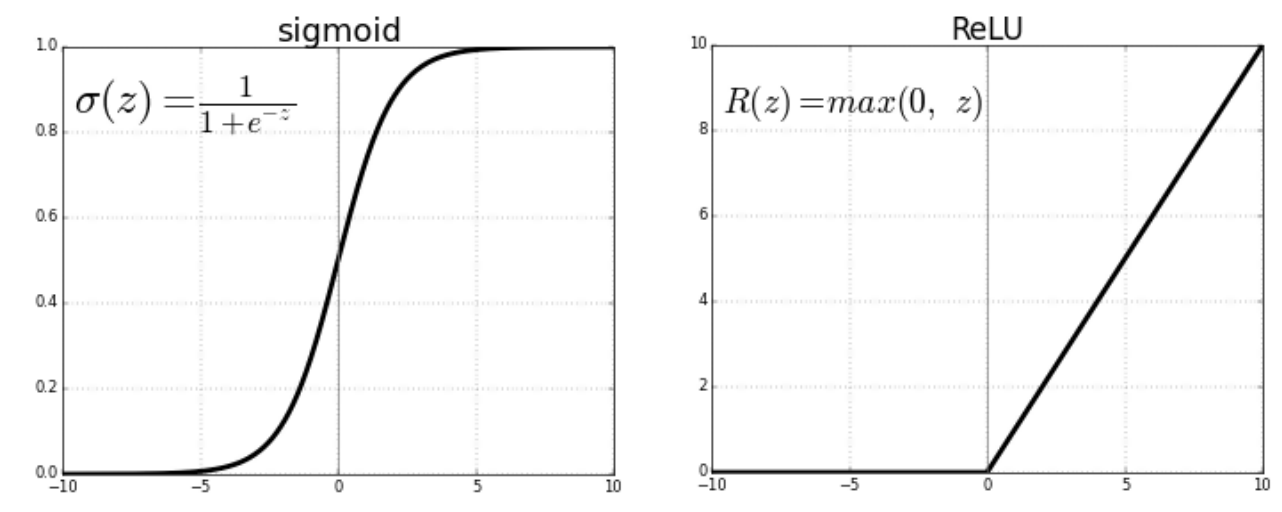


Figure 4: sigmoid and ReLU

Input-shape

we only have to give it the shape (dimensions) of the input on the first layer. It's (7,) since it's a vector of 7 features

Dense

The first argument in the Dense function is the number of hidden units, a parameter that you can adjust to improve the accuracy of the model

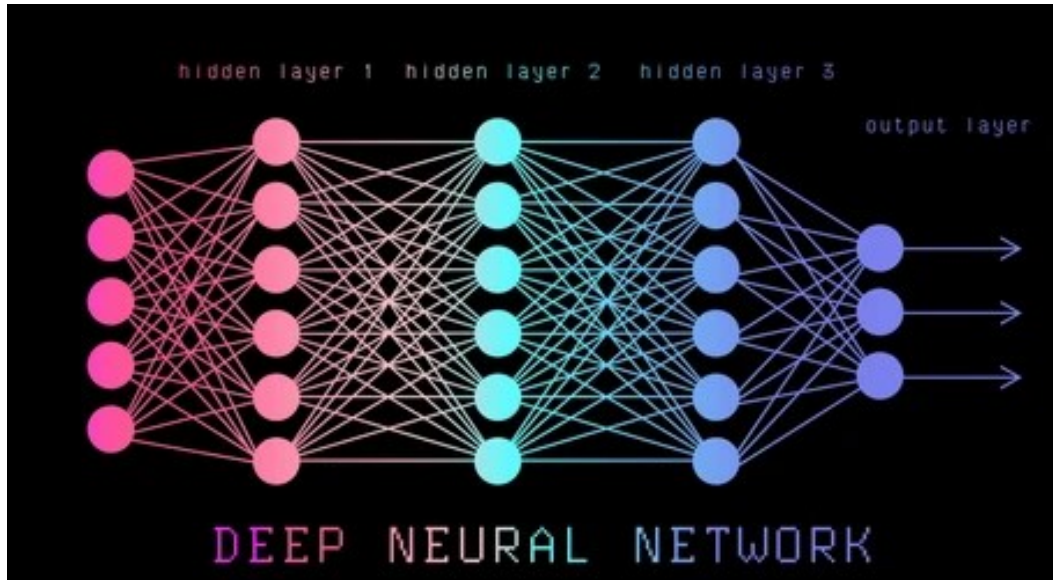


Figure 5: Neural Network

3.2 Keras model fit

```
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
H=model.fit(X_train, y_train,validation_split=0.33,epochs=200, batch_size=1, verbose=1)
print(H.history.keys())
```

Figure 6: train code

- **Loss:** the goal of the neural network is to minimize the loss function, There are many functions we can use. We pick binary-crossentropy because our label data is binary (1) diabetic and (0) not diabetic.
- **Optimizer-adam:** use the optimizer function adam, Adaptive moment estimation. It's an algorithm designed to minimize the loss function in the quickest way possible.
- **Epoch:** means how many times to run the model. it is an iterative process. You could add additional epochs, but the accuracy might not change much.
- **Batch size:** means divide the input data into n batches and process each in parallel.
- **Fit():** trains the model, meaning calculates the weights, biases, number of layers, etc.


```

from keras.models import Sequential
from keras.layers import Dense
model = Sequential()
model.add(Dense(7, activation='relu', input_shape
               =(7,)))
model.add(Dense(7, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

```

Above, we talked about the iterative process of solving a neural network for weights and bias. That's done with epochs. Here is the output as it runs those. As you can see the accuracy goes up quickly then levels off.

```

Epoch 1/30
344/344 [=====] - 6s 16ms/step -
  loss: 0.5703 - accuracy: 0.7064 - val_loss: 0.5499 -
  val_accuracy: 0.7000
Epoch 2/30
344/344 [=====] - 2s 5ms/step -
  loss: 0.4947 - accuracy: 0.7703 - val_loss: 0.5187 -
  val_accuracy: 0.7353
Epoch 3/30
344/344 [=====] - 2s 5ms/step -
  loss: 0.4654 - accuracy: 0.7820 - val_loss: 0.5022 -
  val_accuracy: 0.7471

```

4. Results

4.1 Precision

Precision

So, our predictive model is **57%** accurate while [training](#) and **85%** while [Testing](#).

```

17/17 [=====] - 0s 2ms/step - loss: 0.4206 - accuracy: 0.7977
Training Accuracy: 79.77%

8/8 [=====] - 0s 3ms/step - loss: 0.5373 - accuracy: 0.7480
Testing Accuracy: 74.80%

```

Figure 7: Neural Network

4.2 Confusion Matrix

Confusion Matrix

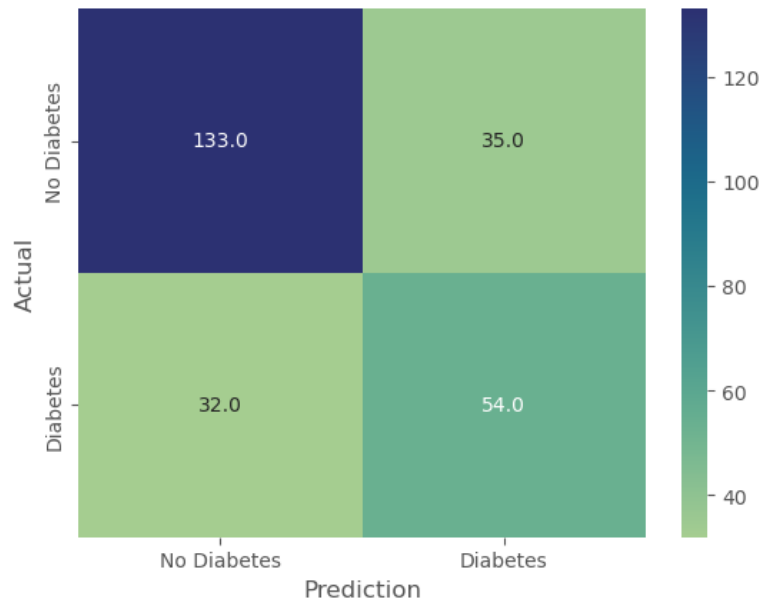


Figure 8: Confusion Matrix

- Total in dataframe(Diabetes)=86
- **wrong prediction=33**
- Total in dataframe(No Diabetes)=168
- **wrong prediction=40**

A carrefull approach can permit us to say the number of (1) outcomes are they low so the model can't predict accuratly this category of persons

4.3 classification Report

classification Report

Here you can see the precision is 61 for Diabetic(1) and 81 for non Diabetics(0) determination

Show a global classification report

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.81	0.79	0.80	168
1	0.61	0.63	0.62	86
accuracy			0.74	254
macro avg	0.71	0.71	0.71	254
weighted avg	0.74	0.74	0.74	254

Figure 9: Classifiacion Report

5. Discussion

Visualize Model Training History in Keras. You can create plots from the collected history data. he example collects the history returned from training the model and creates a chart:

In the same graph

- The accuracy on the training and validation datasets over training epochs
- The loss on the training and validation datasets over training epochs

Training Loss and Accuracy (simple_multiclass_classification)

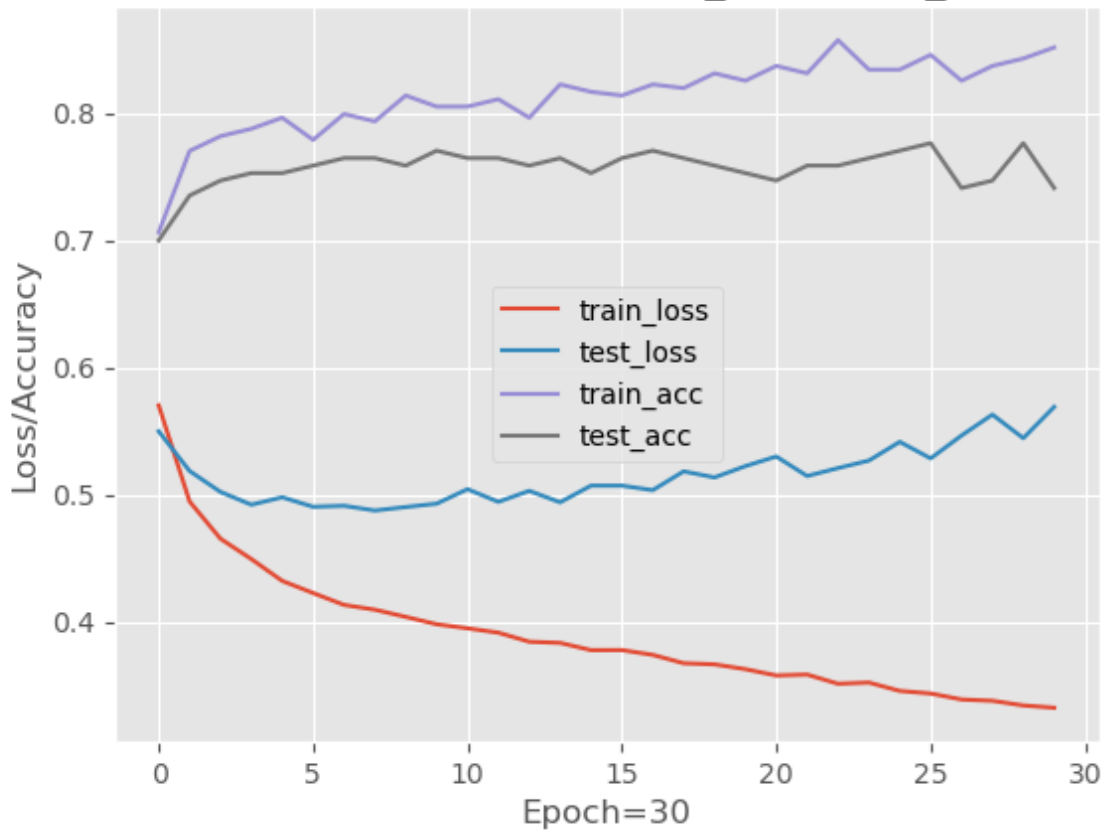


Figure 10: Confusion Matrix

-From the plot of the accuracy, you can see that the model could probably be trained a little more as the trend for accuracy on both datasets is still rising a little bit for the last few epochs

-From the plot of the loss, you can see that the model has comparable performance on both train and validation datasets (labeled test). If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch.

5.1 Limitations and Challenges

The test set accuracy was 79.87% which is not too bad for a simple neural network, but it could certainly be improved. There were only 9 false positives but 22 false negatives. There are many improvements that need to be made to this model to lower false diagnoses. This dataset only has eight categories which might not be enough to truly make accurate predictions. Feature engineering is more likely to be useful than increasing the complexity of this neural network.

6. Conclusion

It is important to note that neural networks can be more computationally intensive to train and may require more data and more time to achieve good performance, compared to some other classification algorithms. Additionally, they can be more difficult to interpret and understand, as they learn patterns in the data through the weights and biases of the network rather than through explicit rules or decision trees.

There are several advantages to using neural networks for classification tasks:

- 1.They are able to learn complex relationships between the input features and the target class.
- 2.They are able to handle large amounts of data.
- 3.They can learn from unstructured data.
- 4.They are flexible and adaptable.
- 5.They can be trained to perform well on a wide range of classification tasks.